



How does population aging affect China's energy consumption?

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Abstract

In China, the proportion of elderly population is growing, influencing economic development and energy consumption. Our study investigates the relationship between population aging and energy consumption in China from 1997 to 2020, considering both short and long-term effects. The analysis employs the pooled mean group (PMG) estimation and explores the underlying mechanisms using mediating effects and threshold effects models. The PMG results reveal a negative long-term impact of population aging on energy consumption, indicating that a 1% increase in population aging leads to a 0.348% decrease in energy consumption. Additionally, GDP per capita and capital stock exhibit positive correlations with energy consumption, while the industrial structure shows a negative correlation. Technological progress is found to significantly increase energy consumption. The mechanism analysis suggests that the mediating role of scale and technological effects contributes to the negative effect of population aging on energy consumption. Furthermore, a nonlinear relationship between population aging and energy consumption is observed, influenced by both population size and technological progress. The policy implications call for a comprehensive approach that addresses elderly population growth, enhances energy efficiency, and promotes sustainable technologies to ensure sustainable economic development.

Keywords Population aging · Energy consumption · PMG · Mediating mechanism · Threshold effect

Introduction

Population aging is a global phenomenon that has profound implications for various aspects of social and economic development, such as labor supply, consumption patterns, health care, and environmental quality. Among these, energy consumption is a crucial factor that affects both economic growth and environmental sustainability. Understanding how population aging influences energy consumption can help policymakers design effective strategies to cope with the challenges and opportunities of an aging society.

China is facing a rapid and unprecedented demographic transition, with the proportion of elderly population (aged 65 and above) increasing from 6.96% in 2010 to 14.2% in 2021.

This means that China has entered into a deeply aging society in 2021. Moreover, China is predicted that around 2035, more than 400 million people will be over 60 years old, making up over 30% of the entire population and starting the heavy aging period in China. At the same time, China is also undergoing a significant transformation of its energy system, aiming to achieve carbon neutrality by 2060 and increase the share of renewable energy sources in its energy mix. How population aging affects China's energy consumption and its implications for economic and environmental goals are important questions that need to be addressed. However, existing studies on the relationship between population aging and energy consumption have yielded mixed and inconclusive results.

Thus, our study focuses on this topic. First, we estimate the long-term relationship between population aging and energy consumption in China using panel data from 1997 to 2020 and pooled mean group (PMG) estimation method. Moreover, we explore the underlying mechanisms of how population aging affects energy consumption in China based on mediating effects and threshold effects models. Additionally, we test the nonlinear relationship between population aging and energy consumption in China using panel threshold regression model with three threshold variables:

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population size, industrial structure, and technological progress. This provides policy implications for achieving sustainable economic development and environmental protection in China under the context of population aging.

The main framework of the paper is as follows: “Literature review” section is literature review. “Theoretical framework” section introduces methods, variables, and data. “Results” section provides results. “Discussion” section presents discussion. “Conclusions” section concludes.

Literature review

Currently, views in academia vary regarding the impact of population aging on energy consumption. These viewpoints can be classified into four different correlations: positive, negative, nonmonotonic and irrelevant. Some studies have concluded that population aging will continue to increase environmental pressure, and energy consumption would show an increasing trend with the rising elderly population. (Menz and Welsch 2012; Huang et al. 2019; Yang et al. 2015). Conversely, some studies suggest a negative correlation because population aging reduces consumption, labor supply, and investment, which indirectly reduces energy consumption. (O’Neill et al. 2012; Kim et al. 2020; Tarazkar et al. 2020; Guo et al. 2016; Wei et al. 2018, Hu et al. 2020, Yu et al. 2022). Moreover, some scholars proved that population aging has a different impact on energy consumption considering urban–rural difference (Zhang and Tan 2016; Fan et al. 2021), an east–west difference (Wang et al. 2017), long-and-short-term differences (Guo et al. 2022), and an income structure difference (Wang and Wang 2021). Dalton et al. (2008) used the threshold analysis and argued that under the low population scenario, population aging influences emissions greatly. Yang and Wang (2020) showed that the trade openness level influences how population aging affects carbon emissions. Finally, an inverted U-shaped curve depicts the correlation between population aging and energy consumption (Li et al. 2018; Balsalobre-Lorente et al. 2021). Several studies, however, found an insignificant correlation between population aging and energy consumption (Liddle 2013; Zheng et al. 2022). Former research also analyzed the population-aging-related influential mechanism on energy consumption. O’Neill et al. (2012) found that carbon emissions are impacted by population aging in the PET model mainly through impacting labor supply. Fan et al. (2021) demonstrated that the nonlinear link between population aging and household carbon emissions in urban areas is influenced by consumption structure and level. They also found that the nonlinear connection between rural family carbon pollution and the aging of rural population can only be explained by income level. Wei and Liu (2022) showed that cost mechanism and consumption upgrading mechanism are important ways for population

