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RESEARCH ARTICLE

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Direct energy rebound effect for road transportation in China

Abstract The enhancement of energy efficiency stands as the principal avenue for attaining energy conservation and emissions reduction objectives within the realm of road transportation. Nevertheless, it is imperative to acknowledge that these objectives may, in part or in entirety, be offset by the phenomenon known as the energy rebound effect (ERE). To quantify the long-term EREs and short-term EREs specific to China's road transportation, this study employed panel cointegration and panel error correction models, accounting for asymmetric price effects. The findings reveal the following: The long-term EREs observed in road passenger transportation and road freight transportation range from 13% to 25% and 14% to 48%, respectively; in contrast, the short-term EREs in road passenger transportation and road freight transportation span from 36% to 41% and 3.9% to 32%, respectively. It is noteworthy that the EREs associated with road passenger transportation and road freight transportation represent a partial rebound effect, falling short of reaching the magnitude of a counterproductive backfire effect. This leads to the inference that the upsurge in energy consumption within the road transportation sector cannot be solely attributed to advancements in energy efficiency. Instead, various factors, including income levels, the scale of commodity trade, and industrial structure, exert more substantial facilitating influences. Furthermore, the escalation of fuel prices fails to dampen the demand for energy services, whether in the domain of road passenger transportation or road freight transportation. In light of these conclusions, recommendations are proffered for the formulation of energy efficiency policies pertinent to road transportation.

Keywords road transportation, direct energy rebound effect, asymmetric price effects, panel data model

1 Introduction

The transport sector accounted for 20% of global energy consumption and 27% of CO_2 emissions related to fossil fuels in 2021 (according to International Energy Agency), signifying its pivotal role in addressing worldwide energy-related CO_2 emissions. In China, the total energy consumption in 2020 reached 4983.14 Mtce (million ton coal equivalent), with transportation contributing approximately 8.29% to the overall energy consumption, making it one of China's major sources of energy-related CO_2 emissions (data source: *China Statistical Yearbook 2022*). With ongoing industrialization and urbanization, the demand for energy within the transport sector is poised for further expansion (Chaudry et al., 2022). According to Peng et al. (2017), if current trends persist, China's vehicle population and fuel demand are projected to reach 481 million and 439 Mtoe (million tons of oil equivalent), respectively, by 2030. This surge in energy consumption within road transportation is intrinsically tied to CO_2 emissions and other pollutants. Among the various subdivisions of the transport sector, road transportation alone accounts for approximately 80% of carbon emissions, with railway transportation following closely behind. Efforts to mitigate greenhouse gas and pollutant emissions in the transportation sector have predominantly centered on enhancing energy efficiency (Feng and Fang, 2022; Song et al., 2023).

In pursuit of resource conservation and environmental sustainability, the Chinese government has implemented a plethora of measures to enhance energy utilization in road transportation. Notably, the Ministry of Transport issued *The Guidance on Building a Low-Carbon*

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Transportation System in 2011, with a primary emphasis on improving transportation system efficiency. This document explicitly outlines reduction targets for energy consumption and CO_2 emissions per passenger transport unit within urban areas. Furthermore, in 2019, the release and implementation of the *Grades and Evaluation Methods of Energy Efficiency and Carbon Dioxide Emission Intensity for Commercial Vehicle for Passenger Transportation* emerged as robust mechanisms for regulating vehicle operations, thereby enhancing energy efficiency and curbing greenhouse gas emissions. Subsequently, the Ministry of Transport introduced the Green Transportation 14th Five-year Development Plan in 2021, which imposes additional requirements pertaining to energy intensity per unit of road transportation. Historical data and a wealth of studies have corroborated that energy efficiency in China's road transportation sector has shown improvement in recent years, albeit against a backdrop of rising total energy consumption (Chen et al., 2019).

A substantial body of literature attests to the effectiveness of energy efficiency improvements in conserving energy and reducing carbon emissions (Rottoli et al., 2021). However, it is worth noting that augmenting energy efficiency often results in decreased per-unit energy service costs (Zha et al., 2022; Chen et al., 2022a). Consequently, the lowered cost of energy services may stimulate increased demand for these services (Zhang et al., 2017). Consequently, the projected energy savings stemming from energy efficiency enhancements may not materialize fully, and in some cases, partial or complete offsets may occur — a phenomenon referred to as the rebound effect (Khazzoom, 1980; Greening et al., 2000; Chen et al., 2022b). For example, enhanced energy efficiency reduces the per-kilometer travel cost for cars, potentially incentivizing greater car usage. This additional demand for consumption could lead to a failure to attain the expected reduction in energy consumption. The concept of the energy rebound effect (ERE) prompts an examination of the intricate relationship among technological progress, energy efficiency, and total energy consumption, thereby necessitating a reevaluation of energy efficiency policy considerations aimed at reducing energy consumption. Consequently, a comprehensive exploration of the potential magnitude of the ERE holds paramount importance in the formulation of policies designed to curtail energy consumption within road transportation.

The demand for passenger transportation and its corresponding energy consumption are experiencing rapid growth in response to elevated living standards and urbanization in China. Simultaneously, demand for freight transportation and its associated energy consumption are surging, driven by advancing urbanization and the restructuring of industrial sectors, often outpacing the rate of growth observed in passenger transportation. Given the distinct functions and fuel consumption patterns inherent in these two road transport modes, it is plausible that their EREs may exhibit variations. Notably, while several studies have estimated the EREs of road passenger transportation in various countries (Wang et al., 2012; Dimitropoulos et al., 2018; Chen et al., 2019; Malmaeus et al., 2023), research regarding the ERE of road freight transportation remains scarce.

Furthermore, enhancing energy efficiency can alter energy consumption behaviors within road transportation. Factors such as road transportation demand, per capita income, and fuel prices tend to form a cointegrating relationship over the long term (Malmaeus et al., 2023). The long-term energy rebound effect (LERE) signifies the magnitude of rebound when these factors reach their cointegrating equilibrium. However, since this equilibrium may deviate from the ideal state in the short term, the rebound magnitude at this juncture is defined as the short-term energy rebound effect (SERE). Due to the distinctive energy utilization structures characterizing road passenger transport and road freight transport, their LERE and SERE are anticipated to differ. Assessing and comparing these two categories of EREs in the context of these transport modes holds substantial value for devising nuanced policy interventions, a topic that has thus far received limited attention. Additionally, numerous studies have explored factors influencing ERE in road transportation, such as energy prices, vehicle load capacity, and economic development (Winebrake and Green, 2017; Xia and Zhang, 2022). However, these factors affect both road passengers and road freight transportation, leaving them vulnerable to bias.

In light of this backdrop, this paper endeavors to quantify the direct ERE within road transportation and investigate the factors influencing it. Our study pertains to the time series spanning 2000 to 2018 and employs a provincial-level nationwide dataset encompassing China's road transport system. The principal contributions of this paper encompass the following: First, it distinguishes between road passenger transportation and road freight transportation, calculating the magnitudes of their respective direct EREs (both short-term and long-term). The LERE of road transportation is assessed through long-run equilibrium equations, while the SERE is measured utilizing a panel error correction model that elucidates the correction mechanism for short-term deviations from the long-run equilibrium. Second, recognizing that regions vary in terms of population densities and economic development levels and therefore exhibit differing sensitivities to price fluctuations, the direct EREs of road freight transportation and road passenger transportation are analyzed at the national level and juxtaposed at the regional level. Third, the paper dissects the factors influencing the ERE of road transportation, with a particular focus on the impact of fluctuating fuel prices. It also explores spatial and temporal disparities in EREs, offering crucial insights for designing tailored policies aimed at mitigating EREs.

The subsequent section will delve into the theoretical and empirical research concerning direct ERE. Section 3 will elucidate the research methods and data employed in this study, while Section 4 will present the comprehensive findings regarding the direct ERE in road transportation. Finally, the paper will conclude with Section 5, which presents the study's conclusions and pertinent policy implications.

2 Literature review

2.1 Theory and measurement of direct ERE

Direct ERE centers on energy products or specific segments of energy product services. When energy efficiency improvements are implemented for energy products or services, the resultant reduction in effective prices tends to stimulate increased consumption of these products or services among consumers. This augmented consumer demand stemming from enhanced energy efficiency constitutes the essence of the direct ERE (Frondel et al., 2008).

