RESEARCH ARTICLE

Direct and economy-wide energy rebound effects in China's transportation sector: a comparative analysis

Xiaoling Ouyang[1] · Junhao Zhang[2] · Gang Du[2]

Abstract

Although the existing literature has evaluated the energy rebound effect (ERE) from various aspects, the estimates of different types of ERE obtained by different methods still deserve further discussion. For this reason, by analyzing the pros and cons of assessment methods, this study offers a comparison between the direct and economy-wide EREs based on China's transportation sector during the period of 2003–2019. Specifically, on the basis of the translog cost function, we use the dynamic ordinary least square (DOLS) method with seemingly unrelated regression (SUR) to evaluate the sectoral direct ERE. Considering that the direct ERE estimation is limited by its strict assumptions, this article further assesses the sectoral ERE from a macro perspective. By constructing the dynamic two-stage panel function, the generalized method of moments (GMM) was adopted to estimate the sectoral economy-wide ERE. The empirical results demonstrate that first, capital and labor relative to energy are Morishima substitutes; second, the sectoral short-term economy-wide ERE in China was 71.60%, while the long-term economy-wide ERE was 32.00% during the study period; third, there are significant regional differences in the EREs of Chinese transportation industry both for the short and long term, and the east China demonstrated the highest sectoral economy-wide ERE.

Keywords Direct energy rebound effect · Economy-wide energy rebound effect · Transportation sector · Regional analysis

Introduction

The transportation sector is a huge consumer of energy (consumed 326 million tons of oil equivalent in 2019), accounting for 15.53% of China's final consumption (CEIC Database 2022). With the further investment in transport infrastructure, the transportation sector in China is expected to show substantial increases in activity and fuel use. Given the impact of the transportation sector on national energy security and air quality, continuous efforts have been made to curb energy use and carbon emissions from various transportation modes.

Upgrade of transport equipment is one of the highest priorities for China' transportation sector to promote energy enhancement and emission reduction. Promoting energy efficiency improvements is also a major focus at the environmental policy level such as the "fuel consumption limits for passenger cars" and "fuel consumption evaluation methods and targets for passenger cars." However, the actual energy-saving effect of such policies is not as efficient as expected due to the existence of the energy rebound effect (ERE). Therefore, the existence of the ERE should be considered when implementing transport energy efficiency improvement policies.

Existing literature has assessed the ERE from various aspects at national, regional, and sectoral levels (Lin and Liu 2013; Shao et al. 2014; Chen et al. 2021). Due to the differences in regional economic development and the unbalanced infrastructure constructions, as well as the industrial

✉ Gang Du
  gdu@dbm.ecnu.edu.cn

  Xiaoling Ouyang
  xlouyang@jjx.ecnu.edu.cn

  Junhao Zhang
  51204402009@stu.ecnu.edu.cn

[1] School of Economics, Faculty of Economics and Management, East China Normal University, Shanghai 200062, China

[2] School of Business Administration, Faculty of Economics and Management, East China Normal University, Shanghai 200062, China

structures, there are significant regional differences in the EREs in China's economic sectors (Wang et al. 2012; Wang et al. 2014; Zhang et al. 2015; Zhang and Lin 2018; Li et al. 2019). Although existing literature confirms the existence of the ERE in China's transportation sector, it is still necessary to further analyze the magnitudes as well as the sectoral short- and long-term EREs and the differences among regions.

This study focuses on the evaluation of ERE in the transportation sector in China and compares the differences between direct and economy-wide EREs. The main contributions of this study are summarized as follows. First, we adopt the dynamic ordinary least squares (DOLS) and seemingly unrelated regression (SUR), which consider the substitutional or complementary relationships between input factors, to evaluate the direct ERE of China's transportation sector. Second, we adopt the generalized method of moments (GMM) and the two-stage dynamic panel data approach to evaluate the sectoral economy-wide ERE. The dynamic function allowed us to evaluate the magnitude of the ERE both in the short and long term, and the GMM can eliminate the "dynamic panel bias" problem compared with the traditional panel regression methods. Third, most of the existing literature on ERE estimates focuses on exploring the characteristics and applicability of different measures while ignoring the comparability of different ERE estimation results. For this reason, we compare the differences between direct and economy-wide ERE estimates in this study. According to the features of these two concepts, substitutional or complementary relationships among input factors are analyzed in the framework of direct ERE estimates. Meanwhile, the short- and long-term comprehensive rebound indicators are calculated in the framework of economy-wide ERE.

The structure of the article is as follows: The "Literature review" section reviews the previous literature about the ERE. The "Methodology" section introduces the methods and models used in the research. The "Data source and processing" section presents the data resource and data processing. The "Empirical results and discussion" section demonstrates the empirical results and analysis. The "Conclusions and implications" section provides the main conclusions and policy suggestions.

Literature review

Energy rebound effect (ERE) refers to the phenomenon that the potential energy consumption reductions resulting from improved energy efficiency are offset by increased energy demand (Saunders 1992). Based on market responses to changes in fuel efficiency, the ERE can be roughly divided into the following three categories: direct rebound effects, indirect rebound effects, and economy-wide rebound effects

(Greening et al. 2000). The direct and indirect EREs are measured from the microeconomic perspective, in terms of the effect of the relative decrease in the price of energy services, and thus cannot consider the long-term effects of changes in the cost of capital (Ouyang et al. 2018a; Liu et al. 2019). The measurement of economy-wide EREs is based on the macro perspective, which takes into account the re-adjustment of price and quantities along with the dynamics of economic growth promoted by efficiency change (Adetutu et al. 2016).

An emerging literature documents the rebound effect of efficiency improvement on transport energy consumption from a specific sector such as urban road passenger traffic (Wang et al. 2012; Lin and Liu 2013), passenger cars (Moshiri and Aliyev 2017), and road freight (Sorrell and Stapleton 2018). The existing studies on the ERE in the transportation industry has the following characteristics: first, most of the literature focuses on estimating the sectoral direct ERE, which and cannot incorporate the effect of dynamic changes in energy efficiency in the estimation; second, the differences between the estimates of the ERE obtained by using different estimation methods are relatively large, and there is a lack of comparative analysis of the estimated results of different types of EREs.

The literature on economy-wide ERE expands the research perspective to the macro-level (Pfaff and Sartorius 2015; Adetutu et al. 2016; Galvin 2020; Adha et al. 2021). The most common approach to estimate the economy-wide ERE is the computable general equilibrium (CGE) model (Broberg et al. 2015; Lu et al. 2017; Zhou et al. 2018; Du et al. 2020), the estimates based on which relies on strict assumptions such as market equilibrium, perfect competition, and constant returns to scale. Several scholars use the macroeconomic models and econometric analysis method (Brockway et al. 2021). For example, based on an energy efficiency index measured by the DEA model, Lin and Du (2015) used the ridge regression method to estimate the translog function of three types of inputs and calculated the final ERE in China during 1981–2011 with an average magnitude of 34.3%. Adetutu et al. (2016) used the two-stage dynamic panel data method and stochastic frontier analysis (SFA) to estimate the magnitude of short-term and long-term ERE of 55 countries from 1980 to 2010. The two-stage dynamic panel method divides the ERE estimation into two stages, which can avoid the use of alternative indicator or assumption for energy efficiency estimation.

The existing literature has analyzed the differences in EREs between regions in China. For example, based on China's provincial data of road passenger transportation from 2003 to 2012, Zhang et al. (2015) used the dynamic panel quantile regression model to calculate the sectoral the short- and long-term ERE in China's regions. Using China's city-level data on road transport from 2003 to 2013, Zhang and

Lin (2018) indicated that the eastern coastal region had the highest fuel efficiency (0.914) and the highest ERE (82.2%), while the northeast region had the lowest energy efficiency (0.612) and the lowest ERE (7.2%). Adopting China's provincial data from 2003 to 2017, Zheng et al. (2022) used the nonlinear least square method to calculate the ERE in the transportation sector under the framework of endogenous growth theory. The result showed a decreasing trend of ERE from eastern to western regions which was attributed to the relationship between supply and demand of products.

