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GREEN DEVELOPMENT AND ENVIRONMENTAL POLICY IN CHINA: PAST, CURRENT AND FUTURE

The impact of population characteristics on transportation CO_2 emissions—does population aging important?

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Abstract

Reducing transportation CO_2 emissions and addressing population characteristic changes are two major challenges facing China, involving various requirements for sustainable economic development. Due to the interdependence of population characteristics and transportation, human activities have become a significant cause of the increase in greenhouse gas levels. Previous studies mainly focused on evaluating the relationship between one-dimensional or multi-dimensional demographic factors and CO_2 emissions, while few studies have reported on the effect of multi-dimensional demographic factors on CO_2 emissions in transportation. Analyzing the relationship between transportation CO_2 emissions is the foundation and key to understanding and reducing overall CO_2 emissions. Therefore, this paper used the STIRPAT model and panel data from 2000 to 2019 to investigate the effect of population characteristics on CO_2 emissions of China's transportation sector, and further analyzed the effect mechanism and emission effect of population aging on transportation CO_2 emissions. The results show that (1) population aging and population quality restrained CO_2 emissions from transportation, but the negative effects of population aging were indirectly caused by economic growth and transportation demand. And with the aggravation of population aging, the influence on transport CO_2 emissions changed and presented a U-shape. (2) Population living standard on transportation CO_2 emissions exhibited an urban–rural difference, and urban living standard was predominant in transportation CO_2 emissions. Additionally, population growth is under a weakly positive effect on transportation CO_2 emissions. (3) At the regional level, the effect of population aging on transportation CO_2 emissions showed regional differences. In the eastern region, the CO_2 emission coefficient of transportation was 0.0378, but not significant. In central and western regions, the influence coefficient of transportation was 0.6539 and 0.2760, respectively. These findings indicated that policy makers should make relevant recommendations from the perspective of coordinating population policy and energy conservation and emission reduction policy in transportation.

Keywords Transport/Transportation CO_2 emissions · Population characteristics · Population aging · STIRPAT model

Introduction

The transportation sector is an important area of global energy consumption and greenhouse gas (GHG) emissions (Wang et al. 2020a). In recent years, with the development of China's economy and the increase of car ownership, the total CO_2 emissions of the transportation sector in China have continued to increase (Yang et al. 2015; Gambhir et al. 2015; Lin and Xie 2014), which makes great challenges to China in reducing carbon dioxide emissions (Li et al. 2019). According to the International Energy Agency statistics, transportation has become the second largest carbon emitting sector in the world, accounting for 25% of global carbon emissions, and is the main contributor to global climate change (IEA 2018). Since the onset of COVID-19, GHG emissions have been effectively mitigated in the short term by reducing economic activity and transport. However, as the economy and transportation recover globally, energy consumption and GHG emission are likely to exceed pre-pandemic levels (Wang and Su 2020; IEA 2022). In China, carbon emissions from the transport sector

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account for about 15% of national terminal emissions, and the average growth rate of carbon emissions from 2013 to 2019 remains above 5%. The transportation sector has been the fastest growing field of GHG emissions in China (Ma et al. 2015). Although improvements in fuel economy have slowed the growth of vehicle energy consumption, it is still difficult to offset the increased carbon emissions caused by the huge transportation demand. For example, the significant increase in transport CO_2 emissions in the UK and the rebound effect of carbon emissions in US transport have made the transport sector the most difficult sector to achieve global carbon reductions (Yang et al. 2019; Brand et al. 2012; Schipper 2011; Marsden and Rye 2010). Therefore, it is of great importance to effectively control carbon emissions of China's transportation sector by studying the factors of CO_2 emissions in China's transportation sector to achieve the goals of the Paris Agreement (Pan et al. 2018). At the same time, the effective control of CO_2 emissions from the transportation sector is not only the objective requirement to achieve China's development of green, low-carbon transportation system, but also the inevitable choice to achieve global low-carbon economy and low-carbon development.

For a long time, energy consumption, technology, economy, and other factors have been considered the main factors affecting carbon emissions from the transportation sector (Li et al. 2021; Feng et al. 2020; Ali et al. 2019; Lin and Xie 2014; Wang et al. 2011). However, the Fifth Assessment Report of the IPCC pointed out that since the 1950s, 95% of greenhouse gas emissions were caused by human activities, of which 11% of the anthropogenic increase in greenhouse gas emissions was from the transportation sector. And due to the interdependence between population and transportation, population-related factors have become an important factor affecting CO_2 emissions in transportation sector (Zarco-Soto et al. 2021; Meng and Han 2018; Wang and Liu 2015; Yang et al. 2015; Liu et al. 2011; Lu et al. 2007). Previous studies have paid particular attention to population size (Li et al. 2022; Sun et al. 2021; Wang et al. 2020b; Salman et al. 2019). However, with the overall progress of China's social and economic development, political system, scientific and technological progress, social value system, and other factors, the Chinese population has more complex characteristics, such as the continuous increase of urbanization rate, the imbalance in age structure, the overall improvement of people's quality, and the remarkable improvement of population living standards. Many changes in population characteristics have changed travel distance, travel mode, and travel demand. However, previous empirical studies have rarely distinguished between different population characteristics, so the importance of population characteristics on CO_2 emissions from transportation may be ignored. Therefore, considering various demographic characteristics, this paper can not only comprehensively analyze the impact of population factors on the transportation industry, but also fill the research gap. At the same time, the results have important practical significance for the management of China's population structure, the sustainable development of the transportation sector, and the early achievement of CO_2 cap target. In addition, the aging of the population is an important factor in the imbalance of the population structure and is a major change in the population characteristics of China, which is related to the stable development of the economy and society. The transportation sector is responsible for the transfer of goods and people in the economic and social fields, which is closely related to the life of the elderly population. Therefore, we need to reorganize the relationship between aging based on the change of demographic characteristics and carbon emissions of the transportation industry.

In terms of influencing factors, scholars have extensively discussed the relationship between individual population characteristics and CO_2 emissions. Lu et al. (2007) and Meng and Han (2018) found that population density reduces CO_2 emissions from transportation, and the same Chen et al. (2020) and Liu et al. (2015) showed that population density helps to reduce pollution. Wang and Li (2019) pointed out that investment in education and knowledge diffusion promotes technological development, increases labor productivity, and reduces CO_2 emissions. Li et al. (2022) also noted that population quality plays a significant role in reducing CO_2 emissions. Another example is Wang et al. (2022) indicated that consumers' education level has a significant impact on new energy vehicle purchase intentions. However, Li et al. (2019) concluded that higher education level promotes CO_2 emissions in eastern China. Wang and Liu (2015) investigated the drives of household transportation emissions in Beijing from the perspective of individual travel characteristics and concluded that per capita disposable income is one of the main drivers of the increase in daily household CO_2 emissions. Li et al. (2019) suggested that there is a long-term relationship between CO_2 emissions and demographic structure. Feng et al. (2020) found that age structure has a stable promoting effect on the growth of CO_2 emissions in the transportation sector, although the effect is relatively small. Wang et al. (2019) revealed that population structural change has a significant nonlinear impact on per capita CO_2 emissions as the population growth rate slows in China. Population aging characteristics are important factors affecting carbon emissions (Wang et al. 2022), but existing studies mainly focus on the assessment of population aging and total CO_2 emissions, and the results remain inconclusive. Li (2020), Tong and Zhou (2020), Kim et al. (2020), and Yang and Wang (2020) pointed out that population aging reduces carbon emissions. They argue that the lifestyle and consumption patterns of the elderly population hinder economic development and reduce carbon emissions. In contrast, Menz and Welsch (2012) found that people aged 60 and older in OECD countries have significantly higher emissions than other age groups. They believed that older people increase carbon emissions due to the cohort effect and weak environmental awareness. Fan et al. (2021) indicated that whether the population is above or below the threshold, aging always has a positive effect on household carbon emissions. In addition, some scholars believe that there is a nonlinear relationship between aging and carbon emissions. For example, Zhang and Tan (2016) pointed out that population aging increases carbon emissions and the level of carbon emissions changes with the degree of population aging. Li (2015) and Wang et al. (2019) found an inverted U-shaped relationship between population aging and carbon emissions in China. Another example is Wang et al. (2023) concluded that there is a U-shaped relationship between income inequality and carbon emission efficiency under the influence of aging. However, Wang and Zhou (2012) concluded that there is a U-shaped between population aging and carbon emissions based on data from nine countries, including the USA, China, Japan, and the UK. From the above literature, it appears that population density can reduce CO_2 emissions. However, there are few previous studies on the relationship between population quality, population living standards, age structure, and greenhouse gasses. The research findings on population aging and carbon dioxide emissions are also controversial, and the research on demographic factors and carbon emissions in transportation is even less.

