Humanities & Social Sciences Communications

ARTICLE

https://doi.org/10.1057/s41599-024-02914-9 OPEN

Check for updates

How aging impacts environmental sustainability—insights from the effects of social consumption and labor supply

Shuyu Li[1], Qiang Wang[2,3]✉ & Rongrong Li[2,3]✉

Population aging is discreetly reshaping the dynamics of social demand and labor supply, introducing potential turbulence to global carbon emissions. Understanding the impact of aging on carbon emissions is imperative for steering the next phase of sustainable development. This study, focusing on China, the world's largest carbon emitter, delved into the intricacies of how population aging influences carbon emissions using a dynamic panel threshold model and a mediated effects model. Geographic heterogeneity within China was also considered. On the one hand, this study incorporated three consumer-side intermediation mechanisms: energy consumption, residential consumption and medical consumption. It was found that the positive driving effect of consumption-side variables on carbon emissions was characterized by an inverted "U"-shaped change in China's highly aging regions, while an asymptotic upward trend of 7.65% was observed in regions with moderate and low aging. On the other hand, this study scrutinized three supply-side mediating mechanisms: industrial structure, R&D innovation and labor supply. The mechanism of supply-side variables on carbon emissions exhibited a shift from robustly positive driving to more nuanced weak positive driving or even negative inhibiting in highly aging regions, while inhibiting effects dominated in regions with moderate and low aging. This study offers a dual perspective encompassing both the production and consumption sides, which lays a foundation for exploring the internal mechanism of aging on carbon emission.

[1] College of Energy and Mining Engineering, Shandong University of Science and Technology, Qingdao 266590, People's Republic of China. [2] School of Economics and Management, China University of Petroleum (East China), Qingdao 266580, People's Republic of China. [3] School of Economics and Management, Xinjiang University, Wulumuqi 830046, People's Republic of China. ✉email: wangqiang7@upc.edu.cn; lirr@upc.edu.cn

Introduction

The latest report released by the World Meteorological Organization (WMO) shows that global atmospheric greenhouse gas emissions have reached a new record high. As the most dominant greenhouse gas, carbon dioxide concentration reaches 413.2 ppm in 2020, accounting for about 66% of the warming effect. Among them, human socio-economic activities are the main cause of global carbon growth. Consequently, changes in the demographic field are bound to trigger new upheavals in carbon emissions. The recently released UN report World Population Prospects 2022 showed that population aging was becoming one of the distinct global trends. The report stated that in 2021, the global population aged 65 and over was 761 million, and this number will increase to 1.6 billion by 2050 (Chen et al. 2022). From the perspective of the structure of social demand and supply patterns, aging is bounded to have new implications for environmental sustainability (Masson-Delmotte et al. 2022).

A large number of scholars have conducted extensive research around the impact of aging on carbon emissions (Yu et al. 2022). Some scholars focus on energy use habits in an aging society, preferring that aging triggers an increase in carbon emissions (Pan et al. 2021), while others propose that aging can reduce carbon emissions by promoting industrial upgrading (Menz and Welsch 2012). These conflicting findings reflect the complexity of the impact of aging on carbon emissions. With the deepening of global aging, the rapid expansion of the absolute elderly population is bound to change the scale and structure of society's consumption to a certain extent. In addition, aging societies have less and less labor entering the production system, while global welfare spending enters a period of terrible expansion, which would inevitably drag down global productivity gains (Mason et al. 2022). Scholars such as Zheng (Zheng et al. 2023) and Meng (Meng et al. 2018) have confirmed that changes in the production and consumption sides of society would exert a more long-term impact on carbon emissions. Therefore, examining the impact of aging on carbon emissions should consider the indirect effects of consumption and production both.

Since the onset of the twenty-first century, China has undergone a phase of rapid development coinciding with a swiftly aging population. As the paramount carbon emitter, understanding the implications of China's future profound aging for carbon emission trends is pivotal for achieving Sustainable Development Goals. However, owing to the influence of geographic diversity and data selection, the mechanism governing the impact of aging on carbon emissions in China has remained in an ambiguous state (Yu et al. 2023). Whether viewed through the lens of production or consumption pathways, the impact of aging on carbon emissions exhibited notable regional variability (Fan et al. 2021). Consequently, a nuanced examination of the mechanism underlying the impact of aging in China necessitates a geographical differentiation to unravel its complex dynamics (Zhang and Tan 2016).

On the basis of existing studies, this study innovates the mechanism of aging on carbon emissions. On the one hand, we refine the mediating channels through which aging affects carbon emissions into two aspects: the production side and the consumption side. Among them, energy consumption, residential consumption, healthcare consumption, industrialization proportion, R&D innovation, and labor supply are regarded as mediating factors. On the other hand, we extend the study at the national level to the level of regions with high, medium, and low levels of aging. The exploration of heterogeneity in stages has practical effects for comprehensively measuring the carbon trajectories under different processes.

The remainder of this paper is organized as follows: the "Literature review" section describes the literature review; the "Methods and data" section constructs the theoretical framework and presents the data and methods; the "Empirical results and analysis" section discusses the main results; and the "Conclusion" section offers conclusions and policy implications.

Literature review

The relationship between aging and carbon emissions. Along with the global prominence of aging, more and more scholars are concerned that population age structure change has a more long-term impact on climate change than population size (Wang et al. 2023b). However, even though such studies have been emerging for a long time, there is no consistent conclusions on the extent of the impact.

The consumption behavior and habits of the elderly differ from those of the younger population due to solidified ideologies and declining physical functions. Taking energy usage as an example, the elderly tends to spend a significant amount of time indoors, implicitly increasing the share of household energy consumption (Shi et al. 2023). Additionally, the rising proportion of hospitalization in an aging society contributes to increased carbon emissions in the healthcare industry (Yang et al. 2022). These factors affirm the close relationship between aging and carbon emissions. Numerous studies indicated a linear impact of population aging on carbon emissions, but there was controversy regarding the direction of this impact. For instance, scholars found that the activity intensity of the elderly was significantly lower than that of other age groups after investigating behavioral attributes across different age stages (An et al. 2020). Similarly, scholars constructing models for household consumption patterns discovered a trend of aging in the consumption of energy-intensive products. In terms of environmental awareness and the tendency to choose energy-efficient products, some analysts argued that there was a positive correlation between aging and carbon emission. For example, research affirmed the environmental consciousness of the working-age population, suggesting that younger individuals were more inclined to use energy-efficient products and adopt low-carbon transportation methods. Seeking empirical evidence, scholars utilizing the STIRPAT model investigated the impact of aging on carbon emissions, finding a tendency toward a positive correlation at the national level (Zhang and Tan 2016). At the regional level, the linear relationship between aging and carbon emissions is influenced by numerous latent variables, resulting in heterogeneity.

Some studies have analyzed the relationship between population aging and carbon emissions from a nonlinear perspective (Feng et al. 2023). Wang et al. used a panel threshold regression approach to examine data from a sample of 154 countries and concluded that there was a threshold between aging and per capita carbon emissions, indicating a nonlinear impact of aging on per capita carbon emissions (Wang et al. 2024b). Certain research suggests that the promotional effect of aging on carbon emissions tends to exhibit a characteristic of initial enhancement followed by a decline. For example, utilizing a threshold regression model and a two-stage instrumental variable regression model, Fan Jianshuang et al. estimated that population aging initially increases carbon emissions in urban households. Still, once the level of aging surpassed a critical threshold, its driving effect on carbon emissions weakened (Fan et al. 2021). In contrast to the arguments of the previous scholars, some scholars have also found that the inhibitory effect of aging on carbon emissions was initially weak and then strengthens (Yang and Wang 2020). The reasons for the diverse outcomes are mostly associated with differences in factors such as industry, region, indicator data, and more (Zhang et al. 2023).

Drivers of carbon emissions endogenous: production-side. Beyond direct relationships, aging exerts indirect effects on carbon emissions through various intermediary variables. From a production perspective, population aging is undeniably instigating a comprehensive transformation in productivity. Through a comprehensive review, this study reveals that the impact of population aging on carbon emissions, via the production-induced pathway, is primarily manifested at three levels: industrial structure, R&D innovation, and labor supply (Mamipour et al. 2019).

Firstly, in terms of industrial structure, population aging induces a "forcing effect" on the industry structure by influencing automation levels and human capital (Jiang et al. 2018). For instance, Bloom et al. found that due to the reduction in the workforce, enterprises were compelled to intensify technological innovation, employing automation and intelligent devices to replace manual labor, thereby swiftly enhancing the factor productivity of enterprises (Bloom et al. 2010). Building upon this, the transformation of industrial structure shifts the intrinsic growth mode of the economy, injecting a cleaner and more efficient development model into resource utilization (Li et al. 2023). Ronald et al. noted that due to population aging, labor resources were becoming increasingly scarce. The demand for the quality of human capital became more stringent, gradually replacing many low-skilled workers with highly skilled and talented individuals, thereby providing impetus for the high-quality development of the manufacturing industry (Lee and Mason 2010).

Secondly, in the realm of research and development (R&D) innovation, funds allocated to elderly care and public health have displaced national investments in R&D activities, thereby curtailing societal innovation capabilities in the short term. However, over the long term, the decline in the proportion of the working-age population resulting from aging is poised to stimulate society to meet production demands through the assimilation of novel technologies, thereby exerting a positive influence on technological innovation (Liu et al. 2022). Gehringer et al., utilizing panel data spanning from 1960 to 2011 from OECD countries, conducted an analysis revealing a positive correlation between life expectancy and productivity (Gehringer and Prettner 2019).

Lastly, on the front of labor supply, population aging elevates the average age of the working-age population, impeding the enhancement of labor force participation efficiency and societal productivity (Fan et al. 2015). Kühn, in his research, pointed out that the impact of elderly workers on the labor market extended beyond the challenge posed by the increasing number of retirees; it also heightened the risk faced by the labor market during economic crises (Kühn et al. 2018). Lisenkova et al. employing a generational overlapping computable general equilibrium model, computed that labor productivity needs to increase by 15% over the next 100 years to offset the output loss caused by population aging (Lisenkova et al. 2013).

Drivers of carbon emissions endogenous: consumption-side. From the perspective of consumption, population aging alters societal product usage demands, thereby influencing the overall consumption structure (Mi et al. 2016). Studies have found that the consumption coefficient of the elderly population is significantly lower than that of the working-age population. However, the overall changes in lifestyles and product preferences of residents in an aging society have led to shifts in the societal consumption structure (Shuai et al. 2014). The environmental impact associated with these changes is no less significant than that of technological innovations.

A review of the literature indicates that the impact of population aging on carbon emissions, through the consumption-induced pathway, is primarily manifested in three dimensions: energy consumption, residential consumption, and medical consumption. Firstly, the mainstream view in academia suggests that aging may lead to a shift in the type of energy consumption from traditional sources to green and clean energy, thereby reducing carbon emissions (Wang et al. 2023a). Some studies, however, indicate that societies with a higher proportion of elderly individuals appear to make the production and distribution of services more energy-intensive. For example, Richard correlated industrial and commercial energy consumption with the proportion of the population aged 65 and above in 14 EU member countries, finding that for every 1% increase in the proportion of elderly individuals, industrial/commercial energy consumption would increase by ~0.9%. Secondly, in terms of residential consumption, the elderly population generally exhibits lower overall consumption capacity, stable consumption structures, and a preference for practical products meeting daily needs. Research suggested that the substantial consumption of durable goods directly lead to a sharp increase in carbon emissions and triggered carbon emissions through inter-industry driving effects. Lastly, in medical consumption, the one-time payment and ongoing hospitalization costs of the elderly population constitute a significant proportion of healthcare expenses. While the carbon intensity of healthcare is not as high as that of industry, the production of medical equipment and drugs still contributes to some carbon emissions (Wu 2019). Cassandra et al. found that the healthcare industry in the United States annually consumed ~479 million tons of carbon dioxide, accounting for nearly 8% of the total national emissions. Among these, hospital care and clinical services were the largest sources of emissions in the healthcare industry, with structural equipment and pharmaceuticals ranking as the third and fourth largest sources, respectively (Thiel and Richie 2022). Thus, it was evident that strengthening guidance and control over consumption behavior were crucial for building a low-carbon consumption model (Chen et al. 2018).