Since the inception and development of ERE theory, direct measurement and econometric methods have consistently been employed for quantifying direct ERE (Sorrell et al., 2009). The direct measurement approach considers energy efficiency as the independent variable and energy consumption as the dependent variable, enabling the determination of the magnitude of the direct ERE by assessing changes in the consumption of energy products or energy services before and after energy efficiency improvements. This concept is visually depicted in Fig. 1 (Mizobuchi, 2008).

In this context, ε_0 denotes the initial energy efficiency level, while ε_1 represents the elevated energy efficiency level ($\varepsilon_0 < \varepsilon_1$). S_0 corresponds to the initial energy service consumption level, and S_1 is the level following improvements in energy efficiency. E_0 signifies energy consumption before energy efficiency enhancements, aligning with the initial energy service consumption level S_0. Conversely, E_1 represents the hypothetical energy consumption when energy efficiency improves without any changes in energy service demand. E corresponds to the actual energy consumption level when energy efficiency has increased, aligned with the actual energy service consumption level S_1.

When energy efficiency rises while energy consumption demand remains constant, the anticipated energy savings amount to ($E_0 - E_1$). However, as energy efficiency increases, energy demand shifts from S_0 to S_1, leading to a shift in the corresponding energy savings, which become ($E_0 - E$). The portion represented by ($E - E_1$) denotes expected energy savings that remain unrealized due to the upswing in energy demand. The ERE under the direct measurement framework can be further articulated as follows:

$$RE = \frac{(E_0 - E_1) - (E_0 - E)}{E_0 - E_1} \times 100\% = \left(1 - \frac{E_0 - E}{E_0 - E_1}\right) \times 100\%. \tag{1}$$

ERE can be categorized into various outcomes, including the super conservation effect ($RE < 0$), zero rebounds ($RE = 0$), partial rebound ($1 > RE > 0$), full rebound ($RE = 1$), and backfire effect ($RE > 1$) (Chen et al., 2022b). While the direct measurement approach provides a straightforward means of illustrating the direct ERE, it is essential to recognize that energy usage can be influenced by additional factors. Therefore, when employing this

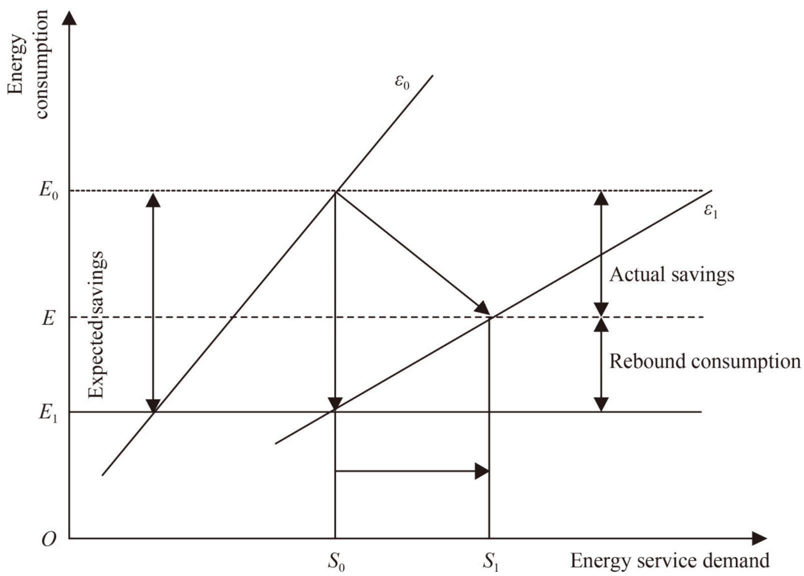

Fig. 1 Direct energy rebound effect.

method to assess ERE, it is advisable to control for other variables. Unfortunately, many studies tend to measure ERE by simply comparing energy usage before and after changes in energy efficiency, often without adequate control and comparison of essential variables, resulting in potentially significant estimation errors (Frondel and Schmidt, 2005).

Hence, in empirical research, econometric methods rooted in elasticity calculations are more frequently employed to compute the direct ERE. Among these methods, one prevalent approach involves utilizing changes in energy service demand attributable to energy efficiency $\eta_\varepsilon(S)$ enhancements as an expression of ERE (Sorrell and Dimitropoulos, 2008):

$$RE = \eta_\varepsilon(S) = \frac{\partial \ln S}{\partial \ln \varepsilon} = 1 + \eta_\varepsilon(E), \tag{2}$$

where S represents energy services, E is the corresponding energy consumption, and energy efficiency $\varepsilon = S/E$ is delineated as the ratio of energy services output to energy input. In the event of an improvement in energy efficiency, energy consumption will decrease, assuming that the demand for energy services remains unchanged. $\eta_\varepsilon(E)$ indicates the elasticity of energy consumption concerning energy efficiency. A positive ERE means $\eta_\varepsilon(S) > 0$, $-1 < \eta_\varepsilon(E) < 0$. If $\eta_\varepsilon(S) = 0.5$, $\eta_\varepsilon(E) = -0.5$, the ERE is 50%. This means that 50% of the anticipated energy reduction will be counterbalanced by the augmented demand for energy services.

Aligning with the energy efficiency definition, we can further derive the price of energy services, $P_S = P_E/\varepsilon$. In the realm of empirical research, acquiring a sufficient dataset of variable energy efficiency can often prove challenging. Consequently, researchers resort to evaluating the direct ERE by scrutinizing the response of energy services demand to variations in the price of energy services $\eta_{P_S}(S)$ (Berkhout et al., 2000):

$$RE = \eta_\varepsilon(S) = -\eta_{P_S}(S) = -\frac{\partial \ln S}{\partial \ln P_S}. \tag{3}$$

Given that data pertaining to energy service prices P_S are more readily available compared to energy efficiency data, Eq. (3) is more commonly employed in empirical research than Eq. (2). In Eq. (3), energy prices are considered exogenous variables, and energy services demand is solely influenced by energy service prices. Nonetheless, it is imperative to note that this definition necessitates precise knowledge of energy service prices, and these prices hinge on both energy efficiency and energy prices ($P_S = P_E/\varepsilon$). Therefore, when energy efficiency remains constant, the direct ERE can be expressed by the elasticity of energy use concerning energy prices $\eta_{P_E}(E)$ (Sorrell and Dimitropoulos, 2008):

$$RE = \eta_\varepsilon(S) = -\eta_{P_E}(E) = -\frac{\partial \ln E}{\partial \ln P_E}. \tag{4}$$

In addition to the abovementioned elastic definitions, when energy consumption data are difficult to obtain, $\eta_{P_E}(S)$ is also used as a measure of direct ERE in some research fields (Matos and Silva, 2011):

$$RE = \eta_\varepsilon(S) = -\eta_{P_E}(S) = -\frac{\partial \ln S}{\partial \ln P_E}. \tag{5}$$

Equation (2) provides the definition of efficiency elasticity for the direct ERE, while Eqs. (3)–(5) elucidate the definitions of price elasticities for the direct ERE. It is worth noting that the definitions of price elasticity are derived from the foundation of efficiency elasticity. Consequently, all three price elasticities must adhere to specific assumptions.[1)] Additionally, the negative form of these price elasticities equates to the efficiency elasticity defined in Eq. (2).

In the realm of empirical research, the selection of elastic definitions is primarily contingent on the availability of data. Given the unavailability of data for energy use within distinct segments of China's transportation industry (including roads, railways, waterways, and aviation), as well as the absence of energy efficiency data, this paper selects $\eta_{P_E}(S)$ (Eq. (5)) to calculate the direct ERE of road transportation in China.