As far as research methods are concerned, there are three common methods to determine the impact of human activities on the environment. The first method is the logarithmic mean division index (LMDI). The model usually decomposes carbon emissions into the product of emission intensity based on economic development, population size, and energy efficiency (Li et al. 2019; Zhang et al. 2019; Chen et al. 2018; Mousavi et al. 2017). The second method is structural decomposition analysis (SDA). Using input–output tables, SDA provides a unified framework to identify the causes of increased carbon emissions (Wang and Han 2021; Dietzenbacher et al. 2020; Xia et al. 2015; Yuan et al. 2015). The third method is the STIRPAT model and its extended form. This model provides an accurate description of the sensitivity of environmental influences to driving forces and not only analyzes the scientific basis of environmental change, but also identifies the factors that are likely to be most responsive to policy (Wu et al. 2021; Kilbourne and Thyroff 2020; Gao et al. 2019; York et al. 2003). Wu et al. (2021) used the extended STIRPAT model to decompose CO_2 emissions from six influencing factors. Similarly, Li et al. (2022) used the extended STIRPAT model to construct the relationship between population factors and carbon emissions. Due to the limitations of the model itself, it is difficult to include demographic factors other than population size in the LMDI and SDA models. Therefore, this paper uses the STIRPAT model to analyze the relationship between population factors and CO_2 emissions from the transportation sector.

In addition, we use panel data to examine the determinants of CO_2 emissions in transport (Zhang et al. 2019; Wang et al. 2014), which offsets the control of individual heterogeneity, parameter estimation, and multicollinearity among variables by traditional time series data or cross-sectional data. Yang et al. (2015) used panel data and a two-way fixed effects model to measure the effects of social economy, urban morphology, and traffic development on CO_2 emissions from the transportation sector, and drew some valuable conclusions. Xu and Lin (2016) also used provincial panel data to examine the nonlinear effects of economic growth, urbanization, and energy efficiency improvement on CO_2 emissions from China's transportation sector. However, these studies did not consider demographic effects, which may lead to an inadequate understanding of the factors influencing CO_2 emissions from the transport sector.

Although the relationship between various demographic factors and CO_2 emissions has been examined in previous studies, there are still obvious shortcomings in the literature to date. First, previous research on demographic characteristics and CO_2 emissions has focused on the macro level, resulting in a lack of evidence for key sectors to reduce emissions. The relationship between population characteristics factors and CO_2 emissions in key sectors is the foundation and key to understanding and achieving overall CO_2 emission reductions. This paper chooses the transportation sector as the research object, which not only enriches and deepens the research on the influencing factors of carbon emissions from transportation, but also provides a new perspective to the literature on population factors and sectoral CO_2 emissions. Second, compared to the previous one-dimensional demographic factor (i.e., population size), this paper provides a multidimensional assessment of the relationship between demographic characteristics factors and CO_2 emissions in transportation to extend previous empirical findings on the influence of demographic factors on CO_2 emissions in typical industry. Third, given the relationship between population aging and CO_2 emissions in transportation, this paper adds an analysis of the influence mechanisms that can better capture the path of aging on CO_2 emissions in transportation and provide a policy basis for mitigating the extent of aging and reducing carbon emissions in transportation. From the perspective of theoretical value, our study selects the transportation industry to analyze the relationship between multidimensional demographic characteristics and key carbon emission industries, which not only promotes the deep integration of China's concept of sustainable population development and the transportation industry, but also provides a theoretical basis for the design of carbon emission reduction policies in the transportation industry. From the perspective of application benefit, this paper explores the impact mechanism of population aging and CO_2 emissions in transportation, which not only helps to clarify the adjustment and optimization of the path of CO_2 emissions in the transportation industry, but also serves as a reference for relevant departments to formulate practical and operational policy recommendations to reduce CO_2 emissions in the transportation.

To fill the knowledge gaps in the existing literature, the content of this paper is structured as follows. First, we constructed a model to calculate CO_2 emissions from transportation in 30 provinces from 2000 to 2019 from direct and indirect paths. Based on the inter-provincial spatio-temporal characteristics map and the regional variation maps, we can trace the regional and provincial development characteristics of CO_2 emissions of China's transportation sector. Second, we used the STIPRAT model to decompose the population factors into population growth, population quality, population living standard, and age structure. Moreover, on the basis of socioeconomic factors, energy intensity, and urban morphology, we construct an individual fixed effects model from panel data to investigate the impact of changes in population characteristics on CO_2 emissions from the transportation sector. We also analyze the mechanism of population aging and CO_2 emissions of China's transportation sector, and illustrate the path of CO_2 emissions in the transportation sector. Finally, due to the differences in geographical environment and economic development, it is necessary to use the data from the East, Central, and West to investigate the impact of population aging on CO_2 emissions in transportation and compare the differences between regions. In this work, we divided the Chinese provincial panel data set into three subsamples, i.e., Eastern, Central, and Western regions, as shown in Table 1.

The framework of the paper is as follows: the "Models and variables" section introduces the method construction and variable calculation in this study. The "Data sources and description" section provides data sources and descriptions. The "Results and discussion" section introduces the research results and discusses the main findings. The "Conclusions and policy implication" section provides the main conclusions and policy recommendations.

Models and variables

Model construction

The IPAT model was first proposed by Ehrlich and Holdren (1971) in the 1970s to study the effects of human activities on the environment. The model briefly explains the causes of environmental problems, but implies the linear assumption that the effects of different variables on I are equal. In fact, population, affluence, and technology have different weights and ways of affecting environmental problems in different countries. Therefore, IPAT still has very limited applicability. To solve this problem, Dictz and Rosa (1994) developed the IPAT model into a stochastic model for empirical hypothesis testing, namely the STIRPAT model. This model has been widely used to study the impact of driving forces on environmental change. The specific model is shown in Eq. (1).

$$I = aP_i^b A_i^c T_i^d e_i \quad (1)$$

where $i = 1, 2, \ldots, N$ represents the cross-sectional size; I, P, A, and T represent environmental impact, population, affluence, and technology, respectively. a represents the constant term; b, c, and d represent the environmental impact elasticity based on P, A, and T respectively, and e represents the error term. After taking logarithms, Eq. (1) can be transformed into Eq. (2).

$$\ln I = a + b\ln P_i + c\ln A_i + dT_i + \ln e_i \quad (2)$$

Table 1 The economic region in China

Region	Province covered
Eastern region	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Central region	Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan
Western region	Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang

The classification criteria refer to China Health Statistics Yearbook

The STIRPAT model allows not only the estimation of each coefficient as a parameter, but also an appropriate decomposition of each factor, which means that new influential factors can be added to the STIRPAT model framework according to the characteristics of each study. In this study, the theoretical STIRPAT model was extended based on previous literature to meet our design requirements.

In this paper, I, A, and T denote the transportation industry CO_2 emissions (TCEs), per capita gross domestic product, and energy density (EI), respectively. P represents population characteristics, which are closely related to transportation CO_2 emissions (Wang and Li 2021; Kim et al. 2020; Meng and Han 2018; Liu et al. 2017; Liddle and Lung 2010). Based on the research content setting, P was decomposed into population growth (population growth rate: PG), population quality (adult illiteracy rate: PL; and higher education ratio: PQ), population living standards (urban per capita consumption expenditure: P_{cu}; and rural per capita consumption expenditure: P_{cr}), and population age structure (population under 14 years old: Age 14–; 15–64 years old, Age 15–64; and over 65 years old, Age 65 +). In addition, Sikder et al. (2022), Wang et al. (2017), and Li and Lin (2015) pointed out that urbanization will increase carbon emissions, and Ali et al. (2019) and Wang and Li (2021) confirmed this conclusion. Li et al. (2019) and Chai et al. (2016) clarified the important impact of total transport turnover on carbon emissions in the transport industry. We also introduce the quadratic term of per capita GDP to observe the existence of environmental Kuznets curve (Yang et al. 2021; Dogan and Inglesi-Lotz 2020; Zoundi 2017). Due to the slow adjustment of industrial structure, energy structure, and related macroeconomic factors, those are not considered in this paper. The extended STIRPAT model is transformed into Eq. (3).

$$\begin{aligned}\ln TCEs_{it} &= a + \beta_1 \ln PGDP_{it} + \beta_2 \left(\ln PGDP_{it}\right)^2 + \beta_3 \ln P_{it} \\ &+ \beta_4 \ln EI_{it} + \beta_5 \ln TRAT_{it} + \beta_6 \ln URB_{it} + e_{it}\end{aligned} \tag{3}$$

where i denotes provinces, $i = 1,2,\ldots,N.t$ denotes year, $t = 1,2,\ldots,T$. Coefficient $\beta_1 - \beta_6$ can be regarded as the percentage of carbon emissions caused by a 1% change in an impact factor when other factors remain unchanged, which is equivalent to the elasticity coefficient. a and e represent constant and random error terms. All variables are in their logarithmic form. Since the population growth rate includes negative values, the logarithm is taken after data preprocessing, which does not change the trend of population growth rate.

Moreover, panel data model can reflect temporal and cross-sectional information. By analyzing panel data, on the one hand, we can obtain information about the CO_2 emissions of transportation and the population characteristics of China, which determine the state of a province from 2000 to 2019. On the other hand, we can obtain information about transportation CO_2 emissions and China's population characteristics factors in different provinces in the same period. Therefore, we can comprehensively test the relationship between transportation CO_2 emissions and population characteristics factors. However, panel data may cause problems of individual heterogeneity and temporal heterogeneity. To address these issues, it is necessary to apply a fixed effects model. The fixed effects model includes both the individual-specific effects model and the two-way fixed effects model. The individual-specific effects model is employed to solve the individual heterogeneity while the two-way fixed effects model can eliminate both individual and temporal heterogeneity problems of a panel data (Sun et al. 2018). Li and Ye (2012) believe that it is best to choose the fixed-effects model when the individual is the whole research group, and the individuals in this article are 30 provinces in China, so the fixed effects model is more suitable for regression. At the same time, the combination of panel data balances the control of individual heterogeneity, parameter estimation, and multicollinearity between variables by traditional time series data or cross-sectional data. The final model combining STIRPAT model and panel data is Eq. (4).

$$\begin{aligned}\ln TCEs_{it} &= a + \beta_1 \ln PGDP_{it} + \beta_2 \left(\ln PGDP_{it}\right)^2 + \beta_3 \ln P_{it} \\ &+ \beta_4 \ln EI_{it} + \beta_5 \ln TRAT_{it} + \beta_6 \ln URB_{it} + u_i + e_{it}\end{aligned} \tag{4}$$

In the regional analysis, because the time dimension is larger than the cross-sectional dimension, we adopt a linear regression model with attached panel corrected standard errors (PCSEs). This approach is usually used to analyze long panel data, improving small sample properties through normalizing the standard error.