Literature summary. Table 1 systematically summarizes the intermediate factors involved in the literature on aging and carbon emissions. As shown in the table, the impact indicators of population aging on carbon emissions are diverse and scattered. Relevant research primarily focuses on either the societal production pathway or the societal consumption pathway, lacking a systematic demonstration that unifies both aspects. Furthermore, this body of research lacks dynamic analyses of response mechanisms across different aging stages. This situation leaves the driving mechanisms of carbon emissions in future aging societies unclear.

This study aims to explore a more comprehensive analytical framework to address the existing dispersion across different perspectives in current research. The innovations in this study are as follows: (1) As depicted in Fig. 1, this research subdivides the intermediate pathways through which aging impacts carbon emissions into two aspects—production and consumption. It selectively filters core elements such as energy consumption, residential consumption, healthcare, industrialization, R&D innovation, and labor participation, providing a thorough overview and summary of existing research. (2) This study examines the impact pathways of aging on carbon emissions from a nonlinear perspective, identifying structural breakpoints in

Table 1 Existing studies on the role of population aging on carbon emissions.

Mechanism	Author	Indicator
Consumption-side	He et al. (2018), Yang and Liu (2017)	Housing consumption
	Thiel and Richie (2022), W. H. Organization (2012)	Pharma consumption
	Mao and Xu (2014), De Meijer et al. (2011)	Medical consumption
	Bardazzi and Pazienza (2017)	Consumption habits
	He et al. (2018)	Electricity consumption
	Soltani et al. (2020), Menz and Kühling (2011), Li et al. (2024)	Residential consumption
	Charlier and Legendre (2021), Song et al. (2018)	Energy consumption
Production-side	Wang et al. (2024c)	Industrial structure
	Wei et al. (2018), Kühn et al. (2018)	Labor productivity
	Lee and Mason (2010)	Manufacturing development
	Jones (2010), Lancia and Prarolo (2012)	Innovation capability
	Gehringer and Prettner (2019), Dixon (2003)	Social productivity
	Acemoglu (2010), Lisenkova et al. (2013)	Technological advances
	Mao and Xu (2014), Can et al. (2021)	Aging industry

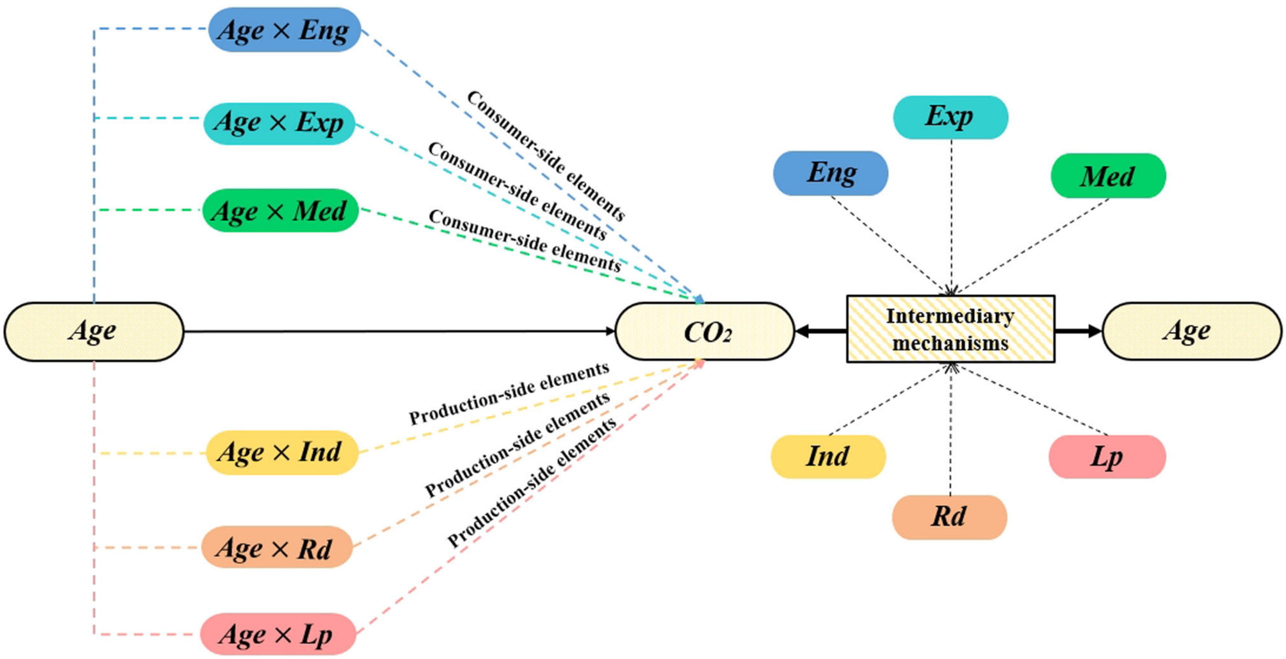

Fig. 1 Pathways of population aging on carbon emissions. This image illustrates the six mechanisms through which aging affects carbon emissions. In the consumption-side mediation mechanisms, it includes energy consumption (Eng), household consumption (Exp), and medical consumption (Med). On the supply side, the mediation mechanisms comprise industrialization level (Ind), research and development innovation level (Rd), and labor participation level (Lp).

factors affecting carbon emissions during the evolutionary process of aging. Distinguished from the majority of studies utilizing static panels, this research employs dynamic provincial-level panel data from China spanning 2000 to 2020, representing a valuable academic endeavor. (3) To mitigate interference from different aging stages on regression results, this study categorizes the investigated regions into three types: high-level aging, medium-level aging, and low-level aging. Within each region, the impacts of the six pathways are separately explored, aiming to elucidate the underlying patterns between aging and carbon emissions. The aforementioned exploration extends the study from theoretical assumptions to empirical deduction, comprehensively revealing the complexity of the impact of changes in population age structure on the societal environment.

Methods and data

Data sources. Panel data can observe the sample data of multiple cross-sections in the time series simultaneously and control the bias caused by heteroskedasticity among different regions. Therefore, this study selects Chinese provincial panel data to measure the impact of population aging on carbon emissions. Considering the missing data of Hong Kong, Macau, Taiwan and Tibet in the China Statistical Yearbook, the data of the remaining 30 provinces and cities from 2000 to 2020 are chosen as the research sample. The types of variables and units set in this study are shown in Table 2, including carbon emissions (explanatory variable), the proportion of elderly population (threshold variable) and six explanatory variables (i.e., energy consumption, per capita consumption expenditures, health care consumption expenditures, industrial structure, share of R&D expenditures, and labor force participation rate).

In terms of data sources, the percentage of the elderly population, per capita residential consumption expenditure, healthcare consumption expenditure, and industrial structure are obtained from the "China Statistical Yearbook". Energy consumption categorized by type is sourced from the "China

Table 2 Explanation of each variable.

Properties	Name	Symbol	Unit
Explained variables	Carbon emissions	CO_2	Millions of tons (Mt)
Threshold variables	Aging	Age	Percentage (%)
Main explanatory variables	Energy consumption	Eng	Million tons of standard coal
	Residential consumption	Exp	RMB
	Medical consumption	Med	RMB
	Industrial structure	Ind	Percentage (%)
	R&D innovation	Rd	Percentage (%)
	Labor supply	Lp	Percentage (%)
Control variables	Population density	Popd	People/square kilometer
	Affluence	Pgdp	RMB
	Service industry	Sep	Percentage (%)
	Urbanization	Urb	Percentage (%)

Energy Statistical Yearbook". The percentage of research and development (R&D) expenditure is derived from the "China Science and Technology Statistical Yearbook". The labor participation rate, defined as the ratio of the labor force to the working-age population, utilizes employment figures from the "China Population and Employment Statistical Yearbook". Additionally, specific carbon emission data for each region in China are not officially disclosed by government agencies. The Intergovernmental Panel on Climate Change (IPCC) provides a method based on energy consumption and carbon emission coefficients, characterized by its scientific, systematic, and comprehensive nature. This method calculates carbon dioxide emissions based on the consumption of various fossil fuels such as raw coal, coke, crude oil, fuel oil, gasoline, kerosene, diesel, liquefied petroleum gas, and natural gas. According to the IPCC-provided method, the formula for calculating carbon emissions in each region is as follows: $CO_{2,j} = \sum_{i=1}^{9} E_{i,j} \times a_i \times f_i$. Here, i represents the ith type of fossil energy source, j represents the jth region, $CO_{2,j}$ is the carbon emissions in the jth province, $E_{i,j}$ is the consumption of the ith energy source in the jth province, a_i is the conversion coefficient of the ith energy source to standard coal, and f_i is the carbon dioxide emission per unit of energy produced. Since the carbon emissions from various energy sources during combustion or usage are essentially fixed, the carbon emission coefficients for each energy source remain stable.

Dynamic panel threshold model. In practical scenarios, the impact of various factors on carbon emissions manifests differences across different stages of aging. For instance, in the early stages of aging, the level of industrialization significantly drived carbon emissions. As the degree of aging increases, the added value of the secondary industry gradually decreases, leading to a weakening effect of industrialization on carbon emissions. Similarly, when the aging level of a region was low, the relationship between effective labor supply and carbon emissions was relatively weak. However, as the aging level crossed a certain critical threshold, the impact of effective labor supply on carbon emissions became more pronounced. To understand the heterogeneous effects of various variables on carbon emissions during different aging stages, identifying the "aging rate" turning point that triggers the structural shift is crucial.

"Threshold effect" accurately describes the phenomenon when a specific variable reaches a critical point, leading to a sudden shift in its development. In this process, the critical point causing a structural change in other variables is referred to as the threshold value. The threshold can be a point in time, such as the implementation of a policy, or it can be represented by a variable. In early research, grouping tests and interaction term methods were common approaches for determining threshold values. The former often suffered from low accuracy due to subjective biases in determining separation points. The latter relied on the sign of the interaction term coefficient to determine the direction of the threshold variable's effect, but the economic significance of the interaction term was often unclear. As research advances, the panel threshold model introduces endogeneity within the system and provides a robust method for statistically testing the significance of threshold effects.

In the development of the threshold regression model, the static panel threshold model based on fixed effects was first proposed by Hansen (1999). This method can accurately and objectively estimate the threshold value based on the internal characteristics of the variables and test the significance of the threshold interval using the "self-sampling" method, which can compensate for the shortcomings of the cross-term model method and the group test method. With continuous research, the problem of bias caused by the explanatory variables as well as the endogeneity of the threshold variables has attracted extensive attention from scholars. To address such problems, Caner and Hansen (2004) proposed two-stage least squares estimation of threshold parameters and generalized moments estimation methods, which were successfully applied to dynamic panel threshold models by Kremer et al. (2013). The dynamic panel threshold model, built upon the static model, incorporates the influence of time, enhancing its ability to capture the dynamic nature of the data (Li et al. 2022). This study draws on Kremer's method to conduct a series of dynamic panel threshold regression analyses on national data with carbon emissions as the explanatory variable and the aging rate as the threshold variable (Seo and Shin 2016).

First, single threshold model on the energy-driven path is set up as shown in Eq. (1):

$$\ln(CO_{2i,t}) = \beta_0 + \beta_1 \ln(\text{eng}_{it}) \times I(\text{age}_{it} \le \gamma) + \beta_2 \ln(\text{eng}_{it}) \times I(\text{age}_{it} > \gamma) + \beta_3 \ln(CO_{2i,t-1}) + \beta_n X_{\text{control}-it} + \varepsilon_{it} + \mu_i \tag{1}$$

Where γ is the threshold value and $I(\cdot)$ is the threshold indicative function, i.e., $I(\cdot) = 1$ when the condition of the expression in parentheses holds, and $I(\cdot) = 0$ on the contrary. In this equation, the effects of energy consumption on carbon emissions are β_1 and β_2 for the two cases of aging rate below the threshold $(\text{age}_{it} \le \gamma)$ and aging rate above the threshold $(\text{age}_{it} > \gamma)$, respectively. The remaining variables β_3 are the parameters to be estimated for the first-order lagged terms of the explanatory variables, β_n are the parameters to be estimated for the other control variables, ε_{it} denotes the independent identically distributed random perturbation terms, and μ_i represents the individual effects of different regions.