To address this issue effectively, price decomposition is considered a viable approach. Gately (1993) was the first to propose a decomposition of fuel price fluctuations into three components: The highest fuel price sequence $P_{it}^{\max}$, the cumulative decrease in fuel price sequence P_{it}^{cut}, and the cumulative rebound in fuel prices P_{it}^{rec}. The price decomposition model can be defined as follows:

$$P_{it} = P_{it}^{\max} \times P_{it}^{\text{cut}} \times P_{it}^{\text{rec}}, \tag{6}$$

$$P_{it}^{\max} = \max\{P_{i1}, P_{i2}, \ldots, P_{it}\}, \tag{7}$$

$$P_{it}^{\text{cut}} = \prod_{m=0}^{t} \min\left\{1, \frac{P_{im-1}^{\max}/P_{im-1}}{P_{im}^{\max}/P_{im}}\right\}, \tag{8}$$

$$P_{it}^{\text{rec}} = \prod_{m=0}^{t} \max\left\{1, \frac{P_{im-1}^{\max}/P_{im-1}}{P_{im}^{\max}/P_{im}}\right\}. \tag{9}$$

Equation (6) can be turned into:

$$\ln P_{it} = \ln P_{it}^{\max} + \ln P_{it}^{\text{cut}} + \ln P_{it}^{\text{rec}}, \tag{10}$$

where the coefficient of P_{it}^{cut} is considered the ERE.

[1)] (1) Exogenous hypothesis: Energy efficiency will not be affected by energy prices, which means $\eta_{P_E}(S) = \partial \ln S/\partial \ln P_E = 0$;
(2) Symmetry hypothesis: Buyers react no change to energy efficiency improvement and energy price decline.

2.2 Research progress of direct ERE from road transportation

Research based on this perspective constitutes one of the most commonly employed approaches to investigate the ERE within the realm of road transportation. Barla et al. (2009) employed a simultaneous equations model to compute the ERE of light passenger cars in Canadian provincial households spanning 1990 to 2004. Their findings indicated that the SERE stood at 8%, while the LERE was 20%. Stapleton et al. (2016) utilized static and dynamic double logarithmic models to examine the ERE concerning private family car travel in the UK. Odeck and Johansen (2016) utilized Norwegian time series data ranging from 1980 to 2011 to gauge the price/income elasticity of fossil fuel consumption and the magnitude of the ERE. Wang et al. (2012) discovered that the direct energy rebound from 1994 to 2009 in urban passenger transportation in China was as high as 96%, indicating that only 4% of the anticipated energy-saving target had been realized. Zhang et al. (2015) determined that the LERE at the national level was 26.56%, while at the subregional levels of eastern, central, and western China, it stood at 31.30%, 100.36%, and 42.67%, respectively. Several studies have focused on EREs across the entire road transportation sector. Zheng et al. (2022) ascertained that the SERE and LERE of China's road transportation sector were 82% and 123%, respectively. Meanwhile, Dimitropoulos et al. (2018), through a meta-analysis covering 1120 calculations, reported SERE estimates ranging from 10% to 12% and long-term effects in the range of 26% to 29%.

It is noteworthy that research on the ERE of road freight transportation has lagged behind that of road passenger transport. Matos and Silva (2011) determined that the direct ERE of freight transportation in Portugal over the period from 1987 to 2006 was approximately 24.1%. de Borger and Mulalic (2012) utilized time series data from 1980 to 2007 to investigate the SERE and LERE of road freight transportation in Denmark. Their results indicated the SERE of 10% and the LERE of 17%. Additionally, the research revealed that while rising energy prices indeed reduce the energy consumption of road freight transportation, the degree of restraint was relatively modest, approximately in the range of 13% to 22%. Sorrell and Stapleton (2018), drawing upon time series data, applied a range of models to estimate the direct ERE of British road freight transportation spanning 1970 to 2014, with calculated results varying from 21% to 137%. The average ERE was approximately 61%. Wang and Lu (2014) employed a double logarithmic model to evaluate the direct ERE of regional road freight transportation from 1999 to 2011 in China. The research outcomes revealed a significant ERE within China's road freight transportation sector. At the national level, the direct ERE reached 84%, while at the subregional levels of eastern, central, and western China, it stood at 52%, 80%, and 78%, respectively.

In the estimation of ERE, it is customary to consider factors that may influence it within the scope of the study. Building upon theoretical analysis, Böhringer and Rivers (2021) identified key drivers of the ERE, including economic composition, energy prices, economic growth, and labor supply. Notably, they observed that the contribution of labor supply to the ERE was negligible. Jiang and Lin (2013) investigated the impact of refined oil pricing mechanisms on the ERE of urban passenger transportation, revealing that the oil pricing mechanism was the primary factor behind the backfire effect. Chai et al. (2016) utilized a simultaneous equations model to scrutinize the influence of road capacity, efficiency policies, and technological progress on fuel consumption, subsequently measuring the ERE arising from changes in energy efficiency. Li et al. (2018) explored the ERE of rural road transportation by considering three different expenditure levels and measuring the ERE with and without the inclusion of capital costs. Their findings indicated that when accounting for capital costs, the degree of ERE across three expenditure levels was lower compared to ERE estimates that excluded capital costs. Furthermore, several scholars have initiated investigations focusing on factors such as income levels, population density, consumer behavior, fuel prices, and urbanization levels to assess their impact on the ERE within the realm of road transportation (Gillingham, 2014; Dillon et al., 2015; Safarzyńska and van den Bergh, 2018).

Previous research on the ERE in road transportation has unequivocally established its existence in both the road passenger and freight transportation sectors. However, it is essential to acknowledge that the empirical calculations of ERE for road transportation have yielded diverse results. While the research object remains the same, variations in ERE calculation outcomes can be attributed to differing definitions of ERE, variations in data types, and the utilization of distinct modeling methodologies.

Furthermore, it is noteworthy that existing research has predominantly concentrated on the ERE of road passenger transportation, with relatively limited attention devoted to the ERE of road freight transportation. Consequently, this paper employs panel cointegration and panel error correction models to concurrently assess LEREs and SEREs for both road passenger and road freight transportation. This approach facilitates a comparative analysis of the implementation effects of energy efficiency policies in these two sectors of road transportation.

Additionally, the paper introduces an asymmetric price effect decomposition model, leveraging the cumulative decline in fuel prices derived from the decomposition as the foundation for calculating the direct ERE. This innovative method aims to enhance the accuracy of ERE calculation results.

3 Methodology and data

3.1 Model variants

Road transportation, as a diverse sector, can be further subdivided into two distinct categories: Road passenger transportation and road freight transportation. These two subsectors exhibit varying operational mechanisms and are driven by distinct factors, leading to different responses when confronted with improvements in energy efficiency.

(1) Road passenger transportation

Energy services are commonly quantified using indicators such as average annual mileage, passenger mileage, and passenger turnover (Wang and Lu, 2014; Safarzyńska and van den Bergh, 2018). Given the absence of official annual average vehicle mileage data in China, this paper opts to use passenger turnover as the metric indicator for energy services in road passenger transportation. Passenger turnover is contingent on both the number of passengers transported and the transportation distance. Notably, the upsurge in energy consumption in road transportation correlates with an increase in turnover. Thus, in the absence of statistical data on average annual vehicle mileage in China, road passenger transportation turnover serves as a viable surrogate indicator for energy services. Research has indicated that energy services in road passenger transportation are influenced by factors such as energy prices (Barla et al., 2009), income levels (Wang et al., 2012), and urbanization rates (Gillingham et al., 2016).

Energy Price: An escalation in energy prices prompts consumers to reduce their demand for these goods or services, while a decrease in prices spurs increased demand (assuming these goods or services are normal products). Elevated energy prices elevate the operating costs of the road passenger transportation sector, resulting in reduced consumer demand for energy services. Conversely, a decrease in energy prices encourages consumers to augment their energy service demand in road passenger transportation.

Income Level: An increase in income levels fosters a higher demand for energy consumption, exerting a positive influence on energy demand during this phase. This is attributed to two main factors: First, rising income levels expand consumer demand, leading to increased requirements for enhancing the quality of life, such as leisure travel activities, driving up the demand for energy services in road passenger transportation. Second, as income levels rise, consumers become less sensitive to escalating energy prices (Zhang and Lin, 2018), further driving an increase in road passenger transportation trips. The combined effect of these factors underscores the significant impact of income levels on road passenger services.