structure to affect carbon emissions. Besides, changing the mode of economic development and energy consumption is the mechanism of population aging on carbon emissions. (Yang and Wang 2020) Danish and Hassan (2022) also support the idea that urbanization helps ease energy consumption. Danish et al (2019) reveals that CO₂ emissions are influenced by factors such as real income and population density, while the impact of transport infrastructure on CO₂ emissions is found to be insignificant. These earlier studies, however, didn’t explicitly examine the long-term impacts of China’s aging on energy consumption, whose mechanisms are also not investigated in-depth, especially not focusing on the nonlinear relationship.

Therefore, our research focuses on these issues. First, we collect the data for 23 years from 1997 to 2020 to study the long-term relationship between China’s population aging and energy consumption using the pooled mean group (PMG) estimation. Second, we consider the mediating effect of population aging on energy consumption from three perspectives (i.e., scale effect, structural effect, and technological effect). Third, the non-linear relationship between population aging and energy consumption are tested considering three threshold variables: population size, industrial structure, and technological progress.

Theoretical framework

The theoretical framework of our study draws upon three main theories: the demographic transition theory, the life cycle hypothesis, and the environmental Kuznets curve. These theories provide valuable insights into how population aging influences economic development, consumption patterns, and environmental quality in China. The first theory, the demographic transition theory, suggests that population aging occurs as a result of declining fertility and mortality rates during a country’s socio-economic development. Population aging has multifaceted effects on economic development, consumption patterns, and environmental quality. For instance, it may diminish labor supply, investment, and innovation, thereby potentially decelerating economic growth and altering energy demand. Moreover, population aging can bring about changes in consumption preferences and behavior, such as an increased inclination towards staying at home or utilizing more healthcare services, thereby impacting energy usage patterns. Furthermore, population aging can shape environmental awareness and attitudes, which in turn can influence energy conservation behavior and support for relevant policies. Based on the demographic transition theory, we hypothesize that population aging has a long-term negative effect on energy consumption in China, as it reduces the total population size and the energy demand.

Another theory relevant to our study is the life cycle hypothesis, which proposes that individuals plan their consumption and savings over their lifetimes in accordance with their income and wealth levels. According to this theory, population aging can influence energy consumption by altering the income and wealth distribution across different age groups. For instance, older individuals may have lower income, but higher wealth compared to younger individuals, leading to different energy consumption decisions. Furthermore, older individuals may exhibit distinct time preferences and risk aversion tendencies, which can affect their choices regarding energy-saving and investment. Based on the life cycle hypothesis, we hypothesize that population aging exhibits a nonlinear impact on energy consumption in China depending on population size and technological progress, as it alters the income and wealth distribution and the consumption and saving behavior of different age groups.

The third theory considered is the environmental Kuznets curve, which posits an inverted U-shaped relationship between economic development and environmental degradation. Within this framework, population aging can impact energy consumption by influencing the level and structure of economic development. For instance, population aging may decrease the demand for energy-intensive goods and services, such as manufacturing and transportation, while simultaneously increasing the demand for less energy-intensive ones, such as education and entertainment. Additionally, population aging can spur technological progress and innovation, leading to improved energy efficiency and reduced energy intensity. Based on the environmental Kuznets curve, we hypothesize that population aging influences energy consumption in China through three mediating mechanisms: scale effect, structural effect, and technological effect, as it affects the level and structure of economic development and the environmental quality.

Supporting empirical evidence from previous studies can be found for these theories. For example, Han et al. (2022) discovered a negative association between population aging and energy consumption in urban China, largely driven by generational shifts in environmental awareness and energy usage habits. O'Neill et al. (2012) found that population aging affects carbon emissions primarily through its impact on labor supply, consumption structure, and technological advancements. Li et al. (2018) demonstrated an inverted U-shaped relationship between population aging and energy consumption in China, indicating a nonlinear effect of demographic transition on energy demand. Besides, some research reveals the significant relationships between innovations and environmental issues (Tang et al. 2022; Zhang et al. 2023).