In addition to the energy-driven path with energy consumption as the main explanatory variable, this study replaced the core explanatory variables energy consumption with residential consumption, medical consumption, industrial structure, R&D innovation, and labor supply, successively setting a single threshold model, as shown in Eqs. (2)–(6):

$$\ln(\mathrm{CO}_{2i,t}) = \beta_0 + \beta_1 \ln(\exp_{it}) \times \mathrm{I}(\mathrm{age}_{it} \le \gamma) + \beta_2 \ln(\exp_{it}) \times \mathrm{I}(\mathrm{age}_{it} > \gamma) + \beta_3 \ln(\mathrm{CO}_{2i,t-1}) + \beta_n \mathrm{X}_{\mathrm{control-it}} + \varepsilon_{it} + \mu_i \tag{2}$$

$$\ln(\mathrm{CO}_{2i,t}) = \beta_0 + \beta_1 \ln(\mathrm{med}_{it}) \times \mathrm{I}(\mathrm{age}_{it} \le \gamma) + \beta_2 \ln(\mathrm{med}_{it}) \times \mathrm{I}(\mathrm{age}_{it} > \gamma) + \beta_3 \ln(\mathrm{CO}_{2i,t-1}) + \beta_n \mathrm{X}_{\mathrm{control-it}} + \varepsilon_{it} + \mu_i \tag{3}$$

$$\ln(\mathrm{CO}_{2i,t}) = \beta_0 + \beta_1 \mathrm{ind}_{it} \times \mathrm{I}(\mathrm{age}_{it} \le \gamma) + \beta_2 \mathrm{ind}_{it} \times \mathrm{I}(\mathrm{age}_{it} > \gamma) + \beta_3 \ln(\mathrm{CO}_{2i,t-1}) + \beta_n \mathrm{X}_{\mathrm{control-it}} + \varepsilon_{it} + \mu_i \tag{4}$$

$$\ln(\mathrm{CO}_{2i,t}) = \beta_0 + \beta_1 \mathrm{rd}_{it} \times \mathrm{I}(\mathrm{age}_{it} \le \gamma) + \beta_2 \mathrm{rd}_{it} \times \mathrm{I}(\mathrm{age}_{it} > \gamma) + \beta_3 \ln(\mathrm{CO}_{2i,t-1}) + \beta_n \mathrm{X}_{\mathrm{control-it}} + \varepsilon_{it} + \mu_i \tag{5}$$

$$\ln(\mathrm{CO}_{2i,t}) = \beta_0 + \beta_1 \mathrm{lp}_{it} \times \mathrm{I}(\mathrm{age}_{it} \le \gamma) + \beta_2 \mathrm{lp}_{it} \times \mathrm{I}(\mathrm{age}_{it} > \gamma) + \beta_3 \ln(\mathrm{CO}_{2i,t-1}) + \beta_n \mathrm{X}_{\mathrm{control-it}} + \varepsilon_{it} + \mu_i \tag{6}$$

In Eqs. (1)–(6), carbon emissions, energy consumption, residential consumption, and medical consumption are expressed in absolute terms, and hence, a logarithmic transformation is applied. Aging, industrial structure, R&D innovation, and labor supply are represented as relative quantities, and thus, their original values are retained. In practical applications, the specific effects of the core explanatory variables on carbon emissions are also determined based on the conditions under which the indicative functions hold and the significance levels of the parameters β_1 and β_2.

Test of threshold effect. To avoid the problem of bias due to endogeneity of variables, this study uses least squares estimation for parameter estimation of the panel threshold model. First, the method of within-group averaging is required to eliminate the individual fixed effects. Taking Eq. (1) as an example, the following form is obtained after within-group averaging:

$$\overline{\ln(\mathrm{CO}_{2i,t})} = \beta_0 + \beta_1 \overline{\ln(\mathrm{eng}_{it})} \times I(\mathrm{age}_{it} \le \gamma) + \beta_2 \overline{\ln(\mathrm{eng}_{it})} \times I(\mathrm{age}_{it} > \gamma) + \beta_3 \overline{\ln(\mathrm{CO}_{2i,t-1})} + \beta_n \overline{X_{\mathrm{control}-it}} + \overline{\varepsilon_{it}} + \mu_i \tag{7}$$

Second, on the basis of the standard form and the mean form of the equation (Lee et al. 2011), the discrete form of the equation is further obtained by subtracting the two:

$$\ln(\mathrm{CO}_{2i,t})^* = \beta_0 + \beta_1 \ln(\mathrm{eng}_{it})^* \times I(\mathrm{age}_{it} \le \gamma) + \beta_2 \ln(\mathrm{eng}_{it})^* \times I(\mathrm{age}_{it} > \gamma) + \beta_3 \ln(\mathrm{CO}_{2i,t-1})^* + \beta_n X_{\mathrm{control}-it}{}^* + \varepsilon_{it}{}^* \tag{8}$$

Third, a specific threshold value γ is taken for the formula that has eliminated individual effects, and least squares are applied to the estimation of the regression parameters to generate the coefficients shown below:

$$\hat{\beta}(\gamma) = [X^*(\gamma)' \ln(\mathrm{eng}_{it})^*(\gamma)]^{-1} \ln(\mathrm{eng}_{it})^*(\gamma)' \ln(\mathrm{CO}_{2i,t})^* \tag{9}$$

The corresponding residual vectors and residual sums of squares are obtained as:

$$\hat{e}^*(\gamma) = \ln(\mathrm{CO}_{2i,t})^* - \ln(\mathrm{eng}_{it})^*(\gamma) \cdot \beta^*(\gamma) \tag{10}$$

$$\mathrm{SSE}(\gamma) = \hat{e}^*(\gamma)' \hat{e}^*(\gamma) \tag{11}$$

Finally, according to the different assignments to γ, these residual sums of squares are compared using the grid search method, and the value of γ corresponding to the smallest residual sum of squares is selected as the threshold value, i.e., $\hat{\gamma} = \mathrm{argminSSE}(\gamma)$. The estimated residual variance of $\hat{\sigma}^2 = \mathrm{SSE}(\gamma)/N(T-1)$ and the estimated regression coefficient of $\hat{\beta} = \hat{\beta}(\hat{\gamma})$ were also obtained.

In order to determine the validity of the empirical results, further tests related to the threshold effect are required. The first is a significance test for the existence of the threshold effect, which is essentially a test for the significance of the regression coefficients. The existence of the threshold effect is determined by observing whether there is a significant difference between the coefficients β_1 and β_2 (Lee et al. 2011). The original hypothesis is $\mathrm{H}_0 : \beta_1 = \beta_2$, i.e., there is no threshold effect; the alternative hypothesis is $\mathrm{H}_1 : \beta_1 \ne \beta_2$, i.e., there is a threshold effect. This test is implemented by constructing an F-statistic, which can be expressed by the following equation:

$$F = \frac{S_0 - S_1(\hat{\gamma})}{\hat{\sigma}^2} \tag{12}$$

The truth test of the threshold estimate is to test whether the estimate of the threshold is equal to the true value by means of the maximum likelihood estimator, where the original hypothesis is that the two are equal and the alternative hypothesis is that the two are not equal. The statistics of the great likelihood ratio are:

$$\mathrm{LR}_n(\gamma) = \frac{S_n(\gamma) - S_n(\hat{\gamma})}{\sigma(\hat{\gamma})^2} \tag{13}$$

Since the distribution of the LR statistic was still non-standard normal, based on the theory of asymptotic distribution, Hansen provided a formula criterion for calculating the critical value based on its cumulative distribution function to determine its rejection domain. The inverse function of the distribution function $\mathrm{c}(\alpha) = -2\log(1 - \sqrt{(1-\alpha)})$ is established, where α is the set significance level, and the values of $\mathrm{c}(\alpha)$ at significance levels of 1, 5, and 10% are calculated as 10.59, 7.35, and 6.53. If $\mathrm{LR}_n(\gamma) > \mathrm{c}(\alpha) = -2\log(1 - \sqrt{(1-\alpha)})$, the original hypothesis is rejected and the alternative hypothesis that the threshold estimates, and the threshold true values are not equal is accepted.

Multi-threshold panel model. A single threshold value divides the regression coefficients of the explanatory variable into two intervals: below the threshold value and above the threshold value. In the actual research process, the complex relationship between variables or the internal structure of threshold variables often leads to the situation of double thresholds. In this case, dual thresholds divide the variable into three stages: below the first threshold, between the first and second thresholds, and above the second threshold. The regression coefficients of the variable exhibit different values in the three intervals. In this study, the constructed double-threshold panel models are shown in (14)–(19) in order:

$$\ln(\mathrm{CO}_{2i,t}) = \beta_0 + \beta_1 \ln(\mathrm{eng}_{it}) \times \mathrm{I}(\mathrm{age}_{it} \le \gamma_1) + \beta_2 \ln(\mathrm{eng}_{it}) \times I(\gamma_1 < \mathrm{age}_{it} \le \gamma_2) + \beta_3 \ln(\mathrm{eng}_{it}) \times \mathrm{I}(\mathrm{age}_{it} > \gamma_2) + \beta_4 \ln(\mathrm{CO}_{2i,t-1}) + \beta_n \mathrm{X}_{\mathrm{control-it}} + \varepsilon_{it} + \mu_i \tag{14}$$

$$\begin{aligned}\ln(\mathrm{CO}_{2i,t}) = {} & \beta_0 + \beta_1 \ln(\exp_{\mathrm{it}}) \times \mathrm{I}(\mathrm{age}_{\mathrm{it}} \le \gamma_1) + \beta_2 \ln(\exp_{\mathrm{it}}) \\ & \times I(\gamma_1 < \mathrm{age}_{it} \le \gamma_2) + \beta_3 \ln(\exp_{\mathrm{it}}) \times \mathrm{I}(\mathrm{age}_{\mathrm{it}} > \gamma_2) \\ & + \beta_4 \ln(\mathrm{CO}_{2\mathrm{i,t-1}}) + \beta_{\mathrm{n}} \mathrm{X}_{\mathrm{control-it}} + \varepsilon_{\mathrm{it}} + \mu_{\mathrm{i}}\end{aligned} \tag{15}$$

$$\begin{aligned}\ln(\mathrm{CO}_{2i,t}) = {} & \beta_0 + \beta_1 \ln(\mathrm{med}_{\mathrm{it}}) \times \mathrm{I}(\mathrm{age}_{\mathrm{it}} \le \gamma_1) + \beta_2 \ln(\mathrm{med}_{\mathrm{it}}) \\ & \times I(\gamma_1 < \mathrm{age}_{it} \le \gamma_2) + \beta_3 \ln(\mathrm{med}_{\mathrm{it}}) \times \mathrm{I}(\mathrm{age}_{\mathrm{it}} > \gamma_2) \\ & + \beta_4 \ln(\mathrm{CO}_{2\mathrm{i,t-1}}) + \beta_{\mathrm{n}} \mathrm{X}_{\mathrm{control-it}} + \varepsilon_{\mathrm{it}} + \mu_{\mathrm{i}}\end{aligned} \tag{16}$$

$$\begin{aligned}\ln(\mathrm{CO}_{2\mathrm{i,t}}) = {} & \beta_0 + \beta_1 \mathrm{ind}_{\mathrm{it}} \times \mathrm{I}(\mathrm{age}_{\mathrm{it}} \le \gamma_1) + \beta_2 \mathrm{ind}_{\mathrm{it}} \times \mathrm{I}(\gamma_1 < \mathrm{age}_{\mathrm{it}} \le \gamma_2) \\ & + \beta_3 \mathrm{ind}_{it} \times I(\mathrm{age}_{it} > \gamma_2) + \beta_4 \ln(\mathrm{CO}_{2\mathrm{i,t-1}}) + \beta_{\mathrm{n}} \mathrm{X}_{\mathrm{control-it}} + \varepsilon_{\mathrm{it}} + \mu_{\mathrm{i}}\end{aligned} \tag{17}$$