Urbanization Rate: The degree of urbanization influences road traffic density, thereby impacting road transportation turnover and energy utilization. When compared with the urbanization rates in developed countries, China possesses substantial potential for future growth. Research conducted by Wang and Lu (2014) demonstrated that the extent of the ERE diminishes as the pace of urbanization rate growth slows down, reaffirming the close connection between ERE and urbanization rates.

(2) Road freight transportation

In the realm of road freight transportation, energy service demand is typically quantified in terms of vehicle mileage or freight transportation mileage, mirroring the approach used for measuring energy service demand in road passenger transportation, which typically employs vehicle mileage and passenger mileage (Stapleton et al., 2016). Accordingly, this paper opts to utilize the freight transportation turnover as the energy service indicator for road freight transportation. Distinct from the factors influencing road passenger transportation turnover, road freight transportation turnover is primarily influenced by energy prices (Tamannaei et al., 2021), industrial structure (Wang et al., 2021), and the scale of commodity transactions (Matos and Silva, 2011).

Energy Price: Freight turnover serves as the representation of energy services in road freight transportation, and fluctuations in energy prices naturally impact it. This resembles the mechanism by which energy prices influence road passenger transportation turnover. Increasing energy prices act as a deterrent to the demand for energy services, while a decline in energy prices stimulates increased demand. Although changes in energy prices have a similar impact mechanism on the energy service demand of both road passenger transportation and road freight transportation, these two sectors may react differently to alterations in energy prices. Consequently, the effects of changes in energy prices on road passenger transportation may differ from those on road freight transportation.

Industrial Structure: Over the past few decades, China has predominantly experienced extensive economic development, emphasizing quantitative growth and the expansion of the secondary industry. This growth has been characterized by the prominence of heavy industries such as construction, steel, and machinery manufacturing, contributing significantly to the overall industrial output. Consequently, there has been a substantial increase in the demand for raw material transportation, intensifying the role of road freight transportation. Excessive transportation intensity in the freight transportation sector can be attributed to this factor.

Scale of Commodity Transactions: In recent years, the rapid growth and evolution of e-commerce, along with the popularity of new sales channels such as live webcasts, has led to a continuous rise in the volume of goods bought and sold online. This surge in commodity transactions not only fuels the expansion of the logistics and transportation industry but also directly contributes to increased road freight transportation. A positive correlation exists between the scale of commodity transactions and the need for freight transportation, with the two exhibiting a mutually reinforcing relationship.

3.2 Panel double logarithmic model

This paper employs the elasticity of energy services to energy price ($\eta_{P_E}(S)$) as the metric for measuring the direct ERE in both road passenger transportation and road freight transportation. In the domain of road passenger transportation, the core variables include road passenger transportation turnover and energy price. Furthermore, this analysis takes into account the influence of income levels and urbanization rates. For road freight transportation, the central explanatory variables consist of road freight transportation turnover and energy price. Additionally, in line with the operational dynamics of road freight transportation, factors such as industrial structure and commodity transaction scale are introduced for examination.

In empirical studies of ERE, the double logarithmic model is widely employed (Sorrell and Dimitropoulos, 2008). This choice is primarily motivated by the fact that the estimated coefficient in the double logarithmic model represents the elasticity of the explained variable concerning the explanatory variable. This aids in explaining ERE through measurements of price elasticity or efficiency elasticity. Additionally, the double logarithmic model helps mitigate the potential effects of heteroscedasticity and variations in data magnitudes. Consequently, this paper utilizes the double logarithmic model to investigate the ERE in road passenger transportation and road freight transportation. Building upon this foundation, the following panel double logarithmic models are formulated to examine the ERE in both sectors:

$$\ln PTKM_{it} = \alpha_0 + \alpha_1 \ln INC_{it} + \alpha_2 \ln P_{it} + \alpha_3 \ln URB_{it} + \varepsilon_{it}, \tag{11}$$

$$\ln FTKM_{it} = \alpha_0 + \alpha_1 \ln CONS_{it} + \alpha_2 \ln P_{it} + \alpha_3 \ln STR_{it} + \varepsilon_{it}, \tag{12}$$

where α_0 represents a constant term and α_i represents an estimated parameter. ε_{it} is a random error term. i and t represent the province-level region and the year, respectively. $PTKM_{it}$ signifies the road passenger transportation turnover volume. $FTKM_{it}$ denotes the road freight transportation turnover volume. INC_{it} is the per capita income level. This paper employs per capita GDP as a representation of income level and adjusts it using the per capita GDP deflator to eliminate price factor influences. The deflation is performed with the research's initial year, 2000, as the base period. Gasoline and diesel are the primary fuel types consumed in the road transportation sector. Both road passenger transportation and road freight transportation involve the utilization of gasoline and diesel. Due to the scarcity of comprehensive statistical data on gasoline and diesel prices across various province-level regions, this paper employs a fuel price index that encompasses the prices of both fuels as a substitute index for fuel price. Additionally, the fuel price index is adjusted to the base period of 2000 to eliminate price fluctuations. URB_{it} represents the urbanization rate, expressed as the proportion of the urban population in a given year to the total permanent population at the year's end. $CONS_{it}$ denotes the commodity transaction scale, presented as an indicator of total retail sales of consumer goods. To account for price variations, this paper employs the consumer price index to adjust total retail sales, converting them into total retail sales at a constant price based on the research starting point. STR_{it} is the industrial structure, expressed as the proportion of the secondary industry in a given year.

3.3 Asymmetric price effects

The essential driver of the ERE is the reduction in the actual cost of energy services due to increased energy efficiency. However, it is important to note that energy prices often fluctuate. When energy prices rise, they may stimulate technological progress, leading to more economical energy consumption. Conversely, when energy prices fall, the cost savings resulting from the price increase are not entirely offset, and energy consumption demand may react asymmetrically to changes in energy prices (Gately, 1993). Therefore, conducting research on the ERE directly with historical fuel price data could result in an overestimation of the calculation results. To accurately reflect the real conditions of fuel prices, it is necessary to decompose the original fuel price data.

Based on Eqs. (6)–(9), this article decomposes the fuel prices of various province-level regions in China from 2000 to 2018. Figure 2 illustrates the trend of fuel prices after decomposition. The trend of the highest fuel price series aligns closely with that of the original fuel price series, indicating that China's fuel prices have generally exhibited year-on-year growth, with occasional declines in a few years. The cumulative recovery fuel price series and the cumulative falling fuel price series remained stable during the initial period. This period corresponds to the upward trend in fuel prices. Consequently, the decomposition results for the cumulative falling fuel price and the cumulative recovery fuel price during this period are both zero. Subsequently, these two series gradually formed a V-shaped pattern, with the timing of the V-shaped opening coinciding with the first decline in fuel prices between 2000 and 2018. The upper and lower sides of the V-shaped opening correspond to the periods of fuel price decline and recovery, respectively. The greater the width of the opening, the more significant the

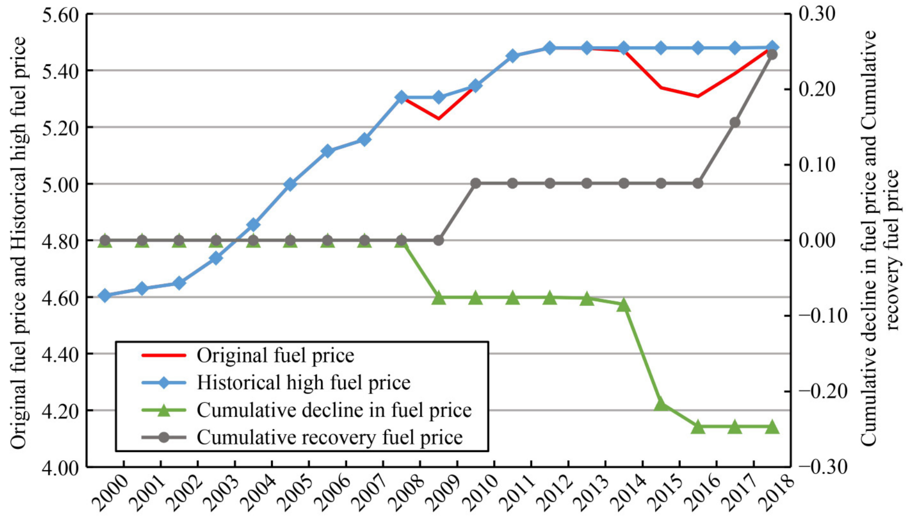

Fig. 2 Decomposition of the fuel price index.

fluctuation in fuel prices. Overall, China experienced more frequent increases than decreases in fuel prices during the period from 2000 to 2018.