Calculation of variables

Calculation of transportation CO_2 emissions

Based on the guidance approach of IPCC (IPCC 2006), we calculated the annual total transportation CO_2 emissions for each province in two parts. The first part is the direct CO_2 emissions that come from the combustion of all types of fossil fuels for the transportation sector. The second part is the indirect CO_2 emissions that come from heat and electricity consumed by the transportation sector. The calculation formula is as follows:

$$TCEs_{it} = \sum_n E_n F_{nit} + e_h H_{it} + e_{it} U_{it} \tag{5}$$

Table 2 The calorific values, CO_2 emission factors and CO_2 emission coefficient of different types of fossil fuels

Fuel	Average low calorific value	Carbon content	Carbon oxidation rate	CO_2 emission coefficient
Raw coal	20,908(KJ/kg)	26.37(kg/GJ)	0.94	1.9003(kg/kg)
Cleaned coal/other washed coal	26,344(KJ/kg)	25.41(kg/GJ)	1	2.4544(kg/kg)
Briquettes	20,700(KJ/kg)	33.6(kg/GJ)	0.90	2.2952(kg/kg)
Coke	28,435(KJ/kg)	29.5(kg/GJ)	0.93	2.8604(kg/kg)
Crude oil	41,816(KJ/kg)	20.1(kg/GJ)	0.98	3.0202(kg/kg)
Gasoline	43,070(KJ/kg)	18.9(kg/GJ)	0.98	2.9251(kg/kg)
Kerosene	43,070(KJ/kg)	19.6(kg/GJ)	0.98	3.0179 (kg/kg)
Diesel oil	42,652(KJ/kg)	20.2(kg/GJ)	0.98	3.0958(kg/kg)
Fuel oil	41,816(KJ/kg)	21.1(kg/GJ)	0.98	3.1705(kg/kg)
Liquefied petroleum gas	50,179(KJ/kg)	17.2(kg/GJ)	1	3.1013(kg/kg)
Other petroleum products	40,200(KJ/kg)	20.0(kg/GJ)	1	2.9480(kg/kg)
Natural gas	38,931(KJ/kg)	15.3(kg/GJ)	0.99	2.1622(kg/m^3)
Liquefied natural gas	—	—	—	2.3300(kg/m^3)

The average low calorific value refers to China Energy Statistical Yearbook Appendix 4 and the 2006 IPCC Guidelines for National Greenhouse Gas (Volume 2 Energy); carbon content refers to the 2006 IPCC Guidelines for National Greenhouse Gas (Volume 2 Energy); carbon oxidation rate refers to the "Provincial Greenhouse Gas Inventory Compilation Guidelines" Development and Reform Office Climate [2011] No. 1041 Document. The CO_2 emission coefficient is calculated via the average low calorific value, carbon content, and carbon oxidation rate

where $TCEs_{it}$ denotes the amount of CO_2 emissions from transportation for province i in year t, F_{nit} is the consumption of fossil fuel n for province i in year t, E_n is the CO_2 emission coefficient of fossil fuel n, U_{it} is the electricity consumption for province i in year t, e_{it} is the electricity CO_2 emission coefficient for province i in year t, and n include raw coal, washed coal, other washed coal, briquette, coke, gasoline, diesel, kerosene, crude oil, liquefied natural gas, other petroleum products, natural gas, and liquefied natural gas; the calorific value, carbon content, and CO_2 emission factors for the different types of fossil fuels are shown in Table 2. H_{it} is the heat consumption for province i in year t, e_h is the CO_2 emission coefficient of heat. The heat is first converted into standard coal, then converted into CO_2. One terajoule (TJ) of heat is equivalent to 34.12 tons of standard coal, and 1 ton of standard coal is equivalent to 2204 kg of CO_2. Therefore, the CO_2 emission coefficient of heat is 75,000 kg/TJ.

The calculation steps of the electricity CO_2 emission coefficient are as follows: Divide the CO_2 emissions generated by thermal power in a province by the total electricity generation in a province to get the CO_2 emissions generated by each kilowatt-hour of electricity in a province, i.e., the CO_2 emission coefficient for electricity in a province. Then the CO_2 emissions generated by the power consumption are obtained by multiplying the annual electricity consumption by the electricity CO_2 emission coefficient. According to the empirical data, 1 kWh consumes about 0.34 kg of coal, and 0.87 kg CO_2 is generated based on the 70% carbon content of coal (considering that the CO_2 emissions from electricity are mainly from thermal power generation, and the CO_2 emissions from hydropower and nuclear power generation are 0). The specific emission coefficient is shown in Appendix 1, by referring to the Provincial Greenhouse Gas Listing Compilation Guidelines published by China's National Development and Reform Commission, the electricity CO_2 emission coefficient calculated in this paper is basically consistent with the average CO_2 emission factor of China's regional power grid in the year of release. Therefore, the calculation method in this paper is considered to provide a scientific and accurate measurement of the result for CO_2 emissions from transportation in China.

Calculation of population factors index

The calculation of population factors index refers to Li (2004). Zhang and Tan (2016) used this indicator to test the relationship between population factors and carbon emissions in China, and verified the importance of population factors in the process of controlling CO_2 emissions.

$$p_{ij} = \left(R_{ij} - R_{\min}\right) / \left(R_{\max} - R_{\min}\right) \times 100 \tag{6}$$

$$p_{ij} = \left(R_{\max} - R_{ij}\right) / \left(R_{\max} - R_{\min}\right) \times 100 \tag{7}$$

where p_{ij}, R_{ij}, $R_{\max}$, and $R_{\min}$ respectively denote the score, current value, maximum value, and minimum value of each demographic characteristic factor in j year of region i. The first step is to calculate the difference for each demographic factor ($R_{\max}$–$R_{\min}$); in the second step, the maximum value is assigned to 100, and the minimum value is assigned to 0; the third step is

Table 3 The weights of each population factor

First-level indicators	Second-level indicators	Weight
Population growth	Population natural growth rate (PG)	0.2
Population distribution	Population intensity (PI)	0.2
Population quality	Adult literacy rate (PL)	0.3
	Higher education rate (PQ)	
Population living standard	Urban consumptive expenditure per capita (P_{cu})	0.3
	Rural consumptive expenditure per capita (P_{cr})	

to quantify the positive indicators (PI, PG, and PL) according to Eq. (6) and the negative indicators (PQ, P_{cu}, and P_{cr}) according to Eq. (7). The weight according to the importance of each population characteristic factors is determined, and the specific value is shown in Table 3. The total index of population characteristic factors is calculated according to Eq. (8).

$$PFI = \sum P = 0.2PI_{ij} + 0.2PG_{ij} + 0.3\left(0.3 \times PL_{ij} + 0.7 \times PQ_{ij}\right) + 0.3\left(P_{cu} \times s_u + P_{cr} \times s_r\right) \quad (8)$$

where PFI represents the comprehensive demographic characteristics including population distribution, population growth, population quality, and population living standard. s_u and s_r represent the proportion of urban population and the proportion of rural population respectively.

Data sources and description

Data sources

In this paper, we used panel data from 30 provinces in China from 2000 to 2019. The provincial population factors and GDP per capita data were mainly collected from the China Statistical Yearbook and China City Statistical Yearbook. Energy consumption data were provided by the China Energy Statistical Yearbook. The measurement indicators of monetary units in this study are calculated at 2000 constant prices. The summary statistics for each variable are presented in Table 4.

Data description

Since transportation-related CO_2 emissions and population aging are two important challenges China has faced in recent years, we describe only the changing characteristics of these two indicators.