$$\begin{aligned}\ln(\mathrm{CO}_{2\mathrm{i,t}}) = {} & \beta_0 + \beta_1 \mathrm{rd}_{\mathrm{it}} \times \mathrm{I}(\mathrm{age}_{\mathrm{it}} \le \gamma_1) + \beta_2 \mathrm{rd}_{\mathrm{it}} \times \mathrm{I}(\gamma_1 < \mathrm{age}_{\mathrm{it}} \le \gamma_2) \\ & + \beta_3 \mathrm{rd}_{it} \times I(\mathrm{age}_{it} > \gamma_2) + \beta_4 \ln(\mathrm{CO}_{2\mathrm{i,t-1}}) + \beta_{\mathrm{n}} \mathrm{X}_{\mathrm{control-it}} + \varepsilon_{\mathrm{it}} + \mu_{\mathrm{i}}\end{aligned} \tag{18}$$

$$\begin{aligned}\ln(\mathrm{CO}_{2\mathrm{i,t}}) = {} & \beta_0 + \beta_1 \mathrm{lp}_{\mathrm{it}} \times \mathrm{I}(\mathrm{age}_{\mathrm{it}} \le \gamma_1) + \beta_2 \mathrm{lp}_{\mathrm{it}} \times \mathrm{I}(\gamma_1 < \mathrm{age}_{\mathrm{it}} \le \gamma_2) \\ & + \beta_3 \mathrm{lp}_{it} \times I(\mathrm{age}_{it} > \gamma_2) + \beta_4 \ln(\mathrm{CO}_{2\mathrm{i,t-1}}) + \beta_{\mathrm{n}} \mathrm{X}_{\mathrm{control-it}} + \varepsilon_{\mathrm{it}} + \mu_{\mathrm{i}}\end{aligned} \tag{19}$$

Where, γ_1 and γ_2 are two different thresholds; β_1, β_2 and β_3 are the regression coefficients of the main explanatory variables in different threshold intervals. When $\beta_1 \neq \beta_2 \neq \beta_3$, the double threshold effect exists.

It is worth noting that the threshold values and the number of thresholds need to be determined according to the theory of minimum residual sum, the significance of the regression parameters is determined based on Bootstrap test, the confidence intervals are established using the theory of asymptotic distribution, and the model estimation results are established based on the significance level, p value, and confidence interval.

Empirical results and analysis

Results of the threshold effect test. This section empirically verifies whether there are jumps or abrupt changes in the impact of each variable on carbon emissions during the evolution of aging. Table 3 presents the threshold effect tests under the aging rate threshold. The first column of the table lists the core explanatory variables of the model, while the second column shows the types of assumptions for single, double, and multiple thresholds. The third column shows the test statistics, while the fourth column presents the values obtained using 300 "self-sampling" simulations. The fifth to seventh columns show the threshold values at 10, 5, and 1% significance levels. The results show that the dynamic panel models with energy consumption (Eng), residential consumption (Exp), medical consumption (Med), industrialization (Ind), R&D and innovation (Rd), and labor supply (Lp) as the core explanatory variables have single thresholds. This suggests that population aging divides the effect of each factor on carbon emissions into two different structural intervals. The effects of the social consumption side and the production side on carbon emissions show two-stage differences in the interval segments above and below the threshold estimates.

Specifically, when the aging level is below the threshold, the coefficients of the impact of the social consumption and production variables on carbon emissions are in a single take. And when the aging level is higher than the threshold value, the coefficients of the impact of the variables on carbon emissions would change abruptly. This means that in the context of population aging, adopting different policy measures according to different stages of aging may produce more effective carbon emission control.

After determining the number of thresholds, this study further tests the veracity of the thresholds using the likelihood ratio function plot. Figure 2 shows that in the model with the core explanatory variable of energy consumption (Eng), the likelihood ratio statistic lies within the confidence interval below the threshold when the aging rate threshold estimate is 4.7491, which proves that the threshold estimate is true and valid. The values of the likelihood ratio function with residential consumption (Exp), medical consumption (Med), industrial structure (Ind), and labor supply (Lp) as the core explanatory variables are the same. The threshold estimate of the aging rate in the model with R&D innovation (Rd) as the core explanatory variable is 4.7573 and passes the 95% confidence interval, so the R&D innovation variable presents a structural breakpoint of the effect on carbon emissions at an aging rate of 4.7573%. The confidence interval provides a range of values that are deemed plausible for a parameter or statistic. This result confirms that there is an abrupt change in the impact of energy consumption, residential consumption, healthcare consumption, industrial structure,

Table 3 Threshold effect tests of multiple driving paths under the threshold of aging.

Explanatory variable	Threshold type	*F*-statistic	*p* value	Threshold value		
				10%	5%	1%
Eng	Single	90.87	0.0233	37.8123	53.3132	102.8507
	Double	−69.99	1.0000	20.2179	26.1245	50.1579
	Multiple	1.79	0.9367	21.7353	31.3700	62.9416
Exp	Single	93.90	0.0033	30.9502	42.6070	84.8832
	Double	−71.64	1.0000	18.9724	25.5980	36.0021
	Multiple	2.26	0.9300	23.8681	35.0651	71.4724
Med	Single	94.83	0.0000	28.4946	41.6356	58.7866
	Double	−72.69	1.0000	22.1954	29.2748	45.2758
	Multiple	1.73	0.9433	14.3299	23.6744	43.6492
Ind	Single	94.26	0.0067	32.1561	40.3095	64.4005
	Double	−77.54	1.0000	14.3976	19.2268	29.8245
	Multiple	1.36	0.9833	15.8163	29.7117	49.9420
Rd	Single	128.80	0.0000	49.3493	58.6557	96.5311
	Double	−73.19	1.0000	26.0164	40.4226	62.4413
	Multiple	0.59	1.0000	23.3318	30.4957	57.2607
Lp	Single	97.27	0.0100	29.1798	41.6733	79.2426
	Double	7.61	0.5333	20.6642	29.1078	49.9822
	Multiple	7.73	0.4533	15.8642	19.0060	49.6084

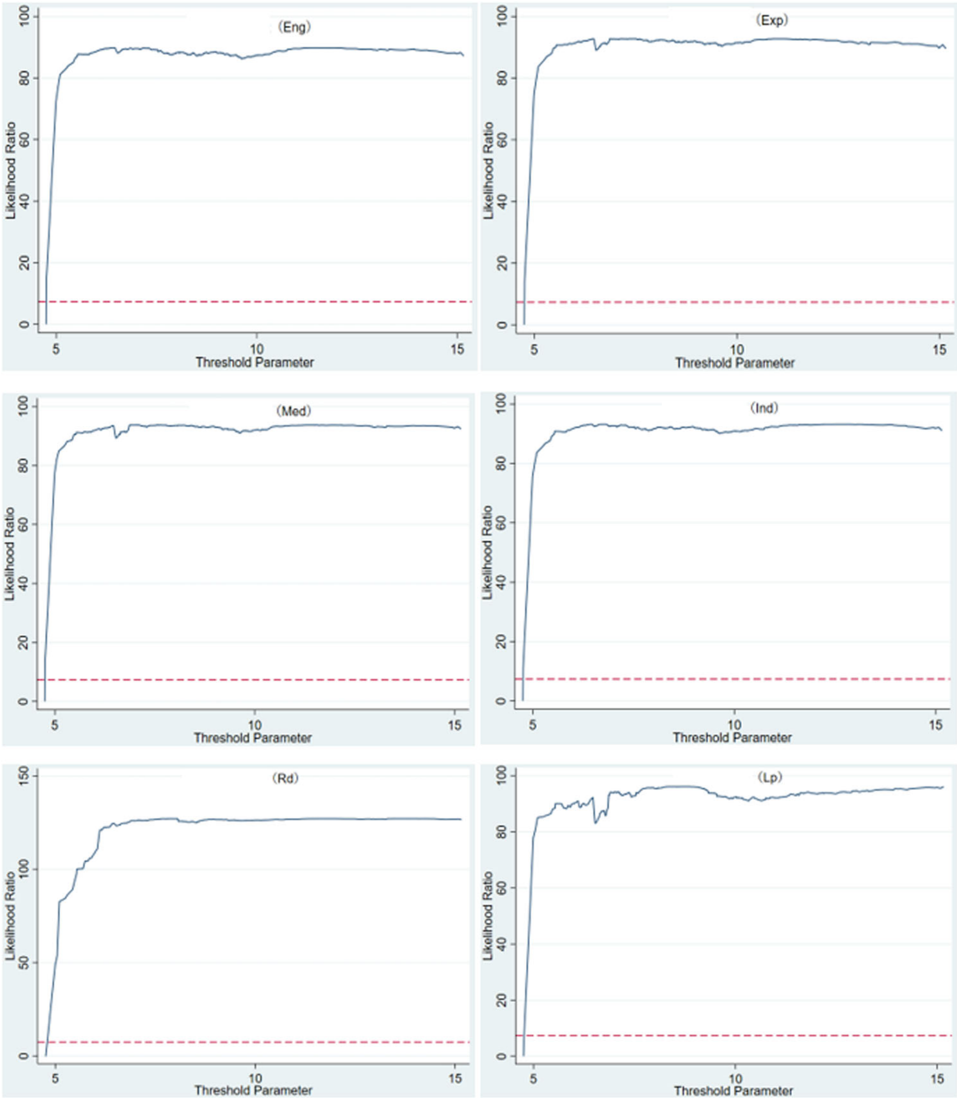

Fig. 2 Threshold estimates and 95% confidence intervals under multiple pathways. This image displays the likelihood ratio functions for each model. The blue line represents the statistical estimate of the threshold, while the red dashed line represents the threshold curve at a 95% confidence level.

R&D innovation and labor supply on carbon emissions during the evolution of aging.

Analysis of threshold regression results for the consumer-side drive path. This subsection further identifies the inner logic of the consumption-side driving mechanism with the help of Stata software. The regression results in Table 4 convey the following messages: (1) For the energy consumption-driven pathway, when the aging rate is below 4.7401%, each 1% increase in energy consumption would lead to a 0.2945% increase in carbon emissions. When the aging rate exceeds the threshold of 4.7401%, each 1% increase in energy consumption would result in a 0.4494% increase in carbon emissions. This conveys that as the level of aging continues to deepen, the positive contribution of energy consumption to carbon emissions becomes more significant, with each unit of energy consumption leading to 50% more increase in carbon emissions than at the beginning of aging. (2) For the residential consumption-driven path, when the aging rate is below 4.7401%, carbon emissions would increase by 0.3201% for every 1% increase in residential consumption expenditure; while once the aging rate exceeds 4.7401%, the increase in carbon emissions rises from 0.3201 to 0.4673% for every 1% increase in residential consumption expenditure. This implies that during the evolution of aging, China's residential consumption shows an enhanced driving mechanism of a small increase in carbon emissions, with a rise of about 15%. (3) For medical consumption, medical consumption expenditure does not show a significant effect on carbon emissions when the aging rate is below 4.7401%; as the aging rate exceeds 4.7401%, each 1% increase in medical consumption expenditure would increase carbon emissions by 0.3627%. This result implies that there is a point-in-time characteristic of the effect of health care consumption level on carbon emissions in China, and that a specific aging threshold is the key factor that triggers the statistical link between the two.

Figure 3 illustrates the impact coefficients of energy consumption, residential consumption, and medical consumption on carbon emissions in two stages. As shown in the figure, the positive stimulating effects of these three variables on carbon emissions are strengthened in the later stages of aging. Specifically, when the level of aging surpasses a certain critical threshold, the stimulating effect of energy consumption on carbon emissions is doubled. The reason behind is that older age groups tend to have a greater preference for energy-intensive products in terms of energy use compared to younger

Table 4 Coefficients and test statistics of the consumption-side driving path.