By substituting Eq. (10) into Eqs. (11) and (12), we can derive the calculation equations for the ERE in road passenger transportation and road freight transportation, accounting for asymmetric price effects, as follows:

$$\ln PTKM_{it} = \alpha_0 + \alpha_1 \ln INC_{it} + \alpha_2^{\max} \ln P_{it}^{\max} + \alpha_2^{\text{cut}} \ln P_{it}^{\text{cut}} + \alpha_2^{\text{rec}} \ln P_{it}^{\text{rec}} + \alpha_3 \ln URB_{it} + \varepsilon_{it}, \tag{13}$$

$$\ln FTKM_{it} = \alpha_0 + \alpha_1 \ln CONS_{it} + \alpha_2^{\max} \ln P_{it}^{\max} + \alpha_2^{\text{cut}} \ln P_{it}^{\text{cut}} + \alpha_2^{\text{rec}} \ln P_{it}^{\text{rec}} + \alpha_3 \ln STR_{it} + \varepsilon_{it}. \tag{14}$$

In Eqs. (13) and (14), $P_{it}^{\max}$ represents the historical highest fuel price series decomposed from the fuel price sequence, illustrating the historical fluctuations in China's highest fuel prices. P_{it}^{cut} is the cumulative decline series of fuel prices, depicting the gradual decline in fuel prices. P_{it}^{rec} represents the cumulative recovery series of fuel price, derived from the decomposition of the fuel price sequence, illustrating the subsequent recovery of fuel prices after a decline.

3.4 Data resources

This paper investigates the direct LEREs and SEREs for road transportation using data spanning from 2000 to 2018. Notably, this study excludes Hong Kong, Macao, Taiwan and Xizang due to data availability considerations. The variables utilized in this research encompass road passenger transportation turnover, road freight transportation turnover, fuel price, per capita income, urbanization rate, and industrial structure. Data for each variable are sourced from the *China Statistical Yearbook* (2001–2019) and the China Economic Network database. Furthermore, the per capita income and fuel price variables are indexed to the base year 2000. Descriptive statistical analysis of these variables is presented in Table 1.

Table 1 The statistical description of the variables

Variables	Unit	Mean	Media	Max	Min	SD
$\ln PTKM$	Billion person-km	5.445	5.600	7.810	1.410	1.033
$\ln FTKM$	Billion ton-km	6.204	6.200	9.050	2.600	1.354
$\ln INC$	yuan	10.073	10.210	11.850	7.890	0.857
$\ln P^{\max}$	–	4.777	4.770	4.840	4.680	0.031
$\ln P^{\text{cut}}$	–	−0.373	−0.340	0.000	−1.000	0.249
$\ln P^{\text{rec}}$	–	0.256	0.230	0.880	0.000	0.206
$\ln CONS$	Billion yuan	7.953	7.990	10.580	4.410	1.228
$\ln URB$	%	−0.728	−0.720	−0.110	−1.630	0.296
$\ln STR$	%	−0.796	−0.750	−0.490	−1.680	0.206

4 Results and discussions

4.1 Road passenger transportation

4.1.1 Unit root test

To bolster the reliability of the test outcomes, this study employs the Levin–Lin–Chiu (LLC) test, Im–Pesaran–Shin (IPS) test, and Harris–Tzavalis (HT) test to assess the stability of each variable in the road passenger transportation equation. Table 2 shows the specific panel unit root test results. Except for $\ln P^{\max}$, the original sequences of all variables fail to reject the null hypothesis of possessing a panel unit root, while the first-order differenced sequences of each variable do not exhibit a panel unit root process. These findings indicate that each variable in the road passenger transportation

Table 2 Results of the panel unit root test

Variables	LLC test	IPS test	HT test	Conclusion
$\ln PTKM$	−1.014	0.212	0.837	Nonstationary
$\Delta\ln PTKM$	-12.790^{***}	-14.706^{***}	-0.080^{***}	Stationary
$\ln INC$	1.136	1.843	0.952	Nonstationary
$\Delta\ln INC$	-9.722^{***}	-8.647^{***}	0.242^{***}	Stationary
$\ln P^{\max}$	-2.638^{***}	-4.574^{***}	0.826	Stationary
$\Delta\ln P^{\max}$	-7.390^{***}	-11.287^{***}	0.172^{***}	Stationary
$\ln P^{\mathrm{cut}}$	5.865	3.901	0.930	Nonstationary
$\Delta\ln P^{\mathrm{cut}}$	-6.882^{***}	-13.124^{***}	-0.045^{***}	Stationary
$\ln P^{\mathrm{rec}}$	0.427	4.676	0.919	Nonstationary
$\Delta\ln P^{\mathrm{rec}}$	-10.912^{***}	-12.550^{***}	-0.041^{***}	Stationary
$\ln UBR$	−0.964	−0.178	0.881	Nonstationary
$\Delta\ln UBR$	-5.606^{***}	-15.277^{***}	-0.002^{***}	Stationary

Notes: (1) Δ represents the first-order difference sequence of variables, and the optimal number of lag periods is automatically determined according to the Schwarz Criterion; (2) ***, **, * indicate that they have passed the 1%, 5%, and 10% significance level tests, respectively (the following ***, **, * have the same meanings).

equation is characterized by a first-order integrated sequence, and the variables display a cointegration relationship.

4.1.2 Panel cointegration equilibration and LERE analysis

Based on the panel unit root test results, it is evident that the first-order differenced sequence of each variable in the road passenger transportation equation successfully passed the panel unit root test, satisfying the prerequisites for a subsequent panel cointegration examination. This study employs three cointegration testing methods, i.e., the Kao test, Pedronic test, and Westerlund test, to assess and scrutinize the cointegration among the variables in the road passenger transportation equation. The specific outcomes of these tests are presented in Table 3. The statistics from both the Kao test and Pedronic test strongly reject the null hypothesis, suggesting the absence of cointegration. Based on the aforementioned panel cointegration test results, it can be concluded that there exists a long-run equilibrium relationship among the variables in the road passenger transportation equation.

Table 3 Results of the panel cointegration test in the road passenger transportation equation

	Statistics	Whole country
Pedroni test	Modified Phillips–Perron t	6.081^{***}
	Phillips–Perron t	-2.755^{***}
	Augmented Dickey–Fuller t	-2.598^{***}
Westerlund test	Variance ratio	−0.948
Kao test	Modified Dickey–Fuller t	-4.173^{***}
	Dickey–Fuller t	-4.059^{***}
	Augmented Dickey–Fuller t	-5.176^{***}
	Unadjusted modified Dickey–Fuller t	-3.818^{***}
	Unadjusted Dickey–Fuller t	-3.918^{***}

Following the confirmation of a cointegration relationship among the variables in the road passenger transportation equation, the cointegration equation for the road passenger transportation panel is subsequently estimated. To determine whether a fixed-effect or random-effect model is more appropriate for this regression process, the Hausman test is employed. The results indicate that the fixed-effect model is the suitable choice for this study. Furthermore, to mitigate the impact of heteroscedasticity stemming from cross-sectional data and autocorrelation arising from time series on the regression outcomes, this paper utilizes the comprehensive generalized least squares method. This method accounts for three factors: Intragroup autocorrelation, intergroup heteroscedasticity, and contemporaneous correlation. It is employed to conduct panel cointegration regression for the road passenger transportation equation. The results of the long-term cointegration equation are provided in Table 4.