Figure 1 shows the total transport-related CO_2 emissions of 30 provinces in 2000 and 2019. From the figure, it can be seen that CO_2 emissions from China's transport sector tend to spread inland from coastal regions and increase rapidly. In 2000, the provinces with higher CO_2 emissions in transportation sector were mainly

Table 4 Descriptive statistics of variables

Variable	Definition (unit)	Min	Max	Mean	St. dev	Obs
TCEs	Transportation CO_2 emissions (ten thousand tons)	52.549	7068.388	1616.302	1268.555	600
PGDP	GDP per capita (ten thousand Yuan)	0.266	1.642	3.472	2.749	600
TRAT	Total transport turnover (100 million ton-km)	99.920	30,453.820	4242.196	4708.477	600
EI	Energy intensity (tons per ten thousand Yuan)	0.208	10.531	1.240	0.903	600
URB	Urbanization rate (percent)	23.200	89.600	51.124	15.188	600
PG	Natural growth rate (permillage)	– 1.900	13.100	5.313	2.894	600
PL	Adult illiteracy rate (percent)	70.430	98.770	92.503	4.829	600
PQ	Higher education rate (percent)	1.828	50.486	10.014	6.982	600
P_{cu}	Urban consumptive expenditure per capita (ten thousand yuan)	3.624	4.827	1.390	0.807	600
P_{cr}	Rural consumptive expenditure per capita (ten thousand yuan)	0.108	3.330	0.606	0.478	600
PFI	Index of population factors except population age structure	8.755	77.951	54.505	12.978	600
Age 14-	Share of people under 14 (percent)	7.560	30.290	17.924	4.632	600
Age 15–64	Share of people aged 15–64 (percent)	63.460	83.840	72.752	3.743	600
Age 65 +	Share of people over 65 (percent)	4.330	16.370	9.323	2.221	600

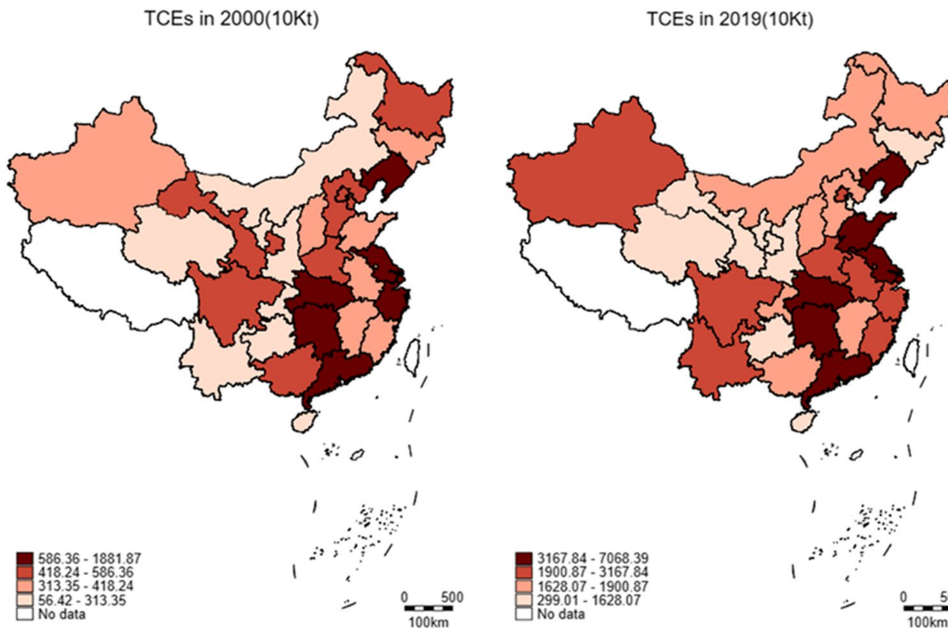

Fig. 1 The spatial–temporal evolution of CO_2 emissions from transportation in China

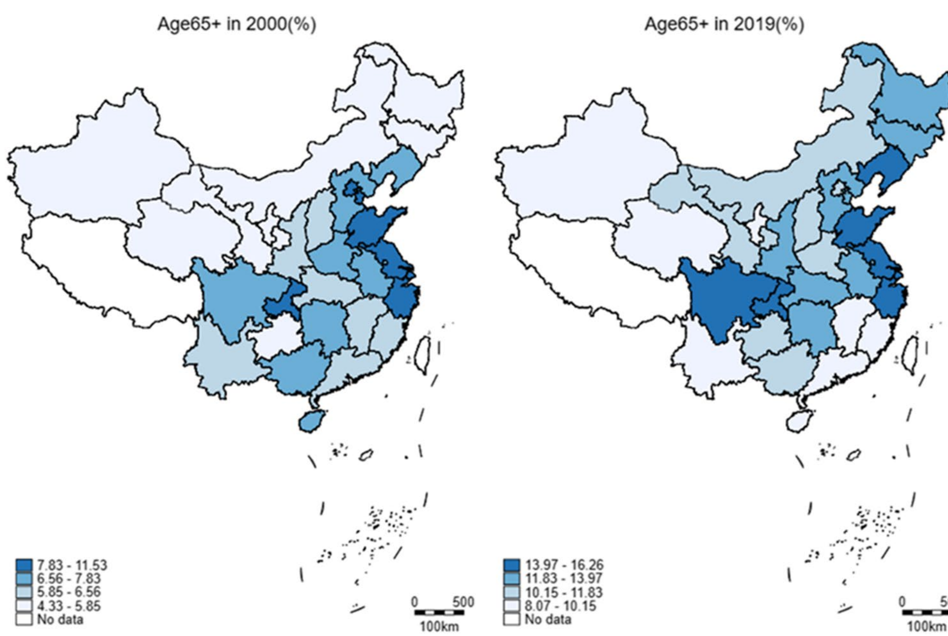

Fig. 2 The spatial–temporal evolution of China's population aging

concentrated in the economically developed eastern coastal regions, such as Guangdong and Shanghai. In 2019, in addition to coastal provinces with high CO_2 emissions in the transportation sector, central and northwestern provinces with relatively developed populations and economies, such as Shandong, Jiangsu, and Hubei, were also affected.

Figure 2 shows the aging population in 30 provinces in 2000 and 2019. In 2000, the areas with the most aging population were mainly in Shanghai, Jiangsu, and Zhejiang, which have developed economies and suitable climates. In 2019, just 20 years from now, the aging population will cover all provinces in China. The provinces with deep aging population are Shanghai, Liaoning, Sichuan, Shandong, Chongqing, Jiangsu, and Zhejiang. In addition to these seven provinces, there are many other provinces with a similar aging rate, which means that more provinces will enter deep aging in the future.

Figure 3 shows the changing trend of CO_2 emissions from regional transport and population aging. From 2000 to 2019, both transportation CO_2 emissions and population aging show a regional imbalance. In terms of

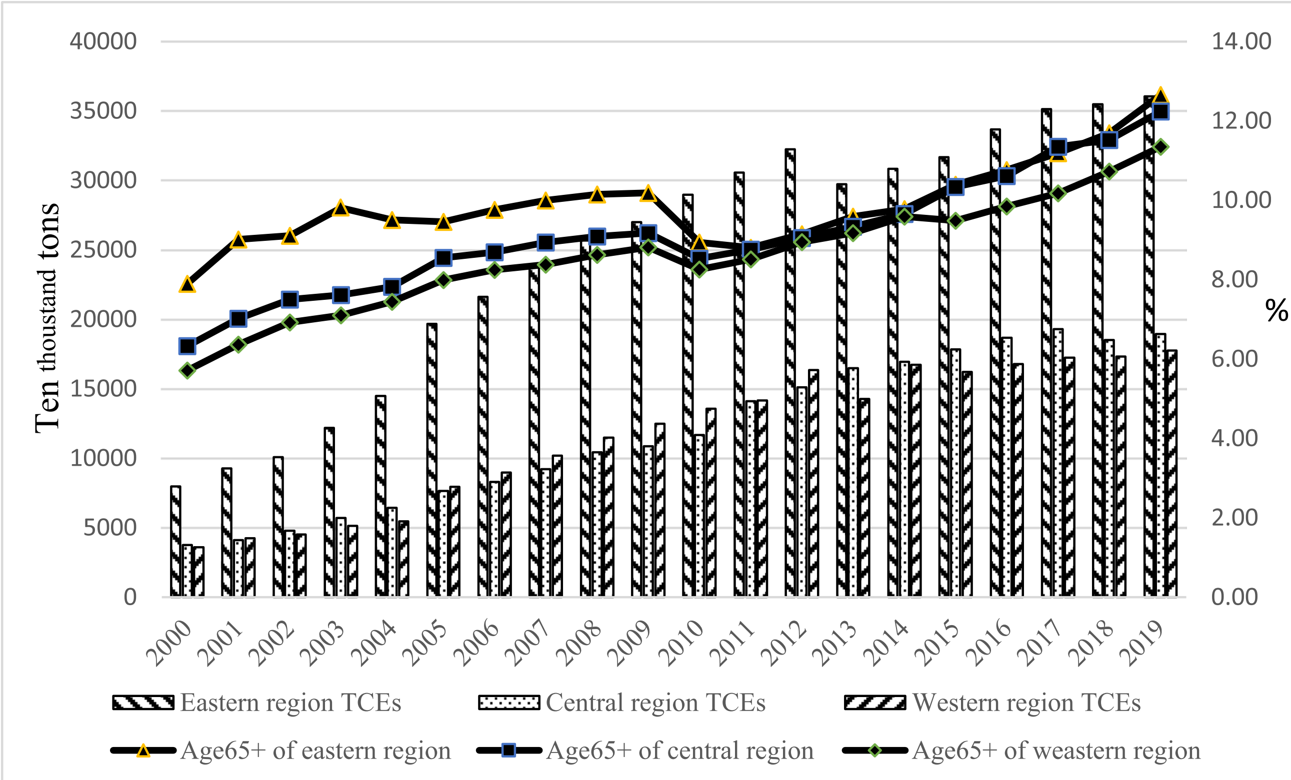

Fig. 3 2000–2019 regional transportation CO_2 emissions and population aging trend

the perspective of CO_2 emissions from the transport sector, the eastern transport sector has the highest carbon emissions, while the central and western transport sectors have similar CO_2 emissions. CO_2 emissions from the transport sector in eastern China are about twice those in the central and western regions. The CO_2 emissions of transportation sector in each region showed a gradual increase. As for the CO_2 growth rate of the regional transportation sector, the western region has the highest growth rate, followed by the central and eastern region. As for the population aging, the aging of the population in the eastern, central, and western regions was staggered between 2000 and 2010, with the highest aging of the population in the eastern region, followed by the central region and lowest in the western region. After 2010, aging levels were similar in the central and eastern regions, while aging levels were still the lowest in the western region, but the gap narrowed. Moreover, the eastern region was the first to enter the aging society (in 2000), followed by the central region (2001), and finally the western region (2003). Overall, the regional imbalance of CO_2 emission from transportation and population aging in the eastern, central, and western regions is consistent with China's level of economic development.