Variable	Coefficient	Standard error	*T*-statistic	*p* value
L1.ln_CO_2	0.4165***	0.1136	3.67	0.001
ln_Eng (Age < 4.7491)	0.2945**	0.1168	2.52	0.017
ln_Eng (Age ≥ 4.7491)	0.4494***	0.1270	3.54	0.001
ln_Exp (Age < 4.7491)	0.3201***	0.0716	4.47	0.000
ln_Exp (Age ≥ 4.7491)	0.4673***	0.1260	3.71	0.001
ln_Med (Age < 4.7491)	0.1446	0.1223	1.18	0.247
ln_Med (Age ≥ 4.7491)	0.3627***	0.0997	3.64	0.001
Control variables	Control			

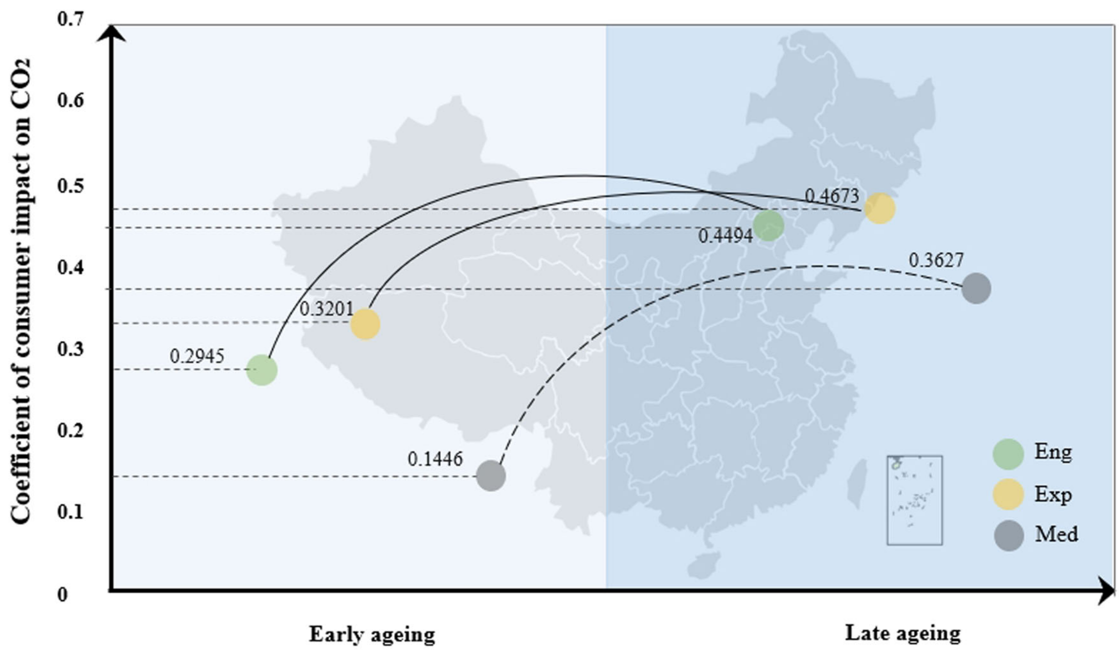

Fig. 3 The influence of the consumption-side driving path within different aging intervals. This image illustrates the variation in the impact of consumption-side factors on carbon emissions. The left section displays the impact coefficients of consumption-side factors during the early stages of aging, while the right section shows the impact coefficients of consumption-side factors during the later stages of aging.

generations. This tendency is mainly reflected in other residential energy use such as building heating, cooking, and water, electricity, and gas. For example, some older people usually rely on heating or insulation to meet their living needs, or are accustomed to taking traditional cooking methods such as coal-fired or natural gas stoves. According to statistics, residential energy consumption is the largest single source of all energy consumption. Thus, the increase of this energy use increases the proportion of carbon emissions consumed in the household. The results of this study reinforce that the stimulating effect of social energy consumption on carbon emissions is doubled when the level of aging crosses a certain threshold. This empirical result is generally consistent with the arguments of Balezentis (2020). The rising trend in energy consumption and carbon emissions caused by aging will have a series of impacts at the societal level (Li et al. 2021). For instance, society may experience increased pressure on energy supply, especially in regions with a higher proportion of elderly individuals. This could lead to a surge in energy prices, thereby affecting the overall economic operation of society.

The growth of the residential consumption coefficient implies that China's aging process has intensified carbon emissions in the residential consumption sector. The statistical results of this study point out that the contribution of China's residential consumption expenditure to carbon emissions is deepening with the deepening of population aging. The reason for this phenomenon is that, driven by both economic growth and population aging, the potential shrinkage of residential consumption levels due to the increasing population aging is overwhelmed by the consumption boom triggered by economic development, and the overall expenditure level still shows a rapid increase over time (Wang et al. 2024a). With the increase in the elderly population, the residential consumption sector may witness the emergence of more markets and services catering to the elderly. This not only provides new opportunities for businesses but also requires the formulation of relevant policies to ensure that these services align with sustainable development needs.

The level of medical consumption has similarly exhibited a positive reinforcement in its simulative effect on carbon emissions. When the society is in the early stage of aging, the number of elderly population and the level of medical consumption are generally low, and the carbon emission caused by medical consumption is not significant at this time. However, when the aging rate exceeds a specific threshold, the size of the elderly population increases significantly and brings about an increase in the demand for social medical services. At the same time, the proportion of medical consumption expenditure in the overall consumption structure would also reach a certain share and have an impact on environmental quality through a series of production channels. For example, medical consumer goods are responsible for a certain share of energy consumption from the production of raw materials, road transportation to sales and use. In the long run, changes in energy consumption in the medical consumer goods sector would inevitably increase energy-carrying carbon emissions, thus leading to a stimulating effect of healthcare spending on carbon emissions.

Analysis of threshold regression results for the production-side drive path. The regression results outlined in Table 5 reveal several noteworthy trends. Firstly, the degree of industrialization consistently exerts a positive influence on carbon emissions throughout the aging evolution. However, it is crucial to highlight that this driving effect significantly diminishes during the later stages of aging compared to the earlier stages. Secondly, the influence of the R&D innovation level on carbon emissions becomes apparent only after surpassing a specific aging threshold. Over the entire survey period, R&D innovation consistently demonstrates a negative impact on carbon emissions, and no structural breakpoints are observed. Lastly, the impact of the labor force participation rate on carbon emissions undergoes a structural shift from being a negative inhibitor to becoming a positive driver throughout the aging process in China.

Table 5 Coefficients and test statistics of the production-side driving path.

Variable	Coefficient	Standard error	*T*-statistic	*p* value
L1.ln_CO_2	0.4030***	0.1195	3.37	0.002
Ind (Age < 4.7491)	0.0231***	0.0214	−1.08	0.006
Ind (Age ≥ 4.7491)	0.0033**	0.0013	2.59	0.015
Rd (Age < 4.7573)	−0.9048	0.6415	−1.41	0.169
Rd (Age ≥ 4.7573)	−0.0157***	0.0053	−2.96	0.006
Lp (Age < 4.7491)	−0.0142	0.0121	−1.17	0.012
Lp (Age ≥ 4.7491)	0.0020	0.0023	0.88	0.007
Control variables	Control			

Figure 4 displays the coefficients of the share of the secondary industry, research and development (R&D) innovation, and labor participation rate on carbon emissions in two stages. As shown in the figure, the stimulative effect of the share of the secondary industry on carbon emissions diminishes in the later stages of aging. This indirectly confirms that population aging will, to some extent, promote the transformation and upgrading of the social industrial structure. During the period of low aging, the secondary industry is in a rapid development stage, and the society is prompted to consume electricity and energy by increasing industrial activities and producing industrial products, which leads to the positive influence of the share of secondary industry on carbon emission more significantly. However, with the increase of aging, the industrial level of the society has made a big improvement. In the process of further aging, the society would certainly prompt the rapid development of high-end service industry and high-tech medical and health care industry and drive the production side of the society to complete the transition from labor-intensive industry-oriented to technology-intensive industry-led, and from low-value-added industry to high-value-added industry.

The characteristics of the impact of R&D innovation on carbon emissions convey that the aging of the population would promote the technological level at a specific stage. When the aging level is low, R&D innovation is at a slower starting stage, and society attaches less importance and support to R&D innovation, so the marginal impact of the increase in research funding on carbon emissions is minimal at this time. As the number of elderly people gradually increases and the number of age-appropriate labor force becomes smaller and smaller, the scarcity of labor leads to an increase in the price of labor factors, and market players would urge enterprises to take relevant measures to improve labor efficiency, such as introducing new technology and equipment and investing in R&D funds. Over time, social production efficiency and green energy-saving products can be improved and

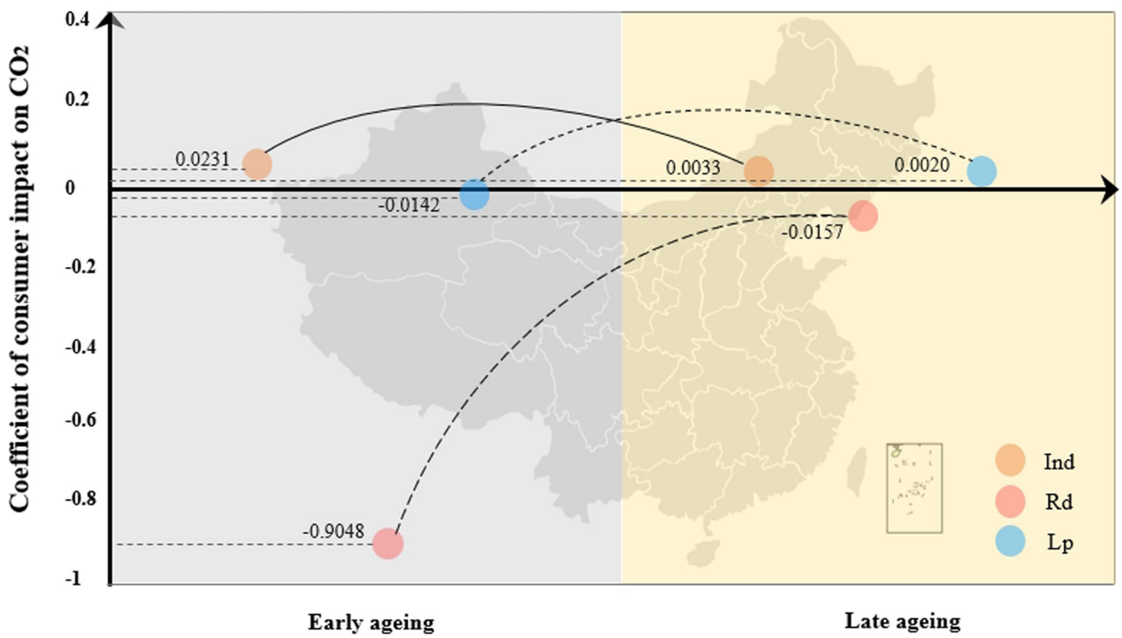

Fig. 4 The influence of the production-side driving path within different aging intervals. This image illustrates the variation in the impact of supply-side factors on carbon emissions. The left section displays the impact coefficients of supply-side factors during the early stages of aging, while the right section shows the impact coefficients of supply-side factors during the later stages of aging.

promoted, and the growth rate of carbon emissions can be effectively controlled.

The impact of the labor participation rate on carbon emissions has shifted from inhibitory to stipulative. Recent population census data indicates that China's labor force participation rate has been on a downward trend in the first decade of the twenty-first century, with a total decrease of 5%. In the backdrop of China's demographic aging, the decline in the juvenile dependency ratio and the substantial influx of the prime working-age population persist as primary drivers continually propelling the rising proportion of the working-age demographic. In a departure from historical trends, the labor force participation rate, having undergone a distinct period of notable decline, has presently shifted toward stimulating carbon emissions through the expansion of industrial value added. Consequently, the envisaged scenario wherein the aging population curtails carbon emissions by reducing labor supply has not materialized in China.