To sum up, although the analysis of the ERE of China's transportation sector has attracted increasing attention of scholars in recent years, there are still some rooms for improvement. Firstly, the estimation results of EREs depend on the corresponding assumptions (Bentzen 2004; Sorrell et al. 2009), and the strict assumptions can make the estimation results prone to bias (Stapleton et al. 2016). The economy-wide ERE overcomes the deficiency of strict assumptions implicit in the estimation of the direct ERE (Yan et al. 2019). Secondly, the estimation of the direct ERE also has its value; for example, through this method, we are able to make a further analysis of factor relationships in the process of factor price elasticity calculation (Sorrell and Dimitropoulos 2008). Therefore, the estimation of the direct ERE can not only provide a reference for the estimation results of the economy-wide ERE, but also can form a useful complement to the estimation of the economy-wide ERE from the perspective of factor input relationship analysis. Finally, regional differences in the ERE are frequently studied from the perspective of direct ERE, and there were insufficient research on the explanations of regional differences from the macro perspective of ERE evaluation.

Methodology

Direct energy rebound effect

Cost-share equation model

This study selects the translog cost function model to construct the cost-share equation of each factor and further estimate the price elasticity among input factors. Referring to Lin and Li (2014), the cost-share equation model based on the translog cost function is constructed by the following steps:

$$Y = Y(K, L, E) \tag{1}$$

where Y is the output of the transportation sector measured by freight and passenger turnover, K is the capital stock of the transportation sector, L is the sectoral employment, and E is the amount of sectoral energy consumption.

Under the assumption that the output level and factor price are exogenous variables, the cost function can be written as follows:

$$C = C(P_k, P_l, P_e, Y) \tag{2}$$

where C is the production cost of the transportation sector; P_k, P_l, and P_e denote the prices of input factors of capital, labor, and energy.

In the framework of the translog cost function, Eq. (2) can be written as:

$$\ln C_t = \alpha_0 + \delta_y \ln Y_t + \sum \delta_i \ln Y_t \ln P_{it} + \frac{1}{2}\delta_{yy}(\ln Y_t)^2 \\ + \sum \alpha_i \ln P_{it} + \frac{1}{2}\sum\sum \beta_{ij} \ln P_{it} \ln P_{jt} + \varepsilon_t; \\ i, j = K, L, E \tag{3}$$

where C_i is the cost, Y_t is the output; P_{it} is the price of the ith input factor, P_{jt} is the price of the jth input factor, and ε_t is the random error.

According to Shepard's lemma, the demand for each factor can be obtained by the partial derivatives of factor prices in the cost function ($X_i = \partial C / \partial P_i$). We took the derivatives of the factor price logarithm on both sides of Eq. (3), assuming that the technological progress is Hicks-neutral, and added the term of the time trend. The cost-share equation is obtained as follows:

$$S_{it} = \alpha_i + \delta_i \ln Y_t + \sum_i \beta_{ij} \ln P_{jt} + \gamma_i T + \varepsilon_{it} \quad i,j = K, L, E \tag{4}$$

where

$$S_{it} = \frac{\partial \ln C_t}{\partial \ln P_{it}} = \frac{P_{it}}{C_t}\frac{\partial C_t}{\partial P_{it}} = \frac{P_{it}X_{it}}{C_t} \tag{5}$$

X_{it} is the input of the ith factor, S_{it} denotes the cost-share of the ith factor, and T is the time trend.

Equation (6) is the simultaneous equations consisting of three equations, which satisfy the following conditions under the framework of neoclassical theory:

$$\sum_i \alpha_i = 1, \quad \sum_i \delta_i = 1, \quad \sum_i \gamma_i = 1 \\ \sum_i \beta_{ij} = \sum_i \beta_{ij} = 0 \\ \beta_{ij} = \beta_{ji} \tag{6}$$

Price elasticity calculation

After estimating the parameters of the above cost-share equation, we focus on the self-price elasticity σ_{it} and the cross-price elasticity σ_{ij}. The self-price elasticity of the energy factor is an alternative index to measure the direct ERE, while the cross-price elasticity of the factors reflects the sensitivity of demand for one factor to the price change of another factor.

Substitution possibilities of other factors on energy can be identified according to the cross-price elasticity (Lin and Tian 2016).

The Allen-Uzawa elasticity of substitution (AES) has been commonly used to measure the substitution elasticity in the existing empirical studies:

$$AES_{ij} = \frac{\beta_{ij} + S_i \, S_j - S_i \omega_{ij}}{S_i \, S_j} \tag{7}$$

If $i=j$, $\omega_{ij}=1$; if $i \neq j$, $\omega_{ij}=0$

The AES is symmetric; that is, $AES_{ij} = AES_{ji}$. The symmetry of AES has the advantages of simplicity and practicability; however, it has the disadvantage of inaccuracy in analyzing the changes in price, interest rate, and other variables (Chitnis et al. 2014). Thus, many scholars adopt the cross-price elasticity (CPE) to amend the AES (Frondel 2004):

$$CPE_{ij} = AES_{ij} + S_i \tag{8}$$

CPE provides reliable estimates of factor self-price elasticity ($i=j$); however, the cross-price elasticity reflected by *CPE* describes the absolute substitution elasticity among factors and has weak explanatory power when the proportion of factors changes relatively. Therefore, we adopt the Morishima elasticity of substitution (MES) proposed by Morishima (1967), which can be used to estimate the sensitivity of the proportion change of two input factors to the price change of one factor:

$$MES_{ij} = CPE_{ij} - CPE_{ii} \tag{9}$$

We use the estimates of parameters in Eq. (4) to calculate the factor self-price elasticities σ_{ii} and the cross-price elasticity among factors (Morishima elasticity of substitution) σ_{ij}:

$$\sigma_{ij} = \frac{\beta_{ii} + S_i^2 - S_i}{S_i} \tag{10}$$

$$\sigma_{ij} = S_i\left(\sigma_{ij}^A - \sigma_{jj}^A\right) = S_j\left(\frac{\beta_{ij} + S_i \cdot S_j - S_i}{S_i \cdot S_j} - \frac{\beta_{ij} + S_j^2 - S_j}{S_j^2}\right) \quad i \neq j \tag{11}$$

Economy-wide energy rebound effect

Short- and long-term economy-wide energy rebound effect

According to Sorrell and Dimitropoulos (2008), the economy-wide ERE is defined as follows:

$$R = 1 + \eta_\xi \tag{12}$$

where η_ξ represents the elasticity of energy consumption relative to energy efficiency $\frac{d \ln E}{d \ln \xi}$ Therefore, the key to meas-

uring the ERE is to estimate the efficiency elasticity of energy consumption.

To estimate η_ξ, we construct an unknown function composed of the natural logarithm of energy price, output, and energy efficiency to represent the natural logarithm of energy consumption according to the economic theory:

$$\ln E_{it}^* = f\left(\ln P^e_{it}, \ln Y_{it}, \ln \xi_{it}\right) + \mu_i + \varepsilon_{it} \tag{13}$$

where the subscript i represents the ith province and t represents time, E_{it}^* represents the optimal energy consumption, P^e_{it} is the price of energy, Y_{it} is the transport turnover, ξ_{it} represents the energy efficiency, μ_i is the intercept of a specific province, and ε_{it} is the error term.