Results and discussion

Table 4 shows that the average value of CO_2 emissions in the transportation sector is 16.1630 million tons, the minimum value is 525.5000 tons (2002, Qinghai Province), the maximum value is 70.6839 million tons (2019, Guangdong Province), and the standard deviation is 12.6856 million tons. In most regions, there is a big difference between the value and the mean value, indicating that there is a big difference in carbon dioxide emissions in China's transportation sector.

National analysis

Analysis of demographic characteristics factors of transport CO_2 emissions

As shown in Table 5, the coefficient of per capita GDP is positive, but its squared form is negative. This result is consistent with previous studies (Chang et al. 2021; Wang and He 2019; Moutinho et al. 2015; Saboori et al. 2012). Total transport turnover and energy intensity exhibit a positive coefficient, while urbanization rate has a negative coefficient. They are correlated with carbon emissions.

Table 5 The results of the regression model of population factors on transportation CO_2 emissions

	A	B	C	D	E	F
lnPGDP	1.7332*** (0.2964)	1.8737*** (0.2996)	1.9250*** (0.3047)	1.8922 *** (0.3062)	1.6473*** (0.3265)	2.2578*** (0.3642)
$(\text{lnPGDP})^2$	−0.1008*** (0.0335)	−0.1135*** (0.0336)	−0.1205*** (0.0342)	−0.1131*** (0.0348)	−0.1023*** (0.0401)	−0.1605*** (0.0396)
lnTRAT	0.1455*** (0.0348)	0.1363*** (0.0347)	0.1304*** (0.0351)	0.1568*** (0.0348)	0.1251*** (0.0355)	0.1448*** (0.0351)
lnURB	−0.8343*** (0.1651)	−0.8558*** (0.1644)	−0.8478*** (0.1644)	−0.8384*** (0.1691)	−0.6669*** (0.1798)	−0.7852*** (0.1804)
lnEI	0.2144*** (0.0577)	0.2500*** (0.0590)	0.2247 *** (0.0576)	0.2154*** (0.0574)	0.1879 *** (0.0582)	0.2212*** (0.0581)
lnPFI		0.3470*** (0.1314)				
lnPG			0.0913** (0.0363)			
lnPQ				−0.0197 (0.0573)		
lnPL				−1.2338*** (0.4586)		
lnP_{cu}					0.4143*** (0.1246)	
lnP_{cr}					−0.2519*** (0.0863)	
lnAge0-14						−0.9188*** (0.2805)
lnAge15-65						−3.8305*** (0.1.130)
lnAge65+						−0.5045*** (0.1800)
cons	−1.6774*** (0.5457)	−2.5773*** (0.6412)	− 2.1394*** (0.5734)	− 0.2731 (0.9023)	−2.2505*** (0.6913)	−5.8629*** (2.2546)
Individual fixed	Yes	Yes	Yes	Yes	Yes	Yes
Hausmann test	0.0002	0.0000	0.0000	0.0000	0.0002	0.0018
Observation	600	600	600	600	600	600
R^2	0.9376	0.9383	0.9311	0.9383	0.9387	0.9386

*, **, and *** are significance at the 10%, 5%, and 1% confidence levels, respectively (the same below)

Regression A is an elementary version that omits additional factors. Regression B shows that there is a positive relationship between the total population factor and CO_2 emission from transportation. Population growth, education level, living standard, and age structure are gradually introduced into the model to ensure the rationality of the estimated coefficients. From regression C to regression E, we can see that the population growth rate exhibits positive coefficient, while the adult illiteracy rate has a negative coefficient. To illustrate the difference between urban and rural areas, regression E shows a positive correlation between urban consumptive expenditure per capita and transportation CO_2 emissions. The impact of urban consumptive expenditure per capita on transportation CO_2 emissions is much larger than that of rural consumptive expenditure per capita. Regression F introduced the age variables. The population share under 14 years old, the population share aged 15–64 years old, and the population share over 65 years old are negatively and significantly correlated with transportation CO_2 emissions.

The mediating effect of population aging on transport CO_2 emissions

Table 5 shows that population aging has a significant impact on CO_2 reduction in transportation, but it is not clear how population aging affects CO_2 reduction in transportation. Based on this, we will examine the effect path of population aging on CO_2 emission reduction and give a reasonable explanation. The economic level is the basic guarantee for the travel of the elderly population, which is closely related to the choice of travel modes for the elderly (Du et al. 2021; Kim and Ulfarsson 2004). Lopreite and Zhu (2020) pointed out that population aging in China shows a significant response to GDP per capita using the Bayes-VAR model. At the same time, the increase of the silver hair family has fueled the silver hair economy, and there is a huge potential for the enterprises and services related to the lives of the elderly. Transportation demand reflects the number of services provided by different modes (Li et al. 2019; Liu and Lin 2018; Böcker et al. 2017), which may reflect the actual demand for travel service of the elderly. Due to the change of physiological structure, the travel needs of the elderly gradually changed from those related to livelihood to those related to personal and family life, medical care, and spiritual and psychological care (Du et al. 2020). The limitation of physical functions means that the travel of the elderly tends to be relatively fixed, the average travel distance is shorter, and the number and frequency of trips decrease with age. Based on the above analysis, we hypothesize that population aging in China may have a promoting effect on economic level and a decreasing effect on transportation demand, while the impact of population aging on transportation CO_2 emissions depends on the relative size of the two effects. To test the significance of each effect, we examined the existence of each mediation effect and set up the following mediation effect model.

$$\ln TCE_{it} = \mu_i + \alpha \ln Age65^+{}_{it} + \theta X_{it} + \varepsilon_{it} \tag{6}$$

$$\ln Y_{it} = \mu_i + \beta \ln Age65^+{}_{it} + \theta X_{it} + \varepsilon_{it} \tag{7}$$

$$\ln TCE_{it} = \mu_i + \gamma \ln Age65^+{}_{it} \lambda \ln Y_{it} + \theta X_{it} + \varepsilon_{it} \tag{8}$$

where X_{it} is a set of control variables, and Y_{it} is the explained variable, which includes economic growth (GDP per capita) and transportation demand (total transport turnover), respectively used to test the economic effect and transportation development effect. Specifically, the control variables in the economic effect equation include total transport turnover, energy intensity, urbanization rate, and population factor index. Control variables in the equation for the transportation development effect include GDP per capita, urbanization rate, energy intensity, and population factors index. The corresponding estimates are shown in Table 6.

In the first step, through the significance test of α, the coefficient of population aging on transportation CO_2 emissions was 0.2952 at the 5% significance level. In the second step, we tested the significance of coefficients β and λ. According to the estimation results, the influence coefficient of population aging on per capita GDP and total transport turnover was 0.3330 and – 0.4157 at the same 1% significance level. The results of the first and second steps showed that the mediating effect was significant. In the third step, we tested the significance of the indirect effect of γ. As shown in Table 6, the coefficient of population aging on CO_2 emissions in the transportation sector was not significant. Therefore, we assumed that the transmission path between population aging and transport CO_2 emissions was a completely indirect effect; i.e., the effect of population aging on transport CO_2 emissions was realized through the economic effect and the transportation demand effect.

The nonlinear characteristics of population aging on transport CO_2 emissions

Based on the results of Table 5 and Table 6, we surmised that population aging might have a nonlinear relationship with CO_2 emissions from the transportation sector. To

Table 6 The results of the mediating effect of population aging on transportation CO_2 emissions

	First-step	Second-step		Third-step
	TCEs	Economic growth	Transportation demand	TCEs
lnAge65+	0.2952** (0.1156)	0.3330*** (0.0641)	-0.4157*** (0.1041)	0.0851 (0.0893)
lnPGDP				0.8692*** (0.0572)
lnTRAT				0.1454*** (0.0355)
Control variables	Yes	Yes	Yes	Yes
Model selection	Fixed effects	Fixed effects	Fixed effects	Fixed effects
Obs	600	600	600	600
Adj-R^2	0.8894	0.9648	0.9399	0.9372

Table 7 The results of individual fixed regression model based on population aging

	H	I
lnPFI	0.3985***(0.1327)	0.3696***(0.1313)
lnPGDP	2.2598***(0.3388)	2.1059***(0.3369)
$(\text{lnPGDP})^2$	−0.1534***(0.0372)	−0.1365***(0.0370)
lnTRAT	0.1324***(0.0352)	0.1397***(0.0348)
lnURB	−0.9815***(0.1708)	−1.0054***(0.1688)
lnEI	0.2763***(0.0595)	0.2806***(0.0588)
lnAge65 +	−1.7794**(0.7008)	−19.6979***(4.6641)
$(\text{lnAge65}+)^2$	0.9424***(0.3566)	20.4102***(5.0236)
$(\text{lnAge65}+)^3$		−6.9413 ***(1.7867)
cons	−2.5331***(0.6388)	3.2876**(1.6257)
Individual fixed	Yes	Yes
Hausmann test	0.0000	0.0000
Obs	600	600
Adj-R^2	0.9389	0.9404

further investigate the relationship between population aging and CO_2 emissions from the transportation sector, we add models H and I. The results are shown in Table 7 by comparing the models. When other variables were fixed, there is a non-linear relationship between population aging and CO_2 emissions from the transportation sector. In models H and I, the coefficient of Age65^+ and $(\text{Age65}^+)^3$ is negative, and the coefficient of $(\text{Age65}^+)^2$ is positive. The coefficients of Age65^+, $(\text{Age65}^+)^2$, and $(\text{Age65}^+)^3$ indicate that there is a U-curve between population aging and CO_2 emissions from the transportation sector.