Heterogeneous effects of different stages of aging. Given the vast size of China, differences in affluence, technology level, and cultural attitudes among the 30 provinces contribute to the uneven distribution of population aging. Ignoring the differences among regions may lead to bias of theoretical regression results in practical application. This study refers to the criteria for an aging society developed by the World Health Organization (Rudnicka et al. 2020), and divides the 30 provinces into highly aging, moderately aging, and low aging regions based on the structural intervals of aging rates of 7%–12%, 12%–14%, and 14%–20%. As shown in Fig. 5, the highly aging regions contain 12 provinces and cities, mainly located in the northeast region, the southeast coastal region, and Sichuan and Chongqing regions. The moderate aging region contains 9 provinces and cities, which are scattered in North China, Central China, and Northwest China. The low-aging region contains 9 provinces and cities, mostly concentrated in Southwest China, South China and Northwest China. Following this division result, this section constructs dynamic panel threshold models for indicator data of high, medium and low aging regions in turn, and compares the coefficient differences of the same elements within different regions to understand the regional heterogeneity effect of aging on carbon emissions.

Carbon emission driving pathways in regions with highly aging. In the demographic evolution of high aging regions, social consumption side variables show a three-stage, significant positive effect on carbon emissions. Figure 6 shows more distinctly the slope parameter changes of the driving effect of carbon emissions in highly aging regions in different threshold intervals. First, the positive driving effect of the social consumption side on carbon emissions shows an inverted "U" shaped variation. The effect of all three variables on carbon emissions peaks in the second process of aging, and then shows a lower positive impact in the third process than in the first. In other words, the first stage of aging stimulates the increase of consumption level and causes a rapid increase of carbon emissions in the consumption sector; while the positive driving effect of social consumption side variables on carbon emissions starts to weaken after the aging level exceeds 15.61%. This further supports that the impact of aging on the consumption side would undergo a transition from the individual resident domain to the integrated social domain as mentioned in the previous section (Fan et al. 2021). In the early and middle stages of the aging process, household carbon emissions experience a significant surge attributable to the heightened utilization of energy-intensive products such as housing, food,

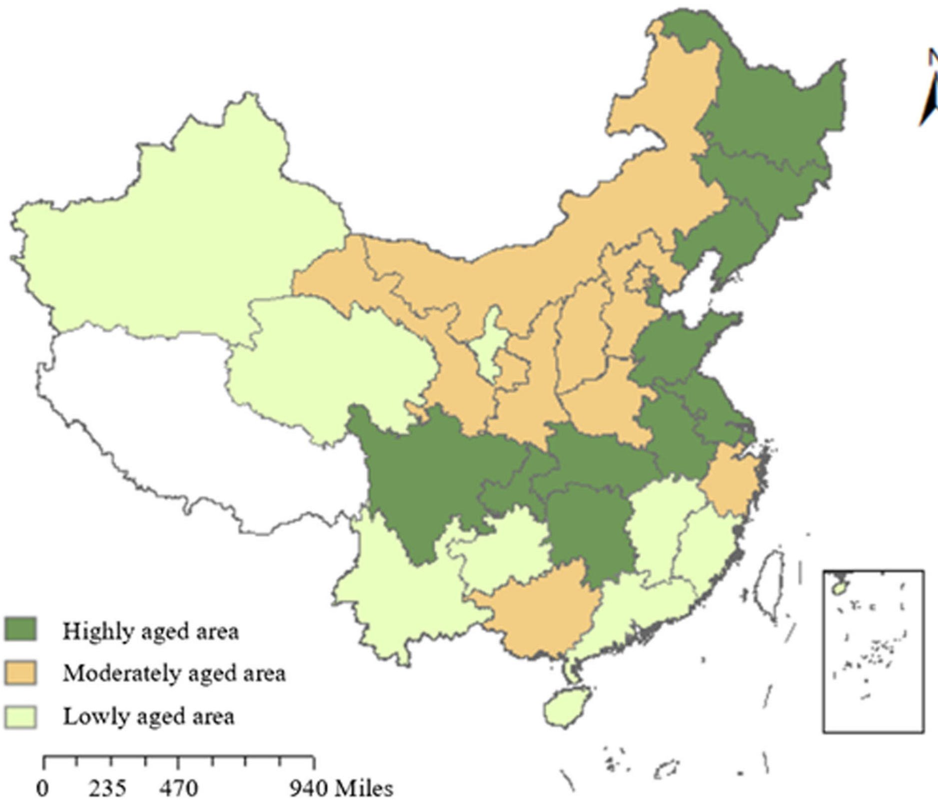

Fig. 5 Results of the regional classification according to the level of aging. This image illustrates the regional categorization of China based on different levels of aging. The green region represents areas with a high level of aging, the yellow region represents areas with a moderate level of aging, and the light green region represents areas with a low level of aging.

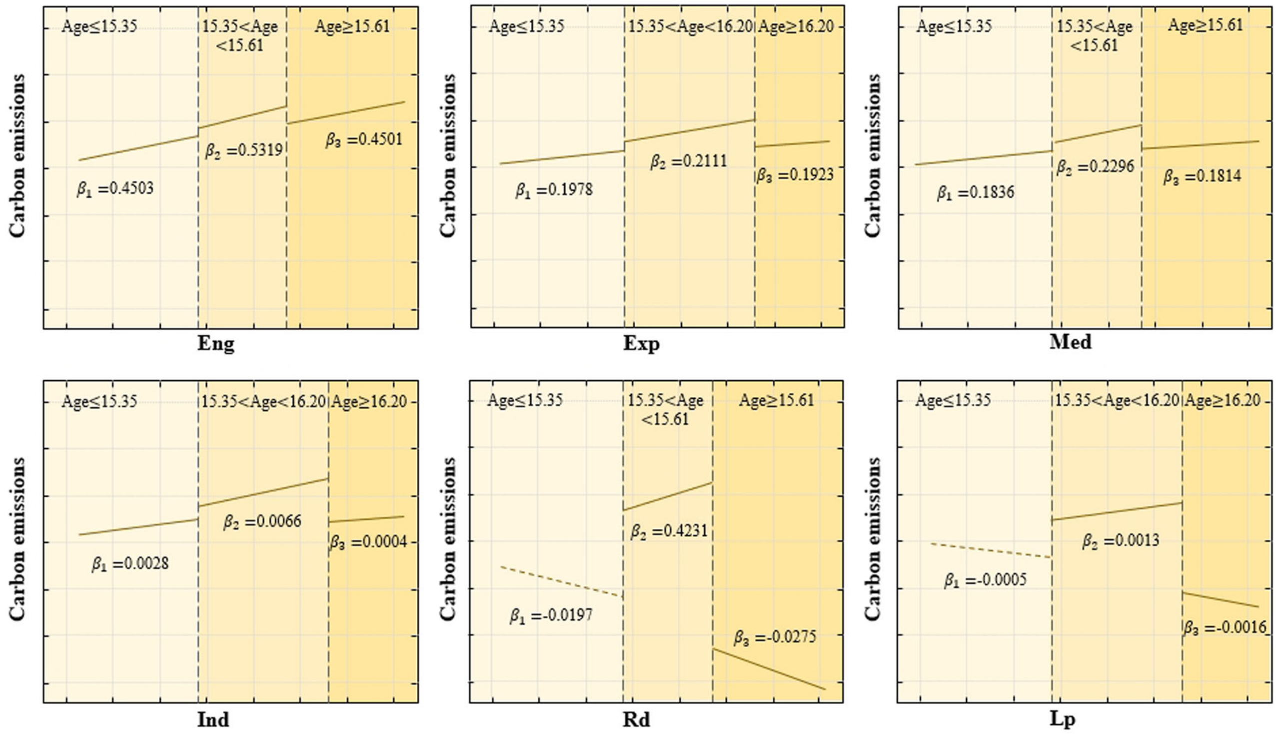

Fig. 6 Changes in slope parameters of CO_2 driving effects in highly aged areas. This image displays the variation in the coefficients of the six influencing factors on carbon emissions within regions characterized by a high level of aging.

and healthcare. Consequently, individual consumption patterns contribute to an elevated carbon emission coefficient during this phase. As the aging process advances, societal dynamics evolve, transitioning from reliance on traditional energy sources to embracing green and clean energy alternatives to meet the escalating demand for household energy consumption. Simultaneously, the tertiary sector, characterized by lower energy dependence, undergoes a reduction in energy consumption and environmental pollution. This social restructuring results in a decline in the carbon emission coefficient during the later stages of aging development. This underscores a three-stage evolution in the impact of aging on the social consumption side within highly aged regions. While the decline in the third stage may not be conspicuously apparent, it signifies the manifestation of a scenario wherein population aging suppresses carbon emissions through the social consumption side.

The mechanism of action of the social production side on carbon emissions is characterized by a change from a positive strong driver to a positive weak driver/negative suppressor. In particular, the magnitude of the effect of industrial structure on carbon emissions increases to 0.66% and then decreases to 0.04%. This pattern suggests that aging initially propels the industrialization process, leading to a rapid surge in carbon emissions during the early stage, followed by a plateauing trend in carbon emissions growth within the industrial sector during the later stage. As for R&D innovation and labor supply, their roles shift from positive drivers to negative inhibitors, with respective negative inhibitions of 2.75 and 0.16%. This implies that they have evolved into emerging factors contributing to the reduction of carbon emissions amid the process of profound aging.

This phenomenon underscores that in regions characterized by advanced aging, transformations in the age structure of the population induce a paradigm shift in the societal production sector. Notably, this includes a reduction in the carbon growth rate attributed to industrial structure optimization and decarbonization on the production side due to technological advancements. The literature has previously posited that aging instigates the transformation and upgrading of the social production sphere by reshaping demand structures and influencing levels of automation and human capital (Cheng et al. 2018). The empirical findings presented in this paper lend support to the assertion that this trend is gaining traction in regions experiencing advanced aging. Looking ahead, the deepening aging process is poised to establish a compelling impetus for enterprises to gravitate toward technology-intensive manufacturing driven by science and technology innovation. This shift is anticipated to elevate the levels of science and technology innovation within society and further propel the high-quality development of industries.