In addition, energy is the power we use for transportation (Li et al. 2019), which indicates that energy consumption cannot be adjusted in an instant, so the actual change of energy consumption can be assumed to be a dynamic process (Adetutu et al. 2016).

$$\ln E_{it} - \ln E_{it-1} = (1 - \delta)\left(\ln E_{it}^* - \ln E_{it-1}\right) \tag{14}$$

E_{it} represents the actual energy consumption, while δ is the adjusted ratio. By combining Eqs. (13) and (14), the following relationship can be obtained:

$$\ln E_{it} = \delta \ln E_{it-1} + (1 - \delta)f\left(\ln P_{it}, \ln Y_{it}, \ln \xi_{it}\right) + \left(\alpha_i + \nu_{it}\right) \tag{15}$$

Among them, $\alpha_i = (1 - \delta)\mu_i$ and $\nu_{it} = (1 - \delta)\varepsilon_{it}$. Furthermore, in order to estimate the elasticity of energy consumption relative to energy efficiency, we use the second Taylor expansion to approximate the value of $f(\ln P_{it}, \ln Y_{it}, \ln \xi_{it})$. Therefore, Eq. (15) can be rewritten as:

$$\begin{aligned}
\ln E_{it} = &\,\delta \ln E_{it-1} + \beta_1 \ln P_{it} + \beta_2 \ln Y_{it} + \beta_3 \ln \xi_{it} \\
&+ \frac{\beta_4}{2} \ln P_{it} \ln \xi_{it} + \frac{\beta_5}{2} \ln Y_{it} \ln \xi_{it} + \frac{\beta_6}{2} \ln P_{it} \ln Y_{it} \\
&+ \frac{\beta_7}{2}\left[\ln \xi_{it}\right]^2 + \frac{\beta_8}{2}\left[\ln Y_{it}\right]^2 + \frac{\beta_9}{2}\left[\ln P_{it}\right]^2 + \left(\alpha_i + \nu_{it}\right)
\end{aligned} \tag{16}$$

Based on Eq. (16), the short-term elastic efficiency can be obtained:

$$\eta_{\xi,it}^{sr} = \frac{\partial \ln E_{it}}{\partial \ln \xi_{it}} = \beta_3 + \frac{\beta_4}{2} \ln P_{it} + \frac{\beta_5}{2} \ln Y_{it} + \beta_7 \ln \xi_{it} \tag{17}$$

The magnitude of the ERE calculated from Eq. (17) is not constant but depends on energy prices, income levels, and energy efficiency, which conforms to the intuition of economic theory.

The calculation of long-term energy efficiency should take into account the adjusted ratio δ, where δ is estimated by Eq. (16). Therefore, we can obtain the long-term efficiency flexibility:

$$\eta_{\xi,it}^{lr} = \frac{\beta_3 + \frac{\beta_4}{2}\ln P_{it} + \frac{\beta_5}{2}\ln Y_{it} + \beta_7 \ln \xi_{it}}{1 - \delta} \qquad (18)$$

Through the above two equations, the short-term and the long-term economy-wide EREs are calculated, respectively. Since all the parameters with estimated can be obtained from Eq. (16), the statistical noise may affect the accuracy of estimates. In response to this problem, we refer to Zhang and Lin Lawell (2017) and use the Delta method to construct a 95% confidence interval based on the estimation results.

Dynamic energy efficiency metrics

As we discussed above, a comprehensive measurement of energy efficiency should incorporate not only the static efficiency of energy use but also the technical change regarding energy use. Accordingly, unlike the static efficiency index suggested by Adetutu et al. (2016), we use a Malmquist energy productivity index (MEPI) as the proxy for the energy efficiency in this study. Following Du and Lin (2017), we measure the total energy productivity based on the Shephard energy distance function which is defined as:

$$D_E^t(K, L, E, Y) = \sup\left\{\theta | (K, L, E/\theta, Y) \in P^t\right\} \qquad (19)$$

where the superscript t denote time; K, L and E denote capital, labor, and energy inputs, respectively; Y denotes desirable outputs; P^t and refers to the production technology at time period t that can be expressed as:

$$P^t = \{(K, L, E) \text{ can produce } Y\} \qquad (20)$$

The Shephard energy distance function describes the maximum reduction of energy input while keeping the other inputs (capital and labor) and the outputs unchanged with a certain level of production technology. The efficiency of energy utilization is usually defined as the ratio of the optimal (minimum) energy input to the actual energy input (Hu and Wang 2006). In this sense, it can be calculated as $1/D_E^t(K, L, E, Y)$. Obliviously, it is a static measurement of energy efficiency which does not considers the energy technological progress.

The Malmquist energy productivity index for province i is defined as:

$$MEPI_i^{t,t+1} = \frac{D_E^t\left(K_i^t, L_i^t, E_i^t, Y_i^t\right)}{D_E^{t+1}\left(K_i^{t+1}, L_i^{t+1}, E_i^{t+1}, Y_i^{t+1}\right)}$$
$$\times \left[\frac{D_E^{t+1}\left(K_i^{t+1}, L_i^{t+1}, E_i^{t+1}, Y_i^{t+1}\right) \times D_E^{t+1}\left(K_i^t, L_i^t, E_i^t, Y_i^t\right)}{D_E^{t+1}\left(K_i^{t+1}, L_i^{t+1}, E_i^{t+1}, Y_i^{t+1}\right) \times D_E^t\left(K_i^t, L_i^t, E_i^t, Y_i^t\right)}\right] \qquad (22)$$
$$\equiv EFFCH_i^{t,t+1} \times TECCH_i^{t,t+1}$$

$EFFCH_i^{t,t+1}$ indicates whether the ith DMU get closer to or farther away from the frontier. In this study, the transportation sector of each province is regarded as a DMU. Thus, it refers to the change of energy utilization efficiency. $TECCH_i^{t,t+1}$ reflects the shift of the production frontier alongside the energy direction, which measures the change of energy technology. Equation (22) shows that the energy productivity change is the result of energy utilization change and energy technology change. It is a dynamic energy efficiency measurement which takes account into both changes in energy utilization efficiency and energy technology.

The data envelopment analysis (DEA) approach can be used to estimate MEPI. As a non-parametric approach, DEA approach is widely used for efficiency measurement in literature. Compared with the other mainstream approach stochastic frontier analysis (SFA), DEA can avoid the potential model misspecification. Under the framework of DEA, the transportation of each province in the data set is regarded as a DMU, and the sectoral energy efficiency of each province during the corresponding period can also be well measured.

Data source and processing

This study employs a panel data set of China's transportation sector in 30 provinces during the 2003–2019 period, including the capital, labor, and energy inputs, as well as its corresponding prices and outputs. The full sample is divided into eastern, central, and western regions according to the Fourth National Economic Census report of the National Bureau of Statistics[1]. Data sources include the CEIC China Premium database (2022) and various yearbooks such as the China Statistical Yearbook, the China Financial Yearbook, and the 2004 China Census Yearbook. All variable concerning prices were converted into the constant prices

$$MEPI_i^{t,t+1} = \left[\frac{D_E^t\left(K_i^t, L_i^t, E_i^t, Y_i^t\right) \times D_E^{t+1}\left(K_i^t, L_i^t, E_i^t, Y_i^t\right)}{D_E^t\left(K_i^{t+1}, L_i^{t+1}, E_i^{t+1}, Y_i^{t+1}\right) \times D_E^{t+1}\left(K_i^{t+1}, L_i^{t+1}, E_i^{t+1}, Y_i^{t+1}\right)}\right]^{1/2} \qquad (21)$$

Equation (21) measures the energy productivity change between time period t. It can be decomposed as:

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[1] Specifically, the eastern region includes Beijing, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin, and Zhejiang; the central region includes Anhui, Heilongjiang, Henan, Hubei, Hunan, Jiangxi, Jilin, and Shanxi; and the western region includes Chongqing, Gansu, Guangxi, Guizhou, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Sichuan, Xinjiang, and Yunnan.

in 2003. Specifically, the source and processing methods of each variable are described as follows:

(1) Input variables

Energy consumption (E)

The terminal energy consumption of coal, oil, natural gas, liquefied petroleum gas (LPG), and electricity was obtained from each province's energy balance table of transportation, warehousing, and the postal sector in the CEIC China Premium database (2022). Due to the different energy units, we converted the physical quantity of different types of energy into a unified unit of million tons of standard coal, referring to the energy standard coal conversion coefficient of the transportation sector adopted by Xie and Hawkes (2015).