Regional analysis

To determine the regional differences between population aging and CO_2 emissions from transportation, we extended our study to the eastern, central, and western regions. The region classification criteria refer to the China Health Statistics Yearbook.

Before PCSE regression, we performed unit root tests for the panel data of the eastern, central, and western regions. The LLC test cannot reject the null hypothesis. Therefore, the regional panel data set contains unit roots. We applied the same test to the first difference of variables, and most statistics reject the null hypothesis of the absence of unit roots. Thus, all-time series in the panel are stationary in the first difference. Next, the panel cointegration test based on the Westerlund error correction is applied to the stationary first difference variables to prove the presence of cointegration. Due to the length limitation, the results of the unit root test and the cointegration test are reported in Appendix 2 and Appendix 3.

Table 8 The results of the linear regression model with attached PCSEs

	The eastern region	The central region	The western region
lnPFI	−0.7228*** (0.1377)	−1.4585*** (0.3144)	−1.4816*** (0.2540)
lnPGDP	5.9645 *** (1.1902)	0.9882 (1.1063)	2.5649*** (0.6564)
$(\text{lnPGDP})^2$	−0.6724 *** (0.1390)	−0.0621 (0.1279)	−0.2293*** (0.0778)
lnTRAT	0.6087*** (0.0553)	0.4097*** (0.0794)	0.6095*** (0.0558)
lnEI	−0.8759*** (0.1820)	0.1080** (0.0526)	−0.1681*** (0.0732)
lnURB	−0.7392*** (0.2845)	−0.5097** (0.2453)	−2.4631*** (0.3033)
lnAge65 +	0.0378 (0.1823)	0.6539*** (0.1832)	0.2760** (0.1435)
cons	−9.7885*** (2.5120)	0.6617 (1.5809)	0.6617 (1.5809)
Obs	220	160	220
R^2	0.6961	0.8448	0.8448

As shown in Table 8, per capita GDP, square forms of per capita GDP, total transport turnover, urbanization rate, and energy intensity coefficients are consistent, but population aging shows differences in CO_2 emissions from the transportation sector. In terms of population aging, the relationship between transportation CO_2 emissions and population aging is insignificant in the eastern region. In the central and western regions, the proportion of people over 65 years old has a positive coefficient. And the influence effect of the central region is greater than that of the western region. From the data, every 1% increase in Age65 + in the central region leads to 0.6539% increase in transport CO_2 emissions, and every 1% increase in Age65 + in the western region leads to 0.2760% increase in transport CO_2 emissions.

The robustness test results

Due to limitations in index replacement and model selection, the robustness test was performed using the data from 2000 to 2016 as a subsample. Specific test results are presented in Tables 9, 10, 11, and 12.

In terms of national population factors and transport-related CO_2 emissions, Table 9 again verifies the different effects of population growth, population quality, population living standard, and population age structure on transport CO_2 emissions. In addition, the mediating effect of population aging on transportation CO_2 emissions shown in Table 10 is consistent with the above test result. Finally, the nonlinear results of population aging

Table 9 Robustness test results of population factors on transport CO_2 emissions

	A	B	C	D	E	F
lnPGDP	1.6575*** (0.3605)	1.7939*** (0.3596)	1.9704*** (0.3767)	1.8237*** (0.3672)	1.8439*** (0.3953)	2.1012*** (0.4476)
$(\text{lnPGDP})^2$	−0.0859** (0.0406)	−0.0974** (0.0404)	−0.1188*** (0.0421)	−0.0989** (0.0418)	−0.1266** (0.0494)	−0.1421*** (0.0493)
lnTRAT	0.1281*** (0.0421)	0.1214*** (0.0417)	0.1090** (0.0424)	0.1463*** (0.0421)	0.1137*** (0.0432)	0.1251*** (0.0429)
lnURB	−0.8779*** (0.2063)	−0.8971*** (0.2044)	−0.9177*** (0.2055)	−0.8886*** (0.2110)	−0.8439*** (0.2192)	−0.7410*** (0.2184)
lnEI	0.2558*** (0.0641)	0.3037*** (0.0653)	0.2711*** (0.0640)	0.2506*** (0.0636)	0.2505*** (0.0652)	0.2504*** (0.0645)
lnPFI		0.4521*** (0.1411)				
lnPG			0.1143*** (0.0426)			
lnPQ				−0.0087 (0.0627)		
lnPL				−1.5451*** (0.4908)		
lnP_{cu}					0.4107*** (0.1531)	
lnP_{cr}					−0.1427 (0.1109)	
lnAge0-14						−1.0578*** (0.3388)
lnAge15-65						−3.9458*** (1.3427)
lnAge65 +						−0.4510** (0.2134)
cons	−1.5011** (0.6534)	−2.5986*** (0.7322)	−2.2003*** (0.6995)	1.0216 (1.0265)	−2.6865*** (0.8655)	6.5063** (2.6482)
Individual fixed	Yes	Yes	Yes	Yes	Yes	Yes
Husman test	0.0003	0.0000	0.0000	0.0003	0.0001	0.0056
Obs	510	510	510	510	510	510
Adj-R^2	0.9345	0.9357	0.9353	0.9356	0.9352	0.9355

Table 10 Robustness test results of the mediating effect of population aging on CO_2 emissions from transport

	First step	Second step		Third step
	TCEs	Economic growth	Transportation demand	TCEs
lnAge65^+	0.5932*** (0.1362)	0.4780*** (0.0731)	-0.4851*** (0.1149)	0.2239 (0.1086)
lnPGDP				0.9015*** (0.0653)
lnTRAT				0.1391*** (0.0426)
Control variables	Yes	Yes	Yes	Yes
Model selection	Fixed effects	Fixed effects	Fixed effects	Fixed effects
Obs	510	510	510	510
Adj-R^2	0.8892	0.9645	0.9473	0.9355

Table 11 Nonlinear robust results of population aging on transport CO_2 emissions

	H	I
lnPFI	0.5423***(0.1434)	0.4464*** (0.1417)
lnPGDP	2.0276 ***(0.4115)	1.7827***(0.4057)
$(\text{lnPGDP})^2$	−0.1227***(0.0451)	−0.0978**(0.0444)
lnTRAT	0.1280***(0.0423)	0.1372***(0.0414)
lnURB	−1.0340***(0.2085)	−1.0006***(0.2040)
lnEI	0.3130***(0.0651)	0.3100***(0.0636)
lnAge65+	−2.1442**(0.8495)	−29.5565***(5.8319)
$(\text{lnAge65+})^2$	1.2100***(0.4426)	31.7412***(6.4438)
$(\text{lnAge65+})^3$		−11.1656***(2.3512)
Cons	−2.1465***(0.7504)	6.5939*** (1.9814)
Individual fixed	Yes	Yes
Hausman test	0.0000	0.0000
Obs	510	510
Adj-R^2	0.9367	0.9395

Table 12 Regional robustness of population aging on transport CO_2 emissions

	The eastern region	The central region	The western region
lnPFI	−0.6119*** (0.1600)	−1.4742*** (0.3342)	−1.8497*** (0.2821)
lnPGDP	6.9212 *** (1.5149)	0.5945 (1.3333)	3.3203*** (0.7545)
$(\text{lnPGDP})^2$	−0.7705 *** (0.1770)	−0.0151 (0.1545)	−0.3212*** (0.0893)
lnTRAT	0.5698*** (0.0646)	0.3803*** (0.0854)	0.6334*** (0.0590)
lnEI	−0.7736*** (0.1943)	0.1520*** (0.0544)	−0.0778 (0.0737)
lnURB	−0.6084*** (0.3090)	−0.4817* (0.2604)	−2.5345*** (0.3142)
lnAge65+	−0.1656 (0.2049)	0.9424*** (0.2099)	0.2646* (0.1463)
cons	−12.1648*** (2.5120)	1.9882 (2.7132)	−0.1945 (1.6972)
Obs	187	136	187
R^2	0.6699	0.8036	0.8460

and transport CO_2 emissions in Table 11 also demonstrate the existence of a U-shaped relationship between them.

As for regional population aging and transportation CO_2 emissions, population aging still has a different effect on transportation CO_2 emissions in Table 12. Population aging has a positive effect on CO_2 emission in the central and western regions, while it is not significant in eastern region.

Overall, the evaluation results of this study are reliable and robust.