Table 4 Estimation of the long cointegration equation in road passenger transportation

Variables	Whole country	Eastern	Central	Western
$\ln INC_{it}$	0.649^{***}	−0.072	0.551^{***}	0.334^{***}
$\ln P_{it}^{\max}$	3.123^{***}	15.378^{***}	1.124^{*}	3.186^{***}
$\ln P_{it}^{\mathrm{cut}}$	-0.157^{***}	−0.126	0.144	-0.254^{**}
$\ln P_{it}^{\mathrm{rec}}$	0.089	0.448^{***}	−0.034	0.214^{*}
$\ln URB_{it}$	-1.125^{***}	-1.139^{***}	-0.488^{***}	-0.224^{*}
C	-17.256^{***}	-69.978^{***}	-5.405^{*}	-13.370^{***}

To begin with, using the elasticity of road passenger transportation turnover in response to fuel price changes as the definition of ERE, it is evident that the LERE for China's road passenger transportation stands at 15.7%. This figure is comparatively lower than that of many other countries, such as Canada (Barla et al., 2009) and the United States (Small and van Dender, 2007). Specifically, the LERE is the lowest in eastern China at 12.6% and the highest in western China at 25.4%. These results imply that over the long term, energy efficiency policies have been effective in the realm of road passenger transportation, as the energy savings resulting from improved efficiency have not been completely offset by ERE. Furthermore, this suggests that lower fuel prices have a relatively weak impact on road passenger transportation demand in eastern China, possibly due to the more congested road traffic network in that region (Wang et al., 2022).

Second, there exists a positive relationship between the cumulative recovery of fuel prices and the demand for energy services in road passenger transportation over the long term. These results indicate that despite rising fuel prices, they have not significantly curbed the demand for energy services in road passenger transportation. One possible explanation is that fuel prices in China are regulated by the government, and nonmarket pricing strategies may not accurately reflect fuel scarcity. Additionally, overall fuel prices remain relatively low. While fuel prices have been increasing, the magnitude of the increase has not outpaced per capita income growth, resulting in a gradual reduction in people's sensitivity to fuel price hikes (Zhang and Lin, 2018). Therefore, simply raising fuel prices alone may not effectively reduce energy consumption in the road transportation sector.

Third, in the long term, the growth of per capita income has a significantly positive impact on road passenger transportation turnover. This could be attributed to the fact that higher per capita income leads to increased participation in leisure and entertainment activities, such as vacations and tourism, which subsequently drives up the demand for energy services in road passenger transportation. Additionally, higher income levels tend to reduce people's responsiveness to rising fuel prices. When income elasticity exceeds price elasticity, fuel prices become relatively more affordable, further stimulating the demand for energy services in road passenger transportation.

Last, the increase in urbanization has a substantial long-term impact on the demand for road passenger transportation energy services. The selected urbanization rate indicator, expressed as the proportion of the urban population to the total permanent population at the end of the year, reflects the ongoing urbanization process in China. As urbanization progresses, the urban population grows, leading to higher road traffic density. However, this can also result in traffic congestion, which can inhibit road passenger traffic trips.

4.1.3 Panel error-correction model and SERE

The panel cointegration test outcomes reveal the presence of a long-run cointegration relationship between road passenger transportation turnover, per capita income, fuel price, and urbanization rate. However, it is important to note that this equilibrium relationship may deviate from the equilibrium state in the short term. To address this and account for short-term dynamics, this study constructs a short-run panel error correction model that includes a lag term to illustrate the correction mechanism when there is a short-run deviation from the long-run equilibrium state. The error correction model is commonly employed to calculate short-run elasticity, and the magnitude of the error correction value signifies its capacity to correct deviations from the long-term equilibrium state.

Based on the results in Table 4, it is straightforward to derive the residual sequence estimated by the long-term cointegration equation of road passenger transportation. This residual sequence can be utilized as an error correction term in the construction of an error correction model. Additionally, to capture short-term dynamic adjustments, the residual error from the preceding period is included as an error correction item in the following panel error correction model (ecm_{it}) for road passenger transportation:

$$\widehat{\varepsilon_{it}} = ecm_{it} = \ln PTKM_{it} - \widehat{\alpha_0} - \widehat{\alpha_1} \ln INC_{it} - \widehat{\alpha_2^{\max}} \ln P_{it}^{\max} - \widehat{\alpha_2^{\text{cut}}} \ln P_{it}^{\text{cut}} - \widehat{\alpha_2^{\text{rec}}} \ln P_{it}^{\text{rec}} - \widehat{\alpha_3} \ln URB_{it}, \tag{15}$$

$$\Delta \ln PTKM_{it} = \beta_0 + \beta_1 \Delta \ln INC_{it} + \beta_2^{\max} \Delta \ln P_{it}^{\max} + \beta_2^{\text{cut}} \Delta \ln P_{it}^{\text{cut}} + \beta_2^{\text{rec}} \Delta \ln P_{it}^{\text{rec}} + \beta_3 \Delta \ln URB_{it} + \gamma ecm_{it-1} + \mu_{it}. \tag{16}$$

The panel error correction model reveals that road passenger transportation turnover is influenced by both short-term variations in the factors and deviations of road passenger transportation turnover from the long-term equilibrium trend. In Eq. (16), the difference sequence of each variable represents the short-term fluctuation of that variable, and $\Delta \ln INC_{it}$ represents the short-term fluctuation of per capita income. γ is the coefficient of error correction and μ_{it} is the random error term. The coefficients associated with the difference series of each variable represent short-term elasticity. Therefore, the coefficient β_2^{cut} in Eq. (16) can be interpreted as the value of the SERE for road passenger transportation. The estimated results of the road passenger transportation panel error correction model are presented in Table 5.

When the elasticity of road passenger transportation turnover to fuel price is used as the measurement index for the ERE, the SERE for China's road passenger transportation is calculated to be 41.0%. This indicates that in the short term, the actual energy savings achieved by China's road passenger transportation were only 59% of the expected energy savings resulting from improved energy efficiency. Among the regions, the lowest SERE was observed in central China at 36.0%, while the highest

Table 5 Estimation of the panel error correction equation in road passenger transportation

Variables	Whole country	Eastern	Central	Western
$\Delta \ln INC_{it}$	0.776***	1.004***	1.024***	0.596***
$\Delta \ln P_{it}^{\max}$	0.957***	−4.440***	1.799***	1.617***
$\Delta \ln P_{it}^{\text{cut}}$	−0.410***	−0.408***	−0.360***	−0.401***
$\Delta \ln P_{it}^{\text{rec}}$	0.292***	0.379***	0.315***	0.080
$\Delta \ln URB_{it}$	0.069	−0.103	0.146	0.189
ecm_{it-1}	−0.016***	−0.060***	−0.004	−0.005*
C	−0.086***	−0.058***	−0.125***	−0.066***

SERE was found in eastern China at 40.8%, and western China had the SERE of 40.1%. It is noteworthy that the SERE for road freight transportation in eastern China was higher than that in western China, which may be attributed to the larger room for travel in eastern China due to its relatively dense population distribution and higher economic development level (Wang et al., 2012). In comparison, the SERE for road passenger transportation was greater than the LERE but did not reach the level of a backfire effect.

Despite the increase in fuel prices, there has been no change in the short-term demand for energy services in road passenger transportation. Therefore, attempts to raise fuel prices as a means to reduce energy use in the road transportation sector may not yield the desired results. The growth of per capita income has a significant impact on road passenger transportation turnover, and this effect is more pronounced in the short run than in the long run. However, short-term changes in the level of urbanization do not have a significant impact on road passenger transportation turnover.

4.2 Road freight transportation

4.2.1 Unit root test

Similar to the stability test conducted for the variables in road passenger transportation, this study also employs the LLC test, IPS test, and HT test to analyze the original logarithmic series and the logarithmic first-order difference series of the variables in the road freight transportation equation. The panel unit root tests are carried out at a 95% confidence level. Table 6 provides the detailed results and shows that the first-order difference sequence does not exhibit a panel unit root process. This satisfies the conditions for further panel cointegration testing.