Capital input (K)

Since the estimation method of the capital stock has been relatively mature, we adopt the method of calculating the capital stock of the transportation sector infrastructure proposed by Li and Zhang (2016) and employ the perpetual inventory method (PIM) to estimate the annual capital stock data of the transportation sector. The specific calculation method can be expressed as $K_t = I_t + (1 - \delta) \cdot K_{t-1}$, where K_t and K_{t-1} refer to the capital stocks in the transportation sector of year t and the previous year, respectively. I_t is the investment of fixed assets of the transportation sector that excludes the price factor in year t, and δ stands for the depreciation rate of fixed assets in the transportation sector. The specific index estimation methods are described as follows: (1) Base period capital stock: the total capital stock of infrastructure was obtained by aggregating the capital stock of economic and social infrastructure from all provinces in 2004 (Ouyang et al. 2018b). Given the non-infrastructure capital, we can obtain the total fixed capital of the whole society. The investment price index of fixed assets is converted into prices regarding the index of 2004. The total capital stock of the transportation sector was estimated with the proportion of the transportation sector infrastructure capital that accounted for the national infrastructure capital and the fixed capital of the whole society in 2004. It was converted into prices regarding the index of 2003 based on the fixed asset investment price index to obtain the capital stock at the base period. (2) Fixed assets investment: the provincial fixed assets investment data in the transportation sector were obtained from the CEIC China Premium database (2022), and the investment in the previous years was converted into a constant price in 2003 based on the fixed asset price index. (3) Depreciation rate: the comprehensive depreciation rate of fixed assets in transportation sector was 8.76%.

Labor input (L)

After obtaining the number of employed people in highways, waterways, railways, and aviation in transportation sector from the CEIC China Premium database (2022), the labor input was calculated as the sum of private enterprises and individual employers and employees in urban units from the transportation sector of all provinces.

(2) Output of the transportation sector

The sectoral output is measured by the transport turnover of the transportation sector (100 million tons). The passenger and freight turnovers of the transportation sub-sectors (road, rail, water, aviation) in the CEIC China Premium database (2022) are employed as basic data. Passenger turnover is converted into freight turnover. The conversion ratios of road, rail, water, and aviation were 0.1, 1, 0.3, and 0.075, respectively.

Due to the availability of a more intuitive index "added value of transportation sector," the transport turnover volume is a qualified alternative indicator for measuring output of transportation sector. As a productive sector, the transportation industry directly provides services to consumers while producing products. The transportation turnover volume is a reasonable index to estimate the output of the transportation sector based on pragmatism (Xie et al. 2018). On the other hand, the output of the transportation sector can be measured by constructing a comprehensive index by giving different weights to the transportation turnover volume of different transportation modes.

(3) Price variables

Energy price (P_e)

(1) First, we collected price data for various energy sources of each province in 2004 from the China Coal Sector Statistics Compilation, the Petroleum and Chemical Sector Statistical Yearbooks, and the China Price Yearbooks. Due to the data availability, the prices of crude oil, fuel oil, and kerosene are the data at the national level, while the prices of gasoline, diesel, residential natural gas, and residential electricity are the data at city level, extracting from the energy price data of 36 large and medium-sized cities. (2) The above data are then weighted by the consumption amount to obtain the exact prices of coal, oil, natural gas, liquefied petroleum gas, and electricity. Specifically, the coal price is replaced by the raw coal price directly; the oil price

Table 1 Statistical description of input and output variables.

Variable	Description	Mean	Std. dev.	Min	Max	Obs
E	Energy consumption (million tons of coal equivalent)	9.0208	6.4748	0.2700	36.4242	510
K	Capital input (ten billion CNY)	27.5067	25.2479	0.3708	144.59	510
L	Labor input (ten thousand people)	1.7303	1.0818	0.2011	6.4146	510
p_e	Energy price (million CNY per ton of coal equivalent)	50.0492	13.9437	18.9537	101.3926	510
p_k	Capital price (%)	13.9055	5.1819	2.6565	33.0824	510
p_l	Labor price (one hundred thousand CNY per capita)	40.6425	21.2883	9.8749	138.6566	510
Y	Comprehensive transport turnover (hundred million tons)	4705.098	4919.818	142.67	30453.49	510

Note: In the empirical analysis of the direct ERE, we use S_k, S_l and S_e calculated from Eq.(5) as the dependent variables

is weighted by the final energy consumption of crude oil, fuel oil, gasoline, kerosene, and diesel in the transportation, warehousing, and postal industries; and the natural gas and electricity prices are both weighted by the total consumption of industrial prices and residential prices. (3) Finally, fuel and power price indexes of each province are employed to calculate the energy prices during the study period. The fuel and power price indexes in 2004 are collected from the statistical yearbooks of each province. The data of the 2005–2012 period came from the China City (town) Life and Price Yearbooks, and the data of the 2013–2019 period came from the China Price Yearbooks. We calculated the growth rate of energy price based on the fuel and power price indexes of each province and obtained various energy price data from 2003 to 2019 in combination with prices in 2004. According to the previously mentioned coal conversion standard, we weighted each types of terminal energy consumption to obtain the energy input prices.

Capital price (P_k)

According to Tao et al. (2009), the capital price is calculated as $P_{K,t} = \left(1 + h_t\right)\frac{1-u_t z_t}{1-u_t}\left(q_{t-1}r_{cp,t} + q_t\delta - \gamma_t\right) + q_t\omega_t$, among which h_t refers to the VAT rate, u_t represents the corporate income tax rate z_t is the depreciation deductible present value rate, q_t is the fixed asset investment price index, $r_{cp,t}$ is the return on assets, γ_t is the difference between the investment price index of year t and year t-1, and ω_t is the property tax rate (Ouyang et al. 2019). The specific data processing is reported as follows. (1) Return on assets: the nominal interest rate. We employ the fixed deposit rate of the transactions of the urban and rural residents and units within a year in China Financial Statistics Yearbooks. When there were multiple interest rates in 1 year, we performed a time-weighted average calculation based on the Financial Institutions Interest Rate Adjustment Table. (2) Depreciation deductible present value rate: stipulated by the relevant laws

of China, the straight-line depreciation method is adopted by enterprises. The calculation formula, $z_t = \int_0^r \frac{e^{-rs}}{\tau}ds = \frac{1-e^{-rr}}{r\tau}$, was used, where r stands for the nominal interest rate and τ represents the depreciation period. Based on relevant laws, the depreciation period of the transportation sector is 15 years. (3) Corporate income tax rate: the enterprise income tax rate of each province is calculated, given the total income tax interests and profits of enterprises. (4) VAT rate: the statutory VAT rate of 17% is adopted. (5) Property tax rate: the property tax rate suggested by Tao et al. (2009) is 0.2%.