Discussions

From the above empirical results, economic level and transportation demand are the factors of CO_2 growth in the transportation industry, which is consistent with the conclusions of most researchers (Li et al. 2019). However, energy intensity is not conducive to the reduction of CO_2 in transportation and the result is contrary to many scholars (Feng et al. 2020). This is because at present time, the overall energy utilization rate of China's transportation industry is low, and there is still a considerable distance to achieve the low-carbon target. The degree of urbanization has accelerated the agglomeration of regional population, brought about the economy scale effect, energy use efficiency, and transportation sharing, and helped to reduce CO_2 emissions from transportation. Based on our empirical results, we identified several significant phenomena.

First, population quality reduces CO_2 emissions from China's transportation sector. A reasonable explanation is that the level of education reduces CO_2 emissions by improving national environmental protection awareness. Through education, the awareness of the environmental crisis has been deeply embedded in the hearts of the people, promoting the people's sense of responsibility and participation, and making environmental awareness a habit. The result is consistent with the findings of Hong and Lu (2011) and Ouyang et al. (2015), which indicated that consumers with higher levels of education better understand and become more sensitive to environmental problems. Improving citizens' environmental awareness and behavior will contribute to greater public participation in building a low-carbon life, low-carbon economy, and low-carbon society. Compared with previous studies, this paper directly examines the relationship between quality level of the population and CO_2 emissions from transportation, which is more direct. Improving the national quality level potentially enhances the national environmental awareness and reduces pollution behavior.

Second, the effect of population living standards on CO_2 emissions from transportation shows urban–rural differences. Urban per capita consumption expenditures are more pronounced than rural per capita consumption expenditures. First, economic development and resident income level are the main drivers of CO_2 emissions from per capita transportation (Liu et al. 2011; Yang et al. 2015). Second, the consumption level of urban residents is much higher than that of rural residents, and the income gap between urban and rural areas leads to the consumption differences. In addition, Vera et al. (2021) found that CO_2 emissions from private transport in the richest decile accounted for more than 10% of total CO_2 emissions. Compared with previous studies, this paper puts urban per capita consumption level and rural per capita consumption level in the same model, and the results can more intuitively assess the different effects of population living standard on CO_2 emissions from transportation.

Third, population aging is currently negatively correlated with China's CO_2 emissions from transportation. This negative effect arises from the combined effects of economic growth and transportation demand. Although population aging promoted the growth of China's economy, it led to a decline in transportation demand. The test results of the intermediate effect show that the restraining effect of transportation demand is greater than the effect of economic growth, so aging population has a negative relationship with transportation CO_2 emissions, but this negative correlation is not stable. Regression I showed a U-shaped nonlinear relationship between population aging and transportation CO_2 emissions. This conclusion differs from general perception of people. We believe that there are differences between general CO_2 emissions and transportation CO_2 emissions of population aging. Because most elderly people in China have a relatively hard life experience, and their lifestyle and consumption habits are more economical and environmentally friendly. The low income after retirement and the unguaranteed expected income may objectively drive the elderly to choose a more economical travel (Tong and Zhou 2020). Second, the transportation of the elderly in China differs from that in Western aging countries. The elderly in China often choose to live with their children, prefer short and environmentally friendly routes (i.e., public transportation or walking), and travel infrequently, which contributes to energy conservation and emission reduction in the transportation industry. Finally, China has relatively comprehensive road safety policy for the elderly (i.e., free bus and subway rides). However, as the aging process gradually worsens, spending on medical care and health for the elderly will increase, which will encourage the use of automobiles by the elderly and increase CO_2 emissions from the transportation sector (Du et al. 2021).

Fourth, the effects of population aging on China's transport CO_2 emissions exhibit regional differences. Our results show that population aging increases transport CO_2 emissions in the central and western regions promotes transportation CO_2 emissions, which is consistent with the conclusion of Guo et al. (2022). However, in the eastern region, aging has no significant effect on transport CO_2 emissions, which is contrary to other scholars (Zhang and Tan 2016). These differences may be related not only to the different degree of aging, but also to the level of economic development and social security system in different regions. The results of this paper only show differences in the size of the effect. The eastern region is located on the coast and has excellent climatic conditions, a good investment environment, and greater development potential, which attracts a large number of young and middle-aged people. At the same time, the eastern region has advantages in transportation infrastructure construction and medical safety, so population aging in the eastern region does not currently have a significant impact on CO_2 emissions from transportation. For the western region, due to the vast territory, the daily travel distance of the elderly is relatively long, and the corresponding transportation infrastructure often cannot accommodate the characteristics of the elderly group. Meanwhile, the growth rate of the aging population in the western region is the fastest in the three regions. The contradiction between the rapid growth of the aging population and the relatively backward transportation system makes the relationship between the aging population and CO_2 emission from the transportation sector in the western region more worthy of attention. The central region lies at the center of the national transportation hub and is a major source of labor for China's eastern coastal areas. Due to the massive loss of labor force and many problems in comprehensive transportation, the population aging in the central region has the most serious impact on the transportation field.

Conclusions and policy implication

In this paper, we used the STIRPAT model and panel data of 30 provinces in China from 2000 to 2019 to investigate the relationship between population-related factors and CO_2 emissions in transportation, and further analyzed the impact of population aging on CO_2 emissions in transportation at the national and regional levels. Compared with most studies that focus on single demographic factors and CO_2 emissions, we broaden the research scope to include multiple demographic factors and sink the perspective to the most concerned transportation industry, which can not only intuitively reflect the impact of demographic factors on transportation CO_2 emissions, but also provide a basis for our future in-depth analysis of other aspects of population and transportation CO_2 emissions. Our results show that at the national level, population growth accelerates the CO_2 emissions from the transportation sector, population quality level and population aging can reduce transport CO_2 emissions, but the negative impact of aging is indirectly influenced by economic growth and transportation demand, and as the population ages, CO_2 emission in the transportation sector will change and form a U-curve. The impact of population living standard on CO_2 emission from transportation sector exhibits an urban–rural difference. The population quality is negatively correlated with

China's transport CO_2 emissions. At the regional level, the impact of population aging on transport CO_2 emissions shows regional differences.

Our results provide several important policy implications. First, improving the quality of the population, strengthening human capital investment. The investment in education level is not only conducive to improving residents' environmental awareness and environmental protection behavior, but more importantly, government departments can carry out the National Energy Saving Week, National Low Carbon Day, Environment Day, and other activities in the long run to spread the knowledge of low-carbon environmental protection to the public. Actively create a green travel atmosphere through activities such as Green Travel Publicity Month and Bus Travel Publicity Week. Continuously promoting environmental awareness and guiding environmentally friendly behavior will help reduce CO_2 emissions and achieve the goal of the environmental policy. Second, focus on promoting and implementing corresponding relevant emission reduction measures in cities. Due to the high consumption of urban residents and higher energy intensity, a reasonable environmental policy can encourage urban residents to choose environmentally friendly transportation to reduce CO_2 emissions. In addition, the structure of the urban transportation network and the sharing of transportation infrastructure should be optimized to shorten regional commuting distances and reduce CO_2 emissions from urban transportation. Third, ameliorate the population structure and actively implement the national strategy to cope with population aging. Improve and implement the three-child fertility policy and supportive measures to release the fertility potential and slow down the process of population aging. In the future, a more flexible population policy should be developed to optimize China's age structure. At the same time, the travel needs of the elderly should be taken into account and the popularization of alternative modes of transportation that meet the dual standards of safety and environmental friendliness should be accelerated to meet the transportation needs of the elderly. Finally, more attention should be paid to the long-term trend of population growth and carbon emissions in transportation in the central and western regions. Differences in geography, resource endowments, and government support have led to regional emissions disparities in three regions. To reduce the regional gap, different regions should formulate different strategies.

In spite of this paper making some useful findings, the uncertainties deriving from two aspects were discussed as follows. On the one hand, uncertainty may exist in transportation CO_2 emissions, which was calculated using the energy consumption data of the transportation industry in the region multiplied by the fuel carbon emission coefficient. Although we include the types of energy consumption in the transportation sector as much as possible, there may be omissions. On the other hand, population structure data may also be uncertain. The census in China is conducted every 10 years, which means that the demographic data in most years are projections based on sample surveys of the population and are likely to differ from the reality.

Further research can be done from the following directions. First, this study was conducted at China's provincial scale data, which is a relatively macro scale. As different scales may lead to disparate results, future studies are expected to be performed at smaller urban scales. Moreover, this study assumed that all provinces use the same set of emission coefficients when calculating CO_2 emissions from transportation. Actually, emission coefficients differ from province to province. Therefore, it is expected that more accurate data on CO_2 emissions from transportation will be used in future studies to better address this research topic. Finally, this study employed conventional econometric method without considering the spatial autocorrelation of geographic data. Thus, spatial regression models could be used in future studies to better identify the impacts of demographic characteristics factors on different geographical CO_2 emissions from transportation.