Carbon emission driving pathways in regions with moderate aging. Figure 7 distinctly shows the slope parameter changes of the driving effect of carbon emissions in moderately aging regions in different threshold intervals. First, the positive driving effect of the social consumption side on carbon emissions has a gradual increase in the evolution of aging. In both structural intervals, the magnitude of the effect of all three variables on carbon emissions appears to rise in the second process. That is, the social consumption level in moderately aged areas experiences a shift from low to high. When the aging rate exceeds 12.99%, the increase in the consumption level of the region leads to a further rise in its driving force for carbon emissions. This implies that in moderately aged regions, the impact of aging on society is still dominated by stimulating consumption, with a more significant level of consumption increase in the energy sector. This phenomenon is in line with York's argument that an increase in the proportion of the elderly population makes the production and distribution of society more energy-intensive (York 2007), which leads to an increase in the carbon emission coefficients of the

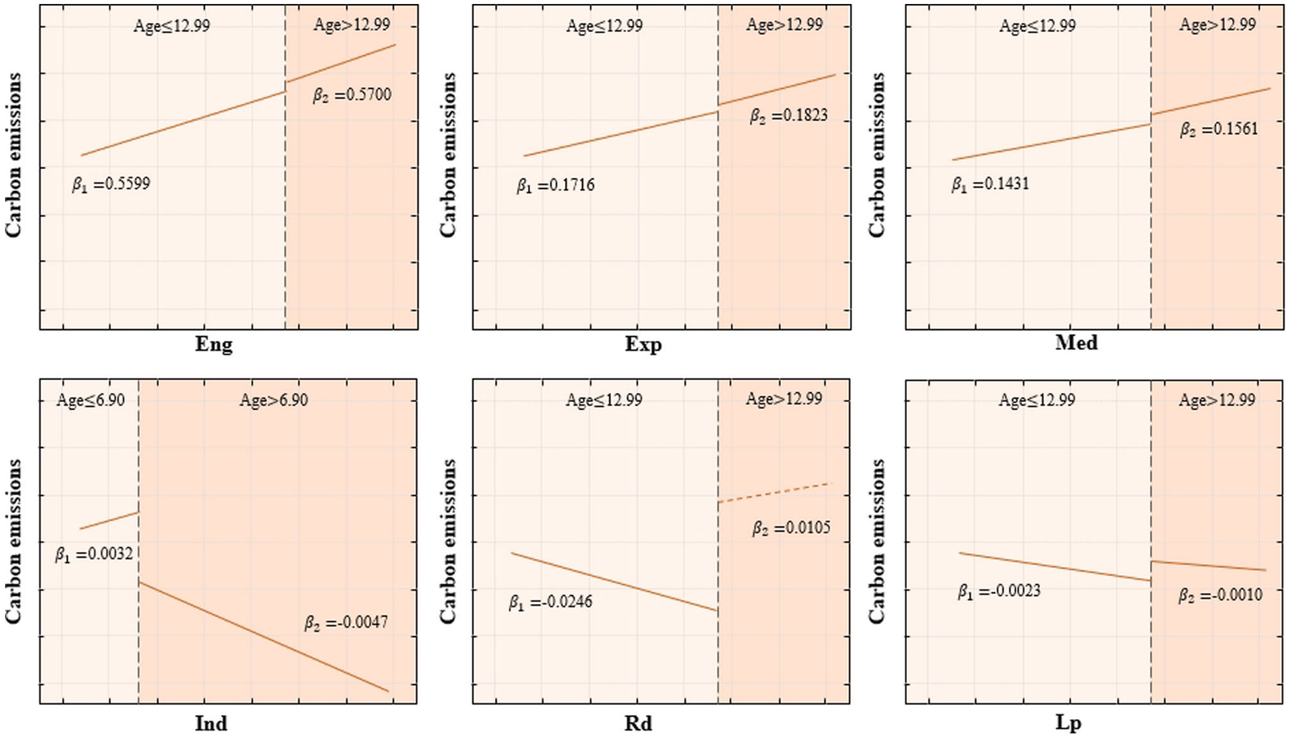

Fig. 7 Changes in slope parameters of CO_2 driving effects in moderate aged areas. This image illustrates the variation in the coefficients of the six influencing factors on carbon emissions within regions characterized by a moderate level of aging.

relevant variables. This also conveys that the aging of the population has not yet taken shape in the region through the social consumption side to curb carbon emissions.

Secondly, during the middle and late stages of population aging, variables on the social production side predominantly exhibit a mitigating impact on carbon emissions. Specifically, the influence of industrial structure on carbon emissions declines from a positive 0.32% to a negative 0.47%. In other words, aging propels the industrialization process, fostering a rapid escalation in carbon emission levels during the early stage, and subsequently contributing to a negative growth in carbon emissions within the industrial sector in the later stage. In the case of both R&D innovation and labor supply, their effects on carbon emissions consistently manifest as negative suppressors, with R&D innovation playing a more pronounced role in contributing to carbon emission reduction. This observation suggests that population aging not only enhances industrial structure and diminishes traditional industrial energy consumption in regions with moderate aging but also steers the production side toward high-quality development through technological advancements and improved labor supply. Beyond its environmental implications, these changes in the social production landscape may catalyze broader societal benefits, fostering innovation-driven economic growth, creating opportunities for skilled employment, and contributing to a more sustainable and resilient economy in regions experiencing moderate aging.

Carbon emission driving pathways in regions with lowly aging. Figure 8 starkly shows the slope parameter changes of the driving effect of carbon emissions in low-aging regions in different threshold intervals. First, the positive driving effect of the social consumption side on carbon emissions has an enhanced trend in the later stages of aging, and the increase is stronger in the second threshold interval than in the moderately aging regions. Specifically, the regression parameters of energy consumption and residential consumption on carbon emissions increase by about 0.4% in the second process of aging, which implies that the aging population is causing the social consumption level in the region to experience a period of rapid growth. The driving effect of healthcare consumption on carbon emissions is particularly significant in the low-level aging region, where each 1% of healthcare spending on average would lead to a 0.4879% increase in carbon emissions. This shows that the effect of social consumption on carbon emissions in low-aging areas increases significantly after crossing a specific threshold, and the driving effect of energy consumption and residential consumption on carbon emissions is particularly pronounced in the late aging period. This further supports the conclusion that the increase in consumption of energy-intensive products and durable goods at the beginning of aging increases carbon emissions sharply (Han et al. 2022).

Secondly, in the context of the social production side, the driving impact of industrial structure on carbon emissions weakens during the aging process. Although the inhibitory effects of R&D innovation and labor supply on carbon emissions are particularly notable in the early stage of aging, the carbon influence of the social production side remains undisclosed in the later stages due to developmental nuances. Specifically, the influence of industrial structure on carbon emissions decreases from 4.43 to 1.25%. Despite the deceleration in the carbon rate within the industrial sector attributed to the aging population, this sector continues to exert the most substantial contribution to carbon emissions among the three major regions. Regarding R&D innovation and labor supply, both consistently demonstrate negative suppression of carbon emissions, with labor supply playing a more impactful role in contributing to carbon reduction.

This observed phenomenon suggests that the aging level in the region has enhanced capital returns and societal technology through the cumulative impact of human capital, steering the region toward the goal of optimizing industrial structure. Beyond

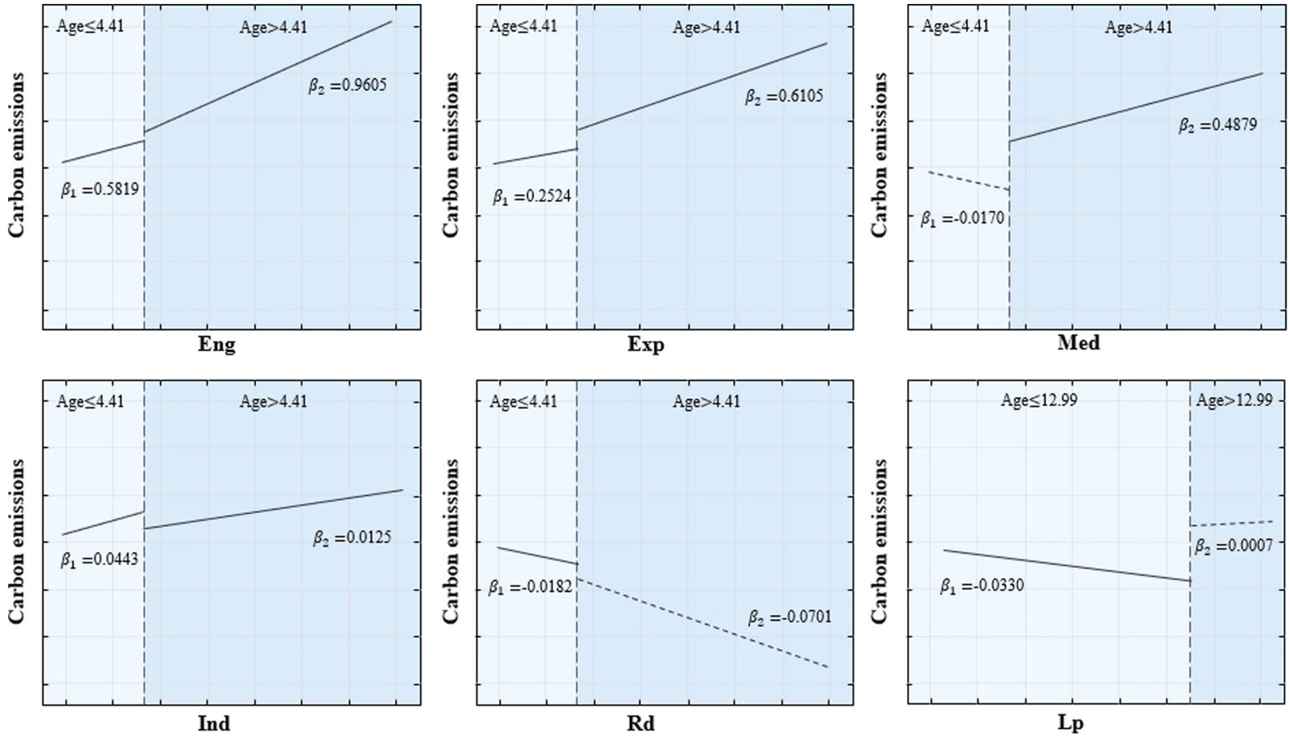

Fig. 8 Changes in slope parameters of CO_2 driving effects in lowly aged areas. This image illustrates the variation in the coefficients of the six influencing factors on carbon emissions within regions characterized by a low level of aging.

its environmental implications, these changes in the social production landscape may have profound societal impacts. The optimization of industrial structure, coupled with advancements in technology and a skilled labor force, can catalyze economic growth, foster innovation-driven industries, and create new employment opportunities. Additionally, as carbon reduction becomes a central focus, these shifts contribute to a more sustainable and resilient society, aligning with broader goals of environmental stewardship and quality of life enhancement in the face of population aging.

Conclusion

This study introduces a dynamic panel threshold regression model to first explore the patterns of the effects of energy consumption, residential consumption, health care consumption, industrial structure, technological progress, and labor supply on carbon emissions. Secondly, we identify the structural breakpoints and changes in effect levels of the multiple impact paths in the aging process. Finally, the spatial heterogeneity of the multiple driving paths of carbon emissions at the national level, in highly aging regions, in moderately aging regions, and low aging regions is identified.

The study reaches the following primary conclusions. First, the heightened preference for energy-intensive products among the aging population in the later stages of aging underscores the urgency for targeted interventions in energy-related carbon emissions. The delayed emergence of the driving effect of healthcare consumption expenditure on carbon emissions emphasizes the need for adaptive policies that address the evolving dynamics of an aging society's impact on consumption structures. Second, the gradual optimization and upgrading of the industrial structure as society ages signify the potential for policies promoting technological progress and capital efficiency. The transition from labor substitution to technological reliance highlights the importance of policies that incentivize and support firms in adopting advanced technologies and improving capital efficiency. Third, the spatial heterogeneity in the impact of aging on carbon emissions underscores the necessity for region-specific policies tailored to address distinctive consumption and production patterns. Areas with lower levels of aging must mitigate carbon emissions through strategic shifts in consumption practices. In regions with higher levels of aging, technological advances in production are needed to achieve a balance between economic development and carbon emissions (Wang et al. 2024c). Policymakers should conscientiously consider these spatial dynamics when crafting policies, ensuring they are well-adapted to provide effective and targeted responses to the environmental challenges posed by population aging across diverse regions.

Our research has some limitations. This study undertakes a quantitative examination of the environmental ramifications associated with population aging, concentrating its analysis on both national and regional scales. The investigation treats the nation and three prominent aging regions as closed population systems. However, it is noteworthy that for urban and rural areas, classified as open population systems, the study regrettably lacks a more comprehensive assessment of the environmental impacts attributed to the aging phenomenon. This is where our future research will focus.