Table 6 Results of the panel unit root test

Variable	LLC test	IPS test	HT test	Conclusion
$\ln FTKM$	0.251	1.776	0.872	Nonstationary
$\Delta\ln FTKM$	-8.328^{***}	-13.231^{***}	-0.002^{***}	Stationary
$\ln CONS$	10.218	2.334	0.873	Nonstationary
$\Delta\ln CONS$	-7.045^{***}	-10.752^{***}	0.084^{***}	Stationary
$\ln P^{\max}$	-2.638^{***}	-4.574^{***}	0.826	Stationary
$\Delta\ln P^{\max}$	-7.390^{***}	-11.287^{***}	0.172^{***}	Stationary
$\ln P^{\mathrm{cut}}$	5.865	3.901	0.930	Nonstationary
$\Delta\ln P^{\mathrm{cut}}$	-6.882^{***}	-13.124^{***}	-0.045^{***}	Stationary
$\ln P^{\mathrm{rec}}$	0.427	4.676	0.919	Nonstationary
$\Delta\ln P^{\mathrm{rec}}$	-10.912^{***}	-12.550^{***}	-0.041^{***}	Stationary
$\ln STR$	-1.453^{*}	0.831	0.920	Nonstationary
$\Delta\ln STR$	-8.391^{***}	-8.402^{***}	0.132^{***}	Stationary

Note: Δ represents the first-order difference sequence of each variable, and the optimal number of lag periods is automatically determined according to the Schwarz Criterion.

4.2.2 Panel cointegration equilibration and LERE analysis

The results of the panel unit root test indicate that each variable in the road freight transportation equation follows a first-order single integer sequence. This suggests the presence of a cointegration relationship between the variables, which satisfies the prerequisites for conducting panel cointegration tests. Building upon this, the paper employs three panel cointegration test methods, namely, the Pedronic test, Kao test, and Westerlund test, to investigate the cointegration relationship among the variables in the road freight transportation equation. The specific results are presented in Table 7. All three tests, Pedronic, Kao, and Westerlund, reject the null hypothesis that "there is no cointegration relationship". These panel cointegration test results affirm that the long-term changes in all the variables of the road freight transportation equation are converging. This indicates the existence of a long-term cointegration relationship among the variables, including road freight transportation turnover, commodity transaction scale, fuel price, and industrial structure.

Table 7 Results of the panel cointegration test in the road freight transportation equation

	Statistics	Whole country
Pedroni test	Modified Phillips–Perron *t*	6.449^{***}
	Phillips–Perron *t*	-5.110^{***}
	Augmented Dickey–Fuller *t*	-4.040^{***}
Westerlund test	Variance ratio	-2.244^{**}
Kao test	Modified Dickey–Fuller *t*	-2.411^{***}
	Dickey–Fuller *t*	-2.300^{**}
	Augmented Dickey–Fuller *t*	-2.675^{***}
	Unadjusted modified Dickey–Fuller *t*	-3.156^{***}
	Unadjusted Dickey–Fuller *t*	-2.673^{***}

The Hausman test suggests that the fixed effect model is suitable for estimating the long-term cointegration equation for road freight transportation. Building upon this, the generalized least squares method is employed to conduct a panel regression estimation on the road freight transportation cointegration equation. The specific regression results are presented in Table 8.

When using the elasticity of road freight transportation turnover to fuel price as the measurement index for ERE, the LERE for China's road freight transportation is estimated to be 48.3%. Within this estimation, the LERE in central China was the lowest at 14.0%, while western China had the highest LERE at 40.6%, and eastern China had the LERE of 24.1%. Importantly, the LERE did not reach the level of a backfire effect, suggesting that the

Table 8 Estimation of the long cointegration equation in road freight transportation

Variables	Whole country	Eastern	Central	Western
$\ln CONS_{it}$	0.548***	0.514***	0.763***	0.603***
$\ln P_{it}^{\max}$	5.142***	15.969***	0.186	3.969***
$\ln P_{it}^{\mathrm{cut}}$	−0.483***	−0.241**	−0.140**	−0.406***
$\ln P_{it}^{\mathrm{rec}}$	1.157***	0.467***	0.927***	1.176***
$\ln STR_{it}$	1.089***	0.548***	1.061***	0.890***
C	−22.104***	−74.376***	0.183	−17.090***

energy savings resulting from improvements in energy efficiency in the road freight sector were not completely offset by the presence of ERE. Comparing regional differences, the LERE of road freight transportation in western China was larger than that in eastern China, possibly due to government-directed investments, such as the implementation of China's Great Western Development Strategy.

Furthermore, considering the regression coefficient of total retail sales of consumer goods, the results from the panel cointegration model consistently show a significant positive effect in the long term. This indicates that the growth of total retail sales of consumer goods has a substantial positive impact on road freight transportation turnover over time. Additionally, the regression coefficient of industrial structure reveals that the output value of the secondary industry significantly promotes the turnover of road freight transportation. This underscores the significant influence of industrial structure on the demand for road freight transportation energy services.

4.2.3 Panel error-correction model and SERE analysis

Given the results of the panel cointegration test among the variables of the road freight transportation equation, it is evident that there exists a long-term equilibrium relationship among variables, including road freight transportation turnover, commodity transaction scale, fuel price, and industrial structure. However, this long-term equilibrium relationship may experience deviations from equilibrium in the short term. Similar to the research on the SERE of road passenger transportation, this paper establishes the following short-term panel error correction model for road freight transportation based on the values of the long-run cointegration equation:

$$\widehat{\varepsilon_{it}} = ecm_{it} = \ln FTKM_{it} - \widehat{\alpha_0} - \widehat{\alpha_1}\ln CONS_{it} - \widehat{\alpha_2^{\max}}\ln P_{it}^{\max} - \widehat{\alpha_2^{\mathrm{cut}}}\ln P_{it}^{\mathrm{cut}} - \widehat{\alpha_2^{\mathrm{rec}}}\ln P_{it}^{\mathrm{rec}} - \widehat{\alpha_3}\ln STR_{it}, \tag{17}$$

$$\Delta\ln FTKM_{it} = \beta_0 + \beta_1\Delta\ln CONS_{it} + \beta_2^{\max}\Delta\ln P_{it}^{\max} + \beta_2^{\mathrm{cut}}\Delta\ln P_{it}^{\mathrm{cut}} + \beta_2^{\mathrm{rec}}\Delta\ln P_{it}^{\mathrm{rec}} + \beta_3\Delta\ln STR_{it} + \gamma ecm_{it-1} + \mu_{it}. \tag{18}$$

The road freight transportation panel error correction model illustrates that in the short term, road freight transportation turnover is influenced by short-term factors, but it is also impacted by deviations from the long-term equilibrium trend. In Eq. (18), the difference sequence of each variable signifies its short-term fluctuations. For example, it represents the short-term change in the retail sales of consumer goods. The coefficients associated with the differential series of various variables indicate their short-term elasticity. Hence, Eq. (18) can be interpreted as the estimated result of the SERE for road freight transportation. Table 9 provides the estimation results of the short-term panel error correction model for road freight traffic.

Table 9 Estimation of the panel error correction equation in road freight transportation

Variables	Whole country	Eastern	Central	Western
$\Delta\ln CONS_{it}$	0.753***	0.613***	0.872***	0.305***
$\Delta\ln P_{it}^{\max}$	9.008***	21.832***	2.168***	7.234***
$\Delta\ln P_{it}^{\mathrm{cut}}$	−0.233***	−0.039	−0.260	−0.318**
$\Delta\ln P_{it}^{\mathrm{rec}}$	1.030***	0.463***	1.058***	1.175***
$\Delta\ln STR_{it}$	0.830***	0.498***	0.720***	0.752***
ecm_{it-1}	−0.045***	−0.013*	−0.052**	−0.093***
C	−0.035***	−0.001*	−0.046	0.025

When using the elasticity of road freight transportation turnover to fuel price as the measure of ERE, we find that the SERE for road freight transportation in China is 23.3%. This is generally lower than the LERE for road freight transportation. Among the regions analyzed, western China has the highest SERE at 31.8%, while eastern China has the lowest at 3.9%. This disparity may also be attributed to government-directed investments (Jia et al., 2020).

In comparison to road passenger transportation, the field of road freight transportation exhibits a certain degree of short-term rigidity. When energy efficiency improves and energy service costs decrease, it is challenging to achieve rapid responses in the short run.

Regarding the cumulative recovery of fuel prices in the short term, there is a simultaneous increase in fuel prices and road freight transportation turnover. In other words, the rise in fuel prices has not acted as a deterrent to the demand for energy services in the road freight transportation sector. Therefore, attempts to reduce energy consumption in road freight transportation by raising fuel prices in the short term may not yield the expected results. This aligns with the impact of rising fuel prices on road freight transportation in the long run.