Appendix 1

Table 13 Provincial electricity CO_2 emission coefficient (unit: $KgCO_2/Kw\ h$)

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Beijing	0.8183	0.8509	0.8345	0.8405	0.8452	0.8555	0.8384	0.8512	0.8698	0.8642	0.8467	0.8453	0.8467	0.8494	0.8582	0.8499	0.8367	0.8505	0.8389	0.8355
Tianjin	0.8694	0.8700	0.8700	0.8700	0.8700	0.8621	0.8700	0.8697	0.8405	0.8154	0.8265	0.8678	0.8665	0.8627	0.8621	0.8597	0.8615	0.8925	0.8664	0.8387
Heibei	0.8650	0.8664	0.8666	0.8675	0.8669	0.8658	0.8568	0.8630	0.7656	0.8524	0.8408	0.8280	0.8105	0.8125	0.8244	0.7982	0.7846	0.8169	0.7802	0.7353
Shanxi	0.8517	0.8465	0.8505	0.8526	0.8531	0.8565	0.8564	0.8466	0.8544	0.8584	0.8510	0.8543	0.8393	0.8446	0.8468	0.8277	0.8109	0.8032	0.7805	0.7663
Inner Mongolia	0.8559	0.8540	0.8572	0.8590	0.8587	0.8582	0.8598	0.8452	0.8439	0.8045	0.7782	0.7723	0.7803	0.7828	0.7944	0.7590	0.7434	0.7339	0.7242	0.7296
Liaoning	0.8463	0.8392	0.8508	0.8442	0.8299	0.8130	0.8256	0.8312	0.8290	0.8361	0.8088	0.8004	0.7875	0.7513	0.7231	0.7094	0.6845	0.6730	0.6379	0.6198
Jilin	0.7367	0.7149	0.7368	0.7636	0.7415	0.7109	0.7572	0.7434	0.6924	0.7364	0.6667	0.7255	0.7266	0.6853	0.7303	0.7103	0.6778	0.6748	0.7026	0.6667
Heilongjang	0.8431	0.8443	0.8414	0.8512	0.8408	0.8483	0.8472	0.8511	0.8386	0.8254	0.8061	0.8043	0.7847	0.7643	0.7926	0.7872	0.7763	0.7788	0.7407	0.7134
Shanghai	0.8700	0.8669	0.8700	0.8698	0.8685	0.8638	0.8695	0.8666	0.8592	0.8583	0.8587	0.8670	0.8663	0.8627	0.8670	0.8643	0.8623	0.8466	0.8535	0.8439
Jiangsu	0.8699	0.8691	0.8692	0.8674	0.8677	0.8676	0.8621	0.8384	0.8244	0.8206	0.8201	0.8238	0.8217	0.8314	0.8192	0.8188	0.8134	0.8031	0.7833	0.7525
Zhejiang	0.7507	0.7272	0.7045	0.6534	0.6464	0.6539	0.6913	0.7132	0.6295	0.7128	0.7030	0.7277	0.6997	0.7142	0.7099	0.6530	0.6459	0.6725	0.6567	0.6150
Anhui	0.8588	0.8320	0.8504	0.8164	0.8420	0.8538	0.8514	0.8504	0.8723	0.8568	0.8557	0.8564	0.8568	0.8534	0.8631	0.8389	0.8244	0.8216	0.8061	0.8029
Fujian	0.4492	0.3674	0.5035	0.6004	0.6313	0.5443	0.5347	0.6063	0.5739	0.6557	0.5712	0.7005	0.6000	0.6216	0.5893	0.4999	0.3901	0.4477	0.4879	0.4763
Jiangxi	0.6411	0.6505	0.6542	0.7409	0.6966	0.7119	0.6813	0.7226	0.7013	0.7304	0.7141	0.7732	0.7348	0.7414	0.7317	0.6960	0.6869	0.7314	0.7289	0.6962
Shandong	0.8699	0.8421	0.8699	0.8699	0.8667	0.8692	0.8680	0.8679	0.8209	0.8606	0.8588	0.8588	0.8510	0.8584	1.0674	0.8442	0.8396	0.9347	0.8251	0.7808
Henan	0.8485	0.8272	0.8522	0.8218	0.8157	0.8282	0.8221	0.8298	0.7787	0.8265	0.8304	0.8305	0.8194	0.8334	0.8394	0.8284	0.8285	0.8196	0.7915	0.7692
Hubei	0.4322	0.4697	0.4790	0.4407	0.3148	0.3212	0.3651	0.3530	0.2610	0.2900	0.3205	0.3810	0.3164	0.4118	0.3529	0.3693	0.3567	0.3483	0.3799	0.4324
Hunan	0.4008	0.4093	0.4040	0.4769	0.4961	0.5443	0.5348	0.5539	0.5138	0.5235	0.5135	0.5690	0.4849	0.5438	0.5070	0.4719	0.4543	0.4777	0.5241	0.5103
Guangdong	0.6990	0.6598	0.6898	0.6467	0.6750	0.6737	0.6648	0.6965	0.6179	0.6807	0.6687	0.6905	0.6659	0.6525	0.6653	0.6327	0.6064	0.6429	0.6426	0.5915
Guangxi	0.3618	0.3459	0.3495	0.4082	0.4414	0.4881	0.4649	0.4535	0.3049	0.3772	0.4583	0.5216	0.4693	0.5348	0.4507	0.3643	0.3712	0.3892	0.4075	0.4743
Hainan	0.6129	0.5671	0.6314	0.6719	0.7468	0.7670	0.7632	0.7699	0.7982	0.7672	0.7830	0.7912	0.7929	0.7564	0.7652	0.7870	0.6046	0.5678	0.5683	0.5347
Chongqing	0.6720	0.6687	0.6935	0.6742	0.5597	0.6367	0.7015	0.6752	0.5889	0.5642	0.5758	0.5880	0.4932	0.6253	0.5619	0.5737	0.5576	0.5587	0.5913	0.5949
Sichuan	0.3220	0.2868	0.3572	0.3774	0.2921	0.3121	0.3135	0.3090	0.2777	0.2827	0.2764	0.2677	0.2378	0.2104	0.1666	0.1251	0.1057	0.0936	0.1070	0.1127
Guizhou	0.4757	0.4765	0.5177	0.5874	0.5922	0.6373	0.6707	0.6159	0.5962	0.6173	0.6084	0.6459	0.5522	0.6153	0.5202	0.4730	0.5091	0.5206	0.5273	0.5282
Yunnan	0.2960	0.3460	0.3822	0.3553	0.3940	0.3831	0.4594	0.4555	0.3261	0.4072	0.3482	0.2999	0.2440	0.1941	0.1374	0.0947	0.0769	0.0708	0.0784	0.0794
Shaanxi	0.7588	0.5641	0.8044	0.7749	0.7960	0.7861	0.8107	0.8016	0.8306	0.7986	0.8017	0.7985	0.8118	0.8025	0.8001	0.7785	0.7829	0.7738	0.7688	0.7380
Gansu	0.5181	0.5295	0.5991	0.6359	0.6395	0.5839	0.5865	0.5966	0.6041	0.5401	0.5521	0.6008	0.5660	0.5349	0.5128	0.5041	0.5045	0.4478	0.4564	0.4204
Qinghai	0.1697	0.2762	0.3151	0.4259	0.3087	0.2242	0.2226	0.2825	0.2818	0.2339	0.1805	0.1724	0.1708	0.1948	0.1947	0.1877	0.2394	0.2239	0.1334	0.1054
Ningxia	0.8179	0.8261	0.8304	0.8393	0.8368	0.8208	0.8227	0.8306	0.8385	0.8242	0.8170	0.8423	0.8226	0.8027	0.8176	0.7663	0.7249	0.7353	0.7391	0.7113
Xinjiang	0.7132	0.6661	1.1775	0.7268	0.7463	0.7448	0.7284	0.7345	0.7224	0.7096	0.7055	0.7267	0.7367	0.7273	0.7315	0.7236	0.7101	0.6891	0.6818	0.6706

Appendix 2

Table 14 The results of panel unit root test for three regions

	The eastern region	The central region	The western region
lnTCE	−9.9304***	−3.9328***	−9.6972***
D. lnTCE	−6.5773***	−7.5537***	−10.7583***
lnPGDP	−6.6284***	−4.6509***	−5.3137***
D. lnPGDP	−2.1052**	−2.2477**	−2.2575**
lnTRAT	−4.5849***	−2.1513**	−3.0309***
D.lnTRAT	−5.6432***	−6.3021***	−5.7801***
lnEI	−0.5734	2.1494	−5.5538***
D.lnEI	−4.1367***	−3.0424***	−4.9515***
lnURB	−10.8152***	−7.9610***	−8.1587***
D.lnURB	−23.3895***	−4.1103***	−5.1918***
lnPFI	−1.9554**	−2.2084**	−1.9582**
D.lnPFI	−14.1944***	−12.3686***	−12.0868***
lnAge65 +	0.8296	−0.6732	−2.9163***
D. lnAge65 +	−13.2673***	−9.2591***	−13.4997***

Appendix 3

Table 15 Cointegration test results in the eastern and central region

Method	Hypothesis	Statistics	Value
Eastern region			
Kao test	$H_0 : \rho = 1$	ADF	−4.4456***
Central region			
Kao test	$H_0 : \rho = 1$	ADF	−4.4333 ***
Western region			
Kao test	$H_0 : \rho = 1$	ADF	−3.4112***

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Data availability We declared that the data and materials presented in this paper are reliable.

Declarations

Ethical approval The authors agree with the ethical standards of this journal. We declare that the present article is original and has not been submitted or published previously to/by another journal and it is not being considered for publication elsewhere.

Consent to participate We declare that the present article is original and the authors give consent to participate in submitting this work.

Consent to publish If the article is accepted, the authors give consent to publish this work in Environmental Science and Pollution Research.

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