Labor price (P_l)

Regarding the labor price calculation method (Lin and Li 2014), the labor remuneration of employees in various sub-sectors of the transportation sector and the sectoral average number of employees are obtained from China Economic Census Yearbooks. Combined with the consumer price index (CPI), the sectoral real wages per capita of each province at the 2004 constant prices are calculated. We then associate them with the actual average wage index to calculate the actual wage growth rate and then obtain the sectoral actual average wages of employees in each province as the labor price. The consumer price index and the actual average wage index are derived from the CEIC China Premium database (2022).

(4) Input factor shares

The input factor shares (S_e, S_k, S_l), are calculated according to Eq. (5). Specifically, the prices of each input factor mentioned above are multiplied by the amount of input to obtain the use cost of each input factor (C_e, C_k, C_l). The share of each factor's cost is the proportion of the input cost of each factor to the total production cost, which is $S_i = C_i/C_T$.

Descriptive statistics of input and output variables are shown in Table 1.

Table 2 Parameter estimation results of the factors share equations (SUR).

Variables	(1)	(2)	(3)
	S_i	S_k	S_e
$\ln p_l$	0.0946*** (0.0072)	−0.2093*** (0.0209)	0.1150*** (0.0179)
$\ln p_k$	−0.0343 (0.0103)	0.2094*** (0.0302)	−0.1752*** (0.0260)
$\ln p_e$	−0.0502*** (0.0085)	−0.1442*** (0.0247)	0.1943*** (0.0212)
Y	−0.0053*** (0.0018)	−0.0194*** (0.0054)	0.0247*** (0.0021)
T	−0.0049*** (0.0008)	0.0367*** (0.0025)	−0.0318*** (0.0021)
cons	0.1123* (0.0437)	0.9941*** (0.1286)	−0.1066 (0.1106)
R^2	0.416	0.610	0.655
Unit root test	−9.4433 {0}	−9.4433 {0}	−9.4433 {0}

Note: The figures in the parentheses are the corresponding t statistic of the parameter estimates. *, **, and *** denote that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively. {0} represents that the unit root does not exist in the data, implying that the data are stationary

Empirical results and discussion

Direct energy rebound effect

As for research methods, estimation errors are likely to occur when the sample size is small by using the OLS (Small and Dender 2007; Jin 2007). Therefore, this study referenced Bentzen (2004), Lin and Li (2014), and Lin and Tian (2016) by using a dynamic least square method (DOLS), which is suitable for small observations and variables with an order list of the whole data. Furthermore, the SUR can handle the problem of serial correlation that may occur by using the DOLS, thus improving the efficiency of estimation (Westerlund 2005). Therefore, combined with the SUR, the DLOS can effectively reduce the small sample bias and simultaneous bias, improving the reliability of estimated results (Stock and Watson 1993; Lin and Tian 2016).

Results of the unit root test (URT) show that *lnY* is stationary after the first-order differential. Considering the nature of the sample data and the application of factors share equations (SUR), this study uses the DOLS framework for parameter estimation. The factor cost-share equation can be written as:

$$S_{it} = \alpha_i + \delta_i \ln Q_t + \sum_i \beta_{ij} \ln P_{jt} + \gamma T + \sum_{r=-m}^{m} \varphi_i \Delta \ln Y_{t+r} + \sum_{k=-n}^{n} \phi_{ij} \Delta \ln P_{j,t+k} + \varepsilon_{it} \tag{23}$$
$$i, j = L, K, E$$

According to the Akaike information criterion (AIC) and Bayesian information criterion (BIC) information guidelines, the first-order leading and lagging terms are selected for the data. As shown in Table 2, most parameters are statistically significant at the 1% and 5% significance levels. For the unit root test of the residuals of each equation, their residual sequences are all white noise processes at the significant level of 1%.

Based on the parameter estimates in Table 2, we further calculate the price elasticity of each input factor in China's transportation sector according to Eqs. (10) and (11). We calculate the self-price elasticity of each input of the transportation sector and the Morishima substitution elasticities between the input factors. The results are reported in Table 3.

As shown in Table 3, we discover that the self-price elasticity and the Morishima substitution elasticity between the input factors are in a reasonable range. The results also indicate that all the substitution elasticities are positive except for labor-energy and capital-labor. The two negative values indicate that when energy or labor price rises, the ratio of labor input to energy input or capital investment to labor input will decline. Particularly, both energy-capital and capital-energy substitution elasticities are positive, reflecting that in the transportation sectors, capital and energy are the Morishima substitutes. However, since the absolute value of energy-capital substitution elasticity is less than the absolute value of capital-energy substitution elasticity, the capital to energy ratio will increase if both maintain the same price growth rate. Furthermore, the capital-energy substitution elasticity is greater than the energy-capital

Table 3 Self-price elasticity and cross-price elasticity of alternatives in China's transportation sector.

$\sigma_{ii}/\sigma_{ij}^M$	Energy (E)	Capital (K)	Labor (L)
Energy (E)	**−0.1089**	0.0933	0.2927
Capital (K)	0.2100	**−0.0779**	−0.4495
Labor (L)	−0.0273	0.0310	**0.2029**

Table 4 Parameter estimation results of the factors share equations.

Variable	Parameter	OLS	FE	*sys*GMM
L.lnE	δ	0.8987*** (0.0118)	0.6481*** (0.0382)	0.5824*** (0.0503)
lnP$_e$	β_1	0.2187 (0.4775)	1.7404** (0.7000)	−1.3984 (0.9956)
lnY	β_2	0.5084*** (0.0957)	0.7557*** (0.1827)	0.8412 (0.6036)
Lnξ	β_3	−4.4200*** (0.3169)	−3.3976*** (0.4861)	−3.1198*** (0.6316)
0.5×lnP$_e$×lnξ	β_4	1.8099*** (0.2003)	1.3415*** (0.2763)	1.2151*** (0.3131)
0.5×lnξ×lnY	β_5	0.1358*** (0.0479)	0.1124 (0.0822)	0.1155** (0.0488)
0.5×lnP$_e$×lnY	β_6	−0.1971*** (0.0524)	−0.2368** (0.0940)	−0.4134 (0.4352)
0.5×[lnξ]^2	β_7	−0.0421 (0.0350)	−0.0661** (0.0269)	−0.0134 (0.0517)
0.5×[lnY]^2	β_8	−0.0078 (0.0108)	−0.0159 (0.0180)	0.0214 (0.0461)
0.5×[lnP$_e$]^2	β_9	0.1234 (0.1326)	−0.1865 (0.1960)	−0.0936 (0.5514)
Cons	α	−2.2531** (0.9282)	−6.4423*** (1.4255)	−6.2654 (2.4634)
AR(1) (p value)				0.0013
AR(2) (p value)				0.5151
Sargan test (p value)				1.0000
N		480	480	480

substitution elasticity, indicating that the change in energy price dominates the substitution relationship between energy and capital.

Given small absolute value of σ_{LE}, the complementary effect between labor and energy is not obvious. However, it is worth noting that the value σ_{EL} is the largest elasticity in Table 3, indicating that there is a significant substitute relationship once the labor price increases in the transportation sectors. Moreover, since the energy cost accounted for the highest share of 51.05% on average in the factor cost share, which shows that the transportation sectors are the energy-intensive sector and the energy price is not flexible. Therefore, when labor price rises, the substitution effect will increase the ratio of energy input to labor input. Since China entered the stage of high-quality development, various changes shaped the labor market. Since 2010, China's labor supply and demand pattern has shifted from total balance to insufficient labor supply. Considering the population structure and labor participation rate, it is expected that the supply scale of available labor in China will decline from 76.134 million to 49.468 million from 2018 to 2050, with an average annual decline rate of 1.34% (Li 2020). As supply decreases, labor price is expected to continue to rise. With the trend of rising price, the substitutional effect of energy input over labor input will increase the energy consumption of the transportation sector in the foreseeable future.