Received: 20 September 2023; Accepted: 6 February 2024;
Published online: 11 March 2024

References

Acemoglu D (2010) When does labor scarcity encourage innovation? J Political Econ 118(6):1037–1078

An H-Y, Chen W, Wang C-W, Yang H-F, Huang W-T, Fan S-Y et al. (2020) The relationships between physical activity and life satisfaction and happiness among young, middle-aged, and older adults. Int J Environ Res Public Health 17(13):4817

Balezentis T (2020) Shrinking ageing population and other drivers of energy consumption and CO2 emission in the residential sector: a case from Eastern Europe. Energy Policy 140:111433. https://doi.org/10.1016/j.enpol.2020.111433

Bardazzi R, Pazienza MG (2017) Switch off the light, please! Energy use, aging population and consumption habits. Energy Econ 65:161–171

Bloom DE, Canning D, Fink G (2010) Implications of population ageing for economic growth. Oxf Rev Econ Policy 26(4):583–612

Can M, Ahmed Z, Mercan M, Kalugina OA (2021) The role of trading environment-friendly goods in environmental sustainability: does green openness matter for OECD countries? J Environ Manag 295:113038

Caner M, Hansen BE (2004) Instrumental variable estimation of a threshold model. Econ Theory 20(5):813–843

Charlier D, Legendre B (2021) Carbon dioxide emissions and aging: disentangling behavior from energy efficiency. Ann Econ Stat 143:71–103

Chen S, Huang Q, Muttarak R, Fang J, Liu T, He C et al. (2022) Updating global urbanization projections under the shared socioeconomic pathways. Sci Data 9(1):137

Chen Z-M, Ohshita S, Lenzen M, Wiedmann T, Jiborn M, Chen B et al. (2018) Consumption-based greenhouse gas emissions accounting with capital stock change highlights dynamics of fast-developing countries. Nat Commun 9(1):3581

Cheng Z, Li L, Liu J (2018) Industrial structure, technical progress and carbon intensity in China's provinces. Renew Sustain Energy Rev 81:2935–2946

De Meijer C, Koopmanschap M, d'Uva TB, Van Doorslaer E (2011) Determinants of long-term care spending: age, time to death or disability? J Health Econ 30(2):425–438

Dixon S (2003) Implications of population ageing for the labour market. Labour Mark Trends 111(2):67–76

Fan J, Zhou L, Zhang Y, Shao S, Ma M (2021) How does population aging affect household carbon emissions? Evidence from Chinese urban and rural areas. Energy Econ 100:105356. https://doi.org/10.1016/j.eneco.2021.105356

Fan T, Luo R, Xia H, Li X (2015) Using LMDI method to analyze the influencing factors of carbon emissions in China's petrochemical industries. Nat Hazards 75:319–332

Feng Y, Wu H, Jin Y, Wang L, Zeng B (2023) How does population aging affect carbon emissions?—Analysis based on the multiple mediation effect model. Environ Sci Pollut Res 30(14):41419–41434

Gehringer A, Prettner K (2019) Longevity and technological change. Macroecon Dyn 23(4):1471–1503

Han X, Wei C, Cao G-Y (2022) Aging, generational shifts, and energy consumption in urban China. Proc Natl Acad Sci 119(37):e2210853119

Hansen BE (1999) Threshold effects in non-dynamic panels: estimation, testing, and inference. J Econ 93(2):345–368

He L-Y, Hou B, Liao H (2018) Rural energy policy in China: achievements, challenges and ways forward during the 40-year rural reform. China Agric Econ Rev 10(2):224–240

Jiang X-t, Wang Q, Li R (2018) Investigating factors affecting carbon emission in China and the USA: a perspective of stratified heterogeneity. J Clean Prod 199:85–92

Jones BF (2010) Age and great invention. Rev Econ Stat 92(1):1–14

Kremer S, Bick A, Nautz D (2013) Inflation and growth: new evidence from a dynamic panel threshold analysis. Empir Econ 44(2):861–878

Kühn S, Milasi S, Yoon S (2018) Population ageing and future labour market challenges. World Employ Soc Outlook 2018(1):45–50

Lancia F, Prarolo G (2012) A politico-economic model of aging, technology adoption and growth. J Popul Econ 25:989–1018

Lee R, Mason A (2010) Fertility, human capital, and economic growth over the demographic transition. Eur J Popul 26(2):159

Lee S, Seo MH, Shin Y (2011) Testing for threshold effects in regression models. J Am Stat Assoc 106(493):220–231

Li R, Li L, Wang Q (2022) The impact of energy efficiency on carbon emissions: evidence from the transportation sector in Chinese 30 provinces. Sustain Cities Soc 82:103880. https://doi.org/10.1016/j.scs.2022.103880

Li R, Wang Q, Guo J (2024) Revisiting the environmental Kuznets curve (EKC) hypothesis of carbon emissions: exploring the impact of geopolitical risks, natural resource rents, corrupt governance, and energy intensity. J Environ Manag 351:119663. https://doi.org/10.1016/j.jenvman.2023.119663

Li R, Wang Q, Li L, Hu S (2023) Do natural resource rent and corruption governance reshape the environmental Kuznets curve for ecological footprint? Evidence from 158 countries. Resour Policy 85:103890. https://doi.org/10.1016/j.resourpol.2023.103890

Li R, Wang Q, Liu Y, Jiang R (2021) Per-capita carbon emissions in 147 countries: the effect of economic, energy, social, and trade structural changes. Sustain Prod Consum 27:1149–1164. https://doi.org/10.1016/j.spc.2021.02.031

Lisenkova K, Mérette M, Wright R (2013) Population ageing and the labour market: modelling size and age-specific effects. Econ Model 35:981–989. https://doi.org/10.1016/j.econmod.2013.09.007

Liu B, Wang J, Li RY, Peng L, Mi L (2022) Achieving carbon neutrality—the role of heterogeneous environmental regulations on urban green innovation. Front Ecol Evol 10:923354

Mamipour S, Yahoo M, Jalalvandi S (2019) An empirical analysis of the relationship between the environment, economy, and society: results of a PCA-VAR model for Iran. Ecol Indic 102:760–769

Mao R, Xu J (2014) Population aging, consumption budget allocation and sectoral growth. China Econ Rev 30:44–65

Mason A, Lee R, Network, N. (2022) Six ways population change will affect the global economy. Popul Dev Rev 48(1):51–73

Masson-Delmotte V, Zhai P, Pörtner H-O, Roberts D, Skea J, Shukla PR (2022) Global warming of 1.5° C: IPCC special report on impacts of global warming of 1.5° C above pre-industrial levels in context of strengthening response to climate change, sustainable development, and efforts to eradicate poverty. Cambridge University Press, Shaftesbury Road, Cambridge

Meng F, Liu G, Hu Y, Su M, Yang Z (2018) From production to consumption: a multi-city comparative study of cross-regional carbon emissions. Energy Procedia 152:744–749. https://doi.org/10.1016/j.egypro.2018.09.239

Menz T, Kühling J (2011) Population aging and environmental quality in OECD countries: evidence from sulfur dioxide emissions data. Popul Environ 33:55–79

Menz T, Welsch H (2012) Population aging and carbon emissions in OECD countries: accounting for life-cycle and cohort effects. Energy Econ 34(3):842–849

Mi Z, Zhang Y, Guan D, Shan Y, Liu Z, Cong R et al. (2016) Consumption-based emission accounting for Chinese cities. Appl energy 184:1073–1081

Pan C, Wang H, Guo H, Pan H (2021) How do the population structure changes of China affect carbon emissions? An empirical study based on ridge regression analysis. Sustainability 13(6):3319

Rudnicka E, Napierała P, Podfigurna A, Męczekalski B, Smolarczyk R, Grymowicz M (2020) The World Health Organization (WHO) approach to healthy ageing. Maturitas 139:6–11

Seo MH, Shin Y (2016) Dynamic panels with threshold effect and endogeneity. J Econ 195(2):169–186

Shi Z, Wu L, Zhou Y (2023) Predicting household energy consumption in an aging society. Appl Energy 352:121899

Shuai C-M, Ding L-P, Zhang Y-K, Guo Q, Shuai J (2014) How consumers are willing to pay for low-carbon products?—Results from a carbon-labeling scenario experiment in China. J Clean Prod 83:366–373

Soltani M, Rahmani O, Ghasimi DS, Ghaderpour Y, Pour AB, Misnan SH et al. (2020) Impact of household demographic characteristics on energy conservation and carbon dioxide emission: case from Mahabad city, Iran. Energy 194:116916

Song C, Bilsborrow R, Jagger P, Zhang Q, Chen X, Huang Q (2018) Rural household energy use and its determinants in China: how important are influences of payment for ecosystem services vs. other factors? Ecol Econ 145:148–159

Thiel C, Richie C (2022) Carbon emissions from overuse of U.S. health care: medical and ethical problems. Hastings Cent Rep 52(4):10–16. https://doi.org/10.1002/hast.1404

Wang Q, Ge Y, Li R (2024a) Does improving economic efficiency reduce ecological footprint? The role of financial development, renewable energy, and industrialization. Energy Environ 1–27. https://doi.org/10.1177/0958305X231183914

Wang Q, Hu S, Li R (2023a) Could information and communication technology (ICT) reduce carbon emissions? The role of trade openness and financial development. Telecommun Policy. https://doi.org/10.1016/j.envres.2022.114637

Wang Q, Ren F, Li R (2024b) Exploring the impact of geopolitics on the environmental Kuznets curve research. Sustain Dev 1–23. https://doi.org/10.1002/sd.2743

Wang Q, Wang L, Li R (2023b) Trade openness helps move towards carbon neutrality—insight from 114 countries. Sustain Dev 32:1081–1095. https://doi.org/10.1002/sd.2720

Wang Q, Wang X, Li R, Jiang X (2024c) Reinvestigating the environmental Kuznets curve (EKC) of carbon emissions and ecological footprint in 147 countries: a matter of trade protectionism. Humanit Soc Sci Commun 11(1):160. https://doi.org/10.1057/s41599-024-02639-9

Wei T, Zhu Q, Glomsrød S (2018) How will demographic characteristics of the labor force matter for the global economy and carbon dioxide emissions? Ecol Econ 147:197–207

W. H. Organization (2012) Health in the green economy: health co-benefits of climate change mitigation-transport sector. World Health Organization

Wu R (2019) The carbon footprint of the Chinese health-care system: an environmentally extended input–output and structural path analysis study. Lancet Planet Health 3(10):e413–e419

Yang T, Liu W (2017) Inequality of household carbon emissions and its influencing factors: case study of urban China. Habitat Int 70:61–71

Yang T, Wang Q (2020) The nonlinear effect of population aging on carbon emission-empirical analysis of ten selected provinces in China. Sci Total Environ 740:140057. https://doi.org/10.1016/j.scitotenv.2020.140057

Yang X, Li N, Mu H, Ahmad M, Meng X (2022) Population aging, renewable energy budgets and environmental sustainability: does health expenditures matter? Gondwana Res 106:303–314

York R (2007) Demographic trends and energy consumption in European Union Nations, 1960–2025. Soc Sci Res 36(3):855–872

Yu M, Meng B, Li R (2022) Analysis of China's urban household indirect carbon emissions drivers under the background of population aging. Struct Change Econ Dyn 60:114–125

Yu Y, Liang Q, Liu L (2023) Impact of population ageing on carbon emissions: a case of China's urban households. Struct Change Econ Dyn 64:86–100. https://doi.org/10.1016/j.strueco.2022.12.001

Zhang C, Tan Z (2016) The relationships between population factors and China's carbon emissions: does population aging matter? Renew Sustain Energy Rev 65:1018–1025. https://doi.org/10.1016/j.rser.2016.06.083

Zhang Y, Dong Q, Ma G (2023) Effects of rural population aging on agricultural carbon emissions in China. Sustainability 15(8):6812

Zheng X, Huang G, Li J, Liu L, Zhai M, Pan X (2023) A sector-disaggregated cross-regional emission analysis for carbon mitigation policies from production and consumption perspectives. Sci Total Environ 895:164973. https://doi.org/10.1016/j.scitotenv.2023.164973

Acknowledgements
This study is supported by Project of Shandong Province Higher Educational "Youth Innovation Science and Technology Plan" Team (No. 2021KJ060).

Author contributions
Shuyu Li: writing—original draft, methodology, formal analysis. Qiang Wang: writing—review and editing, investigation, supervision, funding acquisition. Rongrong Li: writing—review and editing, data curation, validation.

Competing interests
The authors declare no competing interests.

Ethical approval
This article does not contain any studies with human participants performed by any of the authors.

Informed consent
Informed consent was obtained from all participants.

Additional information
Correspondence and requests for materials should be addressed to Qiang Wang or Rongrong Li.

Reprints and permission information is available at http://www.nature.com/reprints

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.