Short-term fluctuations in the total retail sales of consumer goods have a positive effect on road freight transportation turnover, similar to their long-term impact. Whether in the long run or short run, an expansion in the scale of commodity transactions promotes the need for energy services in road freight transportation, leading to increased energy use.

Regarding the coefficient associated with short-term fluctuations in industrial structure, industrial structure still positively affects road freight transportation turnover. However, the short-term impact of industrial structure on road freight transportation turnover is less pronounced than its long-term influence. This is because the influence of industrial structure on road freight transportation turnover typically requires time to accumulate, resulting in a smaller short-term impact compared to the long term.

4.3 Robustness tests

4.3.1 Robustness test for changing the time window width

The results (Table 10) indicate that when we adjust the time window to cover the years from 2004 to 2018, the SERE and LERE for road passenger transportation in China were 15.8% and 28.6%, respectively. For road freight transportation, the SERE and LERE were 58.6% and 45.9%, respectively. In both cases, the ERE observed was a partial rebound effect without reaching the level of a backfire effect. Importantly, the regression coefficients and their significance remained consistent with the results obtained in the benchmark regression, underscoring the robustness of these findings (Li et al., 2019; Liu and Zhang, 2021).

4.3.2 Robustness test for excluding special samples

To assess the robustness of the benchmark regression results, the exclusion of special samples can be an effective method, as suggested in prior research (Li et al., 2021). In this context, special samples refer to regions with strong economies that may have more complex and stringent regional policies, potentially affecting the regression results of ERE (Chen et al., 2022b). In this study, three economically developed province-level regions — Beijing, Shanghai, and Guangdong — were excluded from the robustness test. The results are presented in Table 11. In this analysis, the SEREs and LEREs for China's road passenger transportation were found to be 18.3% and 31.6%, respectively. For road freight transportation, the SEREs and LEREs were 64.3% and 41.5%, respectively. Importantly, the regression coefficients and their significance in this robustness test, excluding the special samples, remained consistent with the results of the benchmark regression, reinforcing the reliability of the findings (Li et al., 2021).

5 Conclusions

This study employed panel cointegration and panel error correction models. We focused on the asymmetric effects of fuel prices using panel data from 30 province-level regions in China (excluding Hong Kong, Macao, Taiwan, and Xizang). The objective is to examine LEREs and SEREs within the domains of road passenger transportation and road freight transportation. The findings can be summarized as follows.

(1) China's road transportation sector exhibits a noteworthy ERE. Specifically, the LEREs for road passenger

Table 10 Robustness test results for changing the time window width

Variables	$\ln PTKM$	Variables	$\Delta\ln PTKM$	Variables	$\ln FTKM$	Variables	$\Delta\ln FTKM$
$\ln INC_{it}$	0.645^{***}	$\Delta\ln INC_{it}$	0.973^{***}	$\ln CONS_{it}$	0.668^{***}	$\Delta\ln CONS_{it}$	0.814^{***}
$\ln P_{it}^{\max}$	2.010^{*}	$\Delta\ln P_{it}^{\max}$	1.403	$\ln P_{it}^{\max}$	8.848^{***}	$\Delta\ln P_{it}^{\max}$	9.823^{***}
$\ln P_{it}^{\text{cut}}$	-0.158^{***}	$\Delta\ln P_{it}^{\text{cut}}$	-0.286^{*}	$\ln P_{it}^{\text{cut}}$	-0.586^{***}	$\Delta\ln P_{it}^{\text{cut}}$	-0.459^{**}
$\ln P_{it}^{\text{rec}}$	-0.404^{**}	$\Delta\ln P_{it}^{\text{rec}}$	0.308^{*}	$\ln P_{it}^{\text{rec}}$	0.839^{***}	$\Delta\ln P_{it}^{\text{rec}}$	1.436^{***}
$\ln URB_{it}$	-1.213^{***}	$\Delta\ln URB_{it}$	−0.733	$\ln STR_{it}$	1.686^{***}	$\Delta\ln STR_{it}$	1.265^{***}
C	-13.975^{***}	ecm_{it-1}	−0.038	C	-40.509^{***}	ecm_{it-1}	-0.202^{***}
		C	0.110			C	-1.181^{***}

Table 11 Robustness test results for excluding special samples

Variables	$\ln PTKM$	Variables	$\Delta\ln PTKM$	Variables	$\ln FTKM$	Variables	$\Delta\ln FTKM$
$\ln INC_{it}$	0.897^{***}	$\Delta\ln INC_{it}$	0.903^{***}	$\ln CONS_{it}$	0.678^{***}	$\Delta\ln CONS_{it}$	0.744^{***}
$\ln P_{it}^{\max}$	1.073	$\Delta\ln P_{it}^{\max}$	1.364	$\ln P_{it}^{\max}$	4.854^{***}	$\Delta\ln P_{it}^{\max}$	9.392^{***}
$\ln P_{it}^{\text{cut}}$	-0.183^{***}	$\Delta\ln P_{it}^{\text{cut}}$	-0.316^{**}	$\ln P_{it}^{\text{cut}}$	-0.643^{***}	$\Delta\ln P_{it}^{\text{cut}}$	-0.415^{**}
$\ln P_{it}^{\text{rec}}$	-0.739^{***}	$\Delta\ln P_{it}^{\text{rec}}$	0.201	$\ln P_{it}^{\text{rec}}$	0.664^{**}	$\Delta\ln P_{it}^{\text{rec}}$	1.470^{***}
$\ln URB_{it}$	-0.958^{***}	$\Delta\ln URB_{it}$	−0.029	$\ln STR_{it}$	1.307^{***}	$\Delta\ln STR_{it}$	1.222^{***}
C	-8.783^{**}	ecm_{it-1}	-0.053^{**}	C	-21.598^{***}	$\eta_{P_E}(S)=\partial\ln S/\partial\ln P_E=0$	-0.149^{***}
		C	0.186			C	-0.874^{***}

transportation and road freight transportation range from 13% to 25% and 14% to 48%, respectively. The SEREs for road passenger transportation and road freight transportation fall within the ranges of 36% to 41% and 3.9% to 32%, respectively.

(2) Road passenger transportation and road freight transportation demonstrate differential responses to improvements in energy efficiency, whether in the short run or the long run. The LERE of road freight transportation surpasses that of road passenger transportation, while the SERE of road passenger transportation exceeds that of road freight transportation.

(3) Regarding the extent of the ERE, whether at the national or subregional level, the ERE observed in road passenger transportation and road freight transportation does not reach the level of a backfire effect. This implies that the ERE is not the underlying cause of the ongoing surge in energy consumption within China's road transportation sector.

(4) The escalation in fuel prices has not substantially impeded the growth of energy services in both road passenger transportation and road freight transportation. Consequently, the current strategy of raising fuel prices to curtail energy consumption in the road transportation sector has not yielded the anticipated outcomes.

Our study carries several policy implications. First, enhancing energy efficiency will remain the primary avenue for achieving energy savings and the consequent reduction in emissions within the road transportation sector. However, the presence of the ERE suggests that solely relying on technological advancements to enhance energy efficiency may not be as effective as anticipated. It is imperative to consider implementing taxation adjustments or other corresponding supplementary measures.

Second, the escalation in fuel prices has not effectively curbed the demand for energy services in road transportation, both in the short and long term. This can be attributed to the government's regulation of fuel prices in China, resulting in generally low fuel prices. When fuel prices accurately reflect their true costs, adjustments may have a more significant impact on energy consumption.

Finally, distinct emission reduction policies and standards can be devised for road passenger transportation and road freight transportation. These measures may involve establishing more stringent fuel efficiency standards for long-term truck operations and increasing the tax rate for road passenger transportation in the short term. Additionally, implementing distance-based road taxes could be an effective tool alongside fuel price interventions, potentially mitigating the magnitude of the ERE in road transportation. The effectiveness of distance-based taxes can be enhanced by making them adaptable in terms of both time and location, considering the variability of the ERE across different circumstances.

Competing Interests The authors declare that they have no competing interests.

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