On further examination of the energy self-price elasticity, the estimated indicator of the direct ERE at the national level, the value of −0.1089 is relatively small, indicating the lack of elasticity of energy input regarding the change of energy price. The possible reasons are summarized as follows. First, as mentioned above, energy, especially oil, the power source and main raw material, is the dominant input factor for the transportation sector. The energy-dependent

industrial structure of China's transportation sector offsets the growth of energy price elasticity to a certain extent. Second, the deepening processes of energy price marketization reform promote the gradual transformation of energy price formation from government regulation to market orientation. However, the price system is still in the process of continuous improvement. Energy prices are low under government intervention, and some parts of energy product prices cannot fully reflect its production, consumption, and environmental costs (Ouyang et al. 2019). Third, China is in the process of accelerating urbanization. With the improvement of living standards and the vigorous development of the logistics sector, the expansion of passengers and freight transportation demand will inevitably lead to the increase in energy demand. However, current technology level and factor endowment hinder the development of alternative energy, thus reducing the possibility of energy substitution. In brief, all the factors mentioned above constitute an obstacle to the increase of energy price elasticity.

Economy-wide energy rebound effect

Unlike static panels, fixed-effects model tends to have "dynamic panel bias" when estimating dynamic panels. System generalized method of moments (GMM) is widely used in the research with dynamic panel data model (Patrícia and Pedro 2017; Li et al. 2019; Istemi et al. 2020). Table 4 shows the estimated results of Eq. (16). We use the least squares method (OLS) and fixed effects model (FE) to estimate the model in order to make a comparison with the result of GMM. It should be noted that the premise hypothesis of the GMM estimation method needs to be verified by AR test and Sargan test. As shown in Table 4, it can be seen that there is no second-order serial correlation in the data

Table 5 Parameter estimation results of the dynamic energy consumption equation.

Province	Short-term economy-wide ERE	95% confidence interval		Long-term economy-wide ERE	95% confidence interval	
Anhui	74.18	69.68	78.68	38.17	16.20	60.14
Beijing	72.71	64.07	81.34	34.65	5.47	63.82
Fujian	81.50	77.56	85.44	55.70	42.13	69.26
Gansu	60.87	52.96	68.78	6.30	−33.04	45.64
Guangdong	72.84	66.22	79.46	34.97	8.77	61.17
Guangxi	74.82	71.04	78.60	39.71	19.29	60.12
Guizhou	77.40	69.45	85.36	45.89	21.73	70.05
Hainan	57.32	47.06	67.58	−2.20	−47.87	43.48
Hebei	79.79	75.48	84.11	51.61	35.71	67.52
Henan	82.66	79.71	85.61	58.49	47.89	69.08
Heilongjiang	78.89	72.46	85.33	49.46	29.29	69.63
Hubei	75.44	72.30	78.57	41.19	22.06	60.32
Hunan	76.41	73.50	79.32	43.51	25.85	61.17
Jilin	36.11	17.67	54.54	−52.98	−129.28	23.32
Jiangsu	74.65	70.45	78.85	39.31	18.18	60.44
Jiangxi	71.41	67.14	75.69	31.55	6.93	56.17
Liaoning	73.42	67.54	79.31	36.37	11.87	60.86
Inner Mongolia	59.96	50.88	69.04	4.12	−37.48	45.73
Ningxia	75.06	63.43	86.89	40.28	7.20	7335
Qinghai	25.44	3.55	47.33	−78.54	−169.19	12.12
Shandong	83.49	79.71	87.28	60.48	49.24	71.72
Shangxi	55.14	44.25	66.03	−7.41	−55.96	41.15
Shaanxi	72.06	67.81	76.32	33.11	9.25	56.97
Shanghai	89.85	83.45	95.25	75.70	62.06	89.34
Sichuan	73.77	68.83	78.71	37.19	14.42	59.97
Tianjin	86.05	81.91	90.19	66.59	57.43	75.76
Xinjiang	87.24	77.14	97.33	69.44	45.86	93.03
Yunnan	63.90	56.20	71.61	13.57	−22.40	49.55
Zhejiang	82.20	79.04	85.36	57.38	45.70	69.07
Chongqing	73.44	68.13	78.75	36.41	12.80	60.02
Eastern	77.62	74.86	80.38	46.41	30.14	62.68
Central	68.78	63.81	73.75	25.25	−2.79	53.28
Western	67.63	61.29	73.97	22.50	−8.17	53.17
National	71.60	67.19	75.50	32.00	6.90	55.88

processing according to the AR teat, and the null hypothesis of the overall exogeneity of the instrument used in the GMM estimation cannot be rejected according to Sargan test. In summary, it can be concluded that the estimation of this research using GMM model is reasonable and effective.

Using the GMM estimation coefficients in Table 4, we use Eqs. (17) and (18) to calculate the economy-wide ERE. Table 5 shows the sectoral average short-term and long-term ERE point estimation results, as well as the specific estimation results for each province within the 95% confidence interval (CI) from 2003 to 2019. The sectoral average short-term ERE across the country is 71.60%, while the sectoral average long-term ERE is 32.00%. The sectoral short-term ERE within the 95% confidence interval falls between 67.19

and 75.50%, and the sectoral long-term ERE within the same confidence interval falls between 6.90 and 59.88%.

We also find the cross-regional difference of the sectoral average economy-wide ERE based on results reported in Table 5. The sectoral average short-term ERE in the eastern provinces is 77.62%, while the sectoral average short-term EREs in the central and western regions are relatively small (68.78% and 67.63%, respectively). The 95% confidence interval of the sectoral short-term ERE in the eastern region falls between 74.86 and 80.38%. In contrast, the sectoral short-term ERE in the central region falls between 63.81 and 73.75%, while the sectoral short-term ERE in the western region falls between 61.29 and 73.97%. The

Fig. 1. Short-term economy-wide ERE of China's transportation sector among regions.
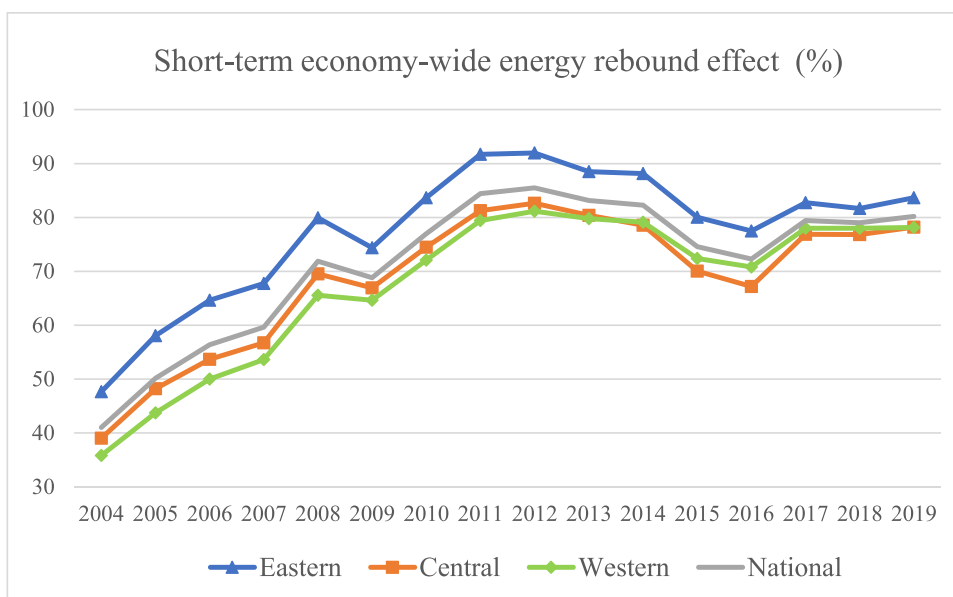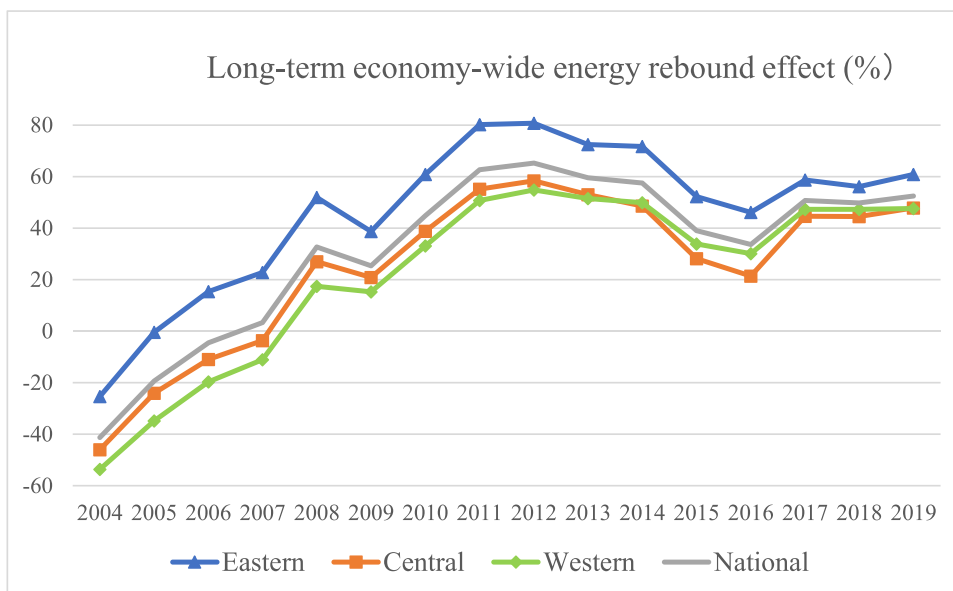

Fig. 2. Long-term economy-wide ERE of China's transportation sector among regions.

sectoral long-term EREs show the similar regional differences (Fig. 1). For details, please see Table 5.

In order to further clarify the regional differences in the economy-wide ERE, this article shows the sub-regional and national trend curves of the short-term ERE and the long-term ERE from 2003 to 2019 in Figs. 2 and 3, respectively.

Through the observation of Fig. 1, all the curves have almost the same shape and generally show a continuous upward trend. It is notable that the magnitude of short-term ERE in the eastern region was higher than the national average from 2003 to 2019, while the magnitudes in the central and western regions were slightly lower than the national average. The above-mentioned differences in dynamic trends

indicate that the relative economy-wide ERE in different regions has been changing over time, and the magnitude of short-term ERE in different regions in China has gradually converged to about 80% over time.

The long-term economy-wide ERE in Fig. 2 has basically the similar shape and trend as the short-term ERE in Fig 1. The main difference lies in the magnitude of the long-term ERE and the gap of long-term ERE magnitude among different regions. In recent years, the magnitudes of the long-term EREs in the central and western regions are about 47%, while the long-term ERE in the eastern region is about 60%, which is significantly higher than the central and western regions.

Fig. 3. Converted turnovers of the transportation sector among China's regions.
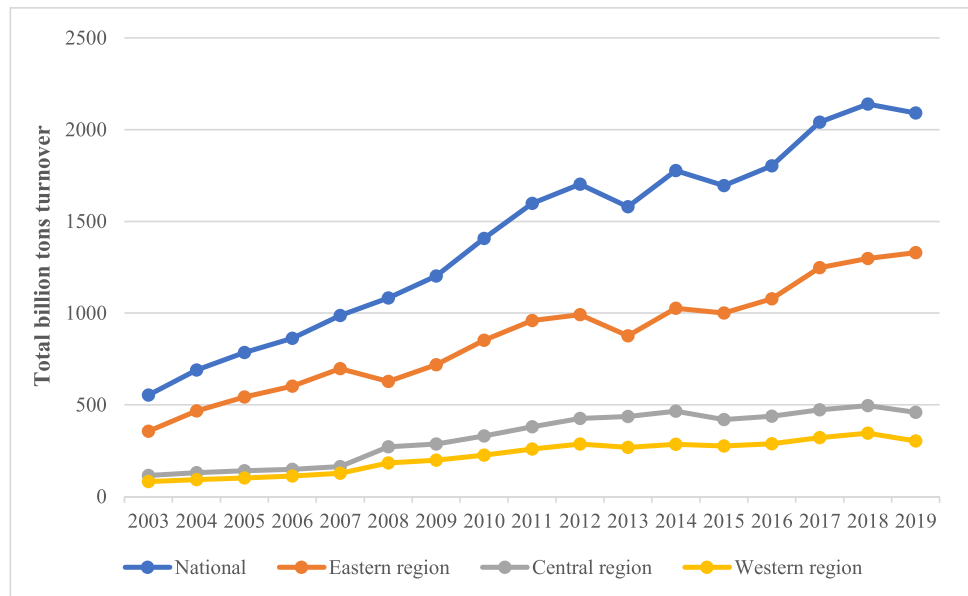
Based on the analysis of the economy-wide ERE magnitude of the transportation sectors, we present the following findings.

First, the sectoral economy-wide EREs in the short-term exist in the eastern, central, and western regions with the average magnitudes of 77.62%, 68.78%, and 67.63%, respectively; while the sectoral economy-wide EREs in the long-term exist in the eastern, central, and western regions with the magnitudes of 46.41%, 25.24%, and 22.50%, respectively. Since the values are all smaller than 100%, indicating that although the energy efficiency policy is not fully effective on account of ERE, the energy-saving target can be fulfilled to some extent due to the improvement of energy efficiency. The magnitude of the sectoral short-term ERE is consistent with the result of other research, that is, the economy-wide ERE may erode more than half of the expected energy savings (Brockway et al. 2021). In addition, our research finds that the short-term ERE is significantly higher than the long-term ERE (Adetutu et al. 2016). On one hand, with the advancement of science and technology and the accumulation of knowledge, the sectoral productivity will continue to increase along with technological advances and energy use efficiency improvements. On the other, with the increased environmental awareness among residents, the concept of green consumption of residents will also force the industry to conserve energy and reduce emission.

Second, both the short-term and long-term economy-wide EREs show a trend of increasing first and decreasing afterwards by reaching the peak in 2012. The sectoral economy-wide ERE of China's east fluctuates slightly around 60%, and the sectoral economy-wide EREs in the central and western regions are about 45%. China's GDP growth target in 2012 was reduced to below 8% for the first time, marking

that China's economy entered a state of new normal, and the gear of growth is shifting from high speed to medium-to-high speed. At the same year, the State Council Information Office of China issued the "China's Energy Policy" white paper, clarifying that maintaining long-term stable and sustainable use of energy resources is an important strategic task of the Chinese government. The government will adopt eight energy development policies including "saving priority" to build a modern energy industry system and realize the sustainable development of energy. At the macro policy level, energy-intensive industries, including transportation industry, have become key areas for energy conservation and emission reduction in China, helping to reduce the long-term economy-wide ERE and effectively achieve energy savings.

Third, the highest sectoral economy-wide ERE exists in China's eastern region, followed by the central region and western region both in the short term and the long term. The ERE in the eastern region is significantly higher than the central and western region, and energy efficiency improvement can bring about 30% of expected energy savings in the short term. In fact, the eastern region, which has the highest level of urbanization, population density, and industrial concentration in China, has the highest density and the best quality of transport infrastructures. As is shown in Fig. 3, the eastern region far exceeds the central and western region in terms of sectoral energy demand size and growth rate. Especially, the average annual growth rate of passenger and freight turnover in the eastern region during 2015–2019 was 7.37%, much higher than that of central (2.28%) and western region (2.34%). At the same time, it was also slightly higher than the national level (5.38%), indicating that eastern region has become the main driving force for transportation demand. Geographically, the eastern region has developed

water transportation system compared to inland China. Six of the top ten airports, including Shanghai Hongqiao, Pudong International Airport, and Capital International Airport, are located in the eastern region, bringing greater demand for civil aviation. Due to the role of transportation hubs of major developed cities, the densities of railways and highways in the eastern region are also much higher than that in the central and western regions (Zhang et al. 2015). Overall, the higher economic development and urbanization level will bring about the higher the proportion of the secondary and tertiary industries, especially the rapid development of the transportation industry. On this foundation, the reduction of the actual transportation cost promoted by energy efficiency improvement will lead to the further expansion of sectoral development in the eastern region, leading to a surge in energy demand. In fact, the existing research showed that the eastern region has the highest absolute amount of the energy saving potential due to the highest share of sectoral energy consumption (Xie et al. 2018). Therefore, the gap of sectoral long-term ERE between eastern region and other regions can be partially explained by the inertia brought about by the historic energy consumption path.

Discussion

This research analyzed the difference of EREs at the national and sub-regional level of transportation industry in China from the perspectives of direct ERE and economy-wide ERE. First of all, we used the self-price elasticity of energy to estimate the magnitude of sectoral direct ERE. The sectoral ERE is evaluated by measuring the change in energy consumption under changes in the price of energy products or services. By adopting the cost share function in addition to the self-price elasticity of the energy input, the substitution or complementarity relationships between various inputs can be measured. According to the relationships of different inputs, reasonable adjustments can be made to the ratio of inputs in the transportation sector to achieve energy saving and emission reduction. However, there exists a strict assumption that changes in energy efficiency can be fully captured by changes in energy prices while using the energy self-price elasticity to measure the direct ERE.

The hypothesis of symmetry between energy efficiency and energy price is questioned by relevant studies (Sorrell et al. 2009; Thomas and Azevedo 2013). Energy prices in China are in the process of marketization, and prices of several types of energy are still regulated by the government. Specifically, the degrees of oil price distortion in the central and western regions are greater than that in the eastern region (Sha et al. 2021), which leads to the result that energy efficiency improvement cannot be directly reflected in energy price changes to a certain extent. In addition, energy efficiency is correlated with the prices of other factor inputs

other than energy price only. The direct ERE measured by price elasticity ignores the change of energy efficiency and other prices of inputs, resulting in potentially large bias in the estimates.

The direct ERE occurs when the increase in energy efficiency reduces the cost of energy products and services, thereby partially increasing energy consumption and offsetting the contribution of energy efficiency on energy conservation. The economy-wide ERE, which measures from the macro perspective, can provide more reliable estimates than the direct ERE. In terms of estimation methods, the economy-wide ERE can avoid the strict hypothesis embedded in the measurement of the direct ERE, which assumes the symmetry between energy efficiency and energy price. The evaluation of the economy-wide ERE also overcomes the endogenous problem to some extent, because it does not require that changes in the actual price of energy products or services will cause the prices of intermediate and final products in the entire industry to adjust accordingly. Therefore, the estimates of the economy-wide ERE are more scientific and reasonable. This article refers to Adetutu et al. (2016) to measure the dynamic energy efficiency at first, and then calculate the sectoral economy-wide ERE in short and long term so as to provide decision basis for scientific and reasonable design of energy saving and emission reduction planning in China's transportation industry.

In summary, this study can provide a useful addition to the existing literature regarding the research content and methodological aspects. First, we use the cost share function to calculate the price elasticity of the input factors, so as to obtain the substitutional or complementary relationships between the input factors in the transportation sector. Second, we evaluate the sectoral economy-wide ERE based on the dynamic energy consumption equation, which avoids the stringent assumptions required for direct ERE estimation, thus enabling more reliable estimates. Third, this study summarizes the advantages and disadvantages of the two types of estimation methods and compares the differences between them in terms of estimation results. Meanwhile, this article reports more systematic and comprehensive estimation results concerning the sectoral ERE in China's regions, which is expected to provide a more reliable reference for energy conservation and emission reduction policy formulation.

Conclusions and implications

This study adopted the dynamic OLS method and the SUR to estimate the direct ERE of the transportation sector in China based on the sectoral panel data of 30 provinces of China from 2003 to 2019. Considering the limitations of the direct ERE in the estimation method, this article further

adopts the dynamic energy consumption and GMM method to estimate the sectoral economy-wide ERE in different regions in China.

First, there exists a substitutional relationship between capital and energy for the transportation sector in China. Specifically, the capital-energy price elasticity is 0.2100, larger than the energy-capital price elasticity, which indicates that capital investment would increase to a greater extent when energy prices rise. The energy-labor price elasticity is 0.2927, indicating that the energy input will increase to a greater extent as labor price rises. Second, the sectoral economy-wide EREs exist in the eastern, central, and western regions, which were 77.62%, 68.78%, and 67.63%, respectively. Third, the magnitudes of sectoral economy-wide ERE are distinct between regions. The eastern region has the largest short-term and long-term economy-wide ERE (77.62% and 46.41%, respectively), followed by the central and western regions.

The policy implications are thus summarized as follows.

First, the public transportation and new-energy vehicles should be further promoted considering the substitutional effect between energy and labor. Results indicate that the promotion of public travel and new energy will ease the dependence on labor inputs and reduce the demand for fuel oil simultaneously. On the one hand, a convenient, economical, and environmentally friendly public transportation environment can be created by accelerating the construction of public transportation systems such as rail transits, trolleybuses, and underground railways. On the other hand, the concept of green and shared development in the transportation sector can be introduced by advocating short distance travel by guiding the establishment of the urban bike-sharing system.

Second, energy efficiency policies of the transportation sector should consider the offsetting effect of the ERE on energy conservation. In fact, one of the important factors affecting the magnitude of the ERE is energy price. From this viewpoint, the marketization process of China's refined oil prices needs to be further improved. China has implemented a more market-oriented pricing mechanism for refined oil products since 2013, by shortening the price adjustment interval from 22 to 10 working days while removing the requirement of oil price change rate (4%). And starting from January 2016, the NDRC of China required that the domestic refined oil prices would no longer be adjusted in line with the international market if the international crude oil price was below $40 per barrel. Therefore, in addition to considering crude oil prices in foreign markets and the supply and demand situation of domestic refined oil products, the pricing mechanism for refined oil products could also take local characteristics into account to better circumvent the ERE on the effectiveness of energy conservation in the transportation industry.

It is also necessary to design and evaluate differentiated energy-saving policies according to local conditions given that the sectoral EREs are distinct among China's regions. China's cities vary significantly in terms of resource endowment and infrastructure, and the economic development among regions is highly uneven. The effect of environmental policies dedicated to improve energy efficiency is bound to be affected by regional EREs. Only by analyzing regional differences can we identify which region's environmental policies can be more effective and which region's energy efficiency improvement policies need to be accompanied by environmental taxes and other policies to achieve better energy conservation and emission reduction effects. The adoption of locally appropriate and phased environmental policies by China's cities is essential to promote the green transformation of urban economies.

Availability of data and materials The CEIC database https://www.ceicdata.com/zh-hans The China Statistical Yearbook http://www.stats.gov.cn/tjsj/ndsj/ The China Financial Yearbook https://data.cnki.net/trade/yearbook/single/n2014020005?z=z003

Declarations

Ethical 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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