Furthermore, we incorporate key terms and concepts such as population aging, energy consumption, economic growth, industrial structure, financial development, population size,

energy intensity, and technological progress. These concepts are measured and operationalized based on existing literature and data sources. We also propose three hypotheses to explore and examine the impact of population aging on energy consumption in China: (1) population aging has a long-term negative effect on energy consumption in China, (2) population aging exhibits a nonlinear impact on energy consumption in China depending on population size and technological progress, and (3) population aging influences energy consumption in China through three mediating mechanisms: scale effect, structural effect, and technological effect. For the scale effect, we argue that population aging reduces the total population size by increasing the mortality rate and decreasing the birth rate, which in turn reduces the total energy demand. For the structural effect, we argue that population aging changes the consumption preferences and behavior of different age groups, such as increasing the demand for less energy-intensive services and decreasing the demand for more energy-intensive goods. For the technological effect, we argue that population aging influences the innovation capacity and adoption of new technologies, which can affect the energy efficiency and intensity.

Methods, variables, and data

Methods

Cross-sectional dependence test

To identify the cross-sectional dependence of series, we employ Breusch and Pagan (1980) LM test and Pesaran (2004) cross-sectional dependence test. By examining the cross-sectional correlation of variables, we could determine the cross-sectional dependence. Then those panel-based surveys can be evaluated. The null hypothesis represents the non-existent cross-sectional independence. Mathematically, this test can be shown as:

$$CSD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^N \sum_{j=i+1}^{N-1} \hat{\rho}_{ij} \right) \sim N(0, 1) \quad (1)$$

where $\hat{\rho}_{ij}$ means the two-way sample correlation coefficient. N means individual and T means year. Additionally, we also test the homogeneity characteristics of variables.

Panel unit root and cointegration tests

- (i) To test for data stationarity, we will execute a unit root test. If we model non-stationary data, there will be pseudo-regression modeling. We use the second-generation unit root test which allows variables' cross-sectional dependence, due to the requirement of the null hypothesis in the first-generation unit

root test to the panel data that it should be of mutually independence in cross-section. We apply the cross-section Im, Pesaran, and Shin (CIPS) and cross-section Augmented Dickey-Fuller (CADF) method to develop the unit root test.

- (ii) After obtaining the panel unit root test's outcomes, the panel cointegration could be applied to examine the variables' long-term equilibrium relationship by applying the Kao (2000) and Pedroni (1999) tests. In this case, the null hypothesis represents no cointegration exists in both tests. According to the seven statistics of Pedroni's (1999) cointegration test and the ADF statistic of Kao's (2000) cointegration test, we identify the cointegration among panel variables and the dependent/independent variables' long-term impacts.

Benchmark model

In our study, we pay attention to the population aging impacts on energy consumption. Therefore, as to the benchmark model, we use age over 60 (*pa*) as an input variable which represents the percentage of the people over 60 in comparison to the general population, energy consumption (*ec*) as an output variable, and gross domestic product per capita (*gdp*), capital stock (*cs*), industry structure (*is*), financial development (*fd*), population scale (*pop*), energy intensity (*ei*), technological progress (*rd*) as control variables. We compensate for possible bias by using a variety of control variables and take the logarithm of them. The function is as follow:

$$\begin{aligned} \ln ec_{it} = & \alpha_i + \beta_1 \ln pa_{it} + \beta_2 \ln gdp_{it} \\ & + \beta_3 \ln cs_{it} + \beta_4 \ln is_{it} + \beta_5 \ln fd_{it} \\ & + \beta_6 \ln pop_{it} + \beta_7 \ln ei_{it} + \beta_8 \ln rd_{it} + \varepsilon_{it} \end{aligned} \quad (2)$$

$$\begin{aligned} \ln ec_{it} = & \alpha_i + \beta_1 \ln pa_{it} I(c < h_1) + \beta_2 \ln pa_{it} I(h_1 \leq c < h_2) + \beta_3 \ln pa_{it} I(h_2 \leq c < h_3) + \beta_4 \ln pa_{it} I(c \\ & \geq h_3) + \beta_5 \ln gdp_{it} + \beta_6 \ln cs_{it} + \beta_7 \ln is_{it} + \beta_8 \ln fd_{it} + \beta_9 \ln pop_{it} \\ & + \beta_{10} \ln ei_{it} + \beta_{11} \ln rd_{it} + \varepsilon_{it} \end{aligned} \quad (3)$$

where *c* refers to the threshold variable which here indicates population, industrial structure, and technological progress. *hI* refer to the threshold value. In addition, *I* is the indicative function, which equals to 1 while the number in brackets was correct, otherwise, it equals to 0. According to Eq. (3), we can test the effect of population aging on energy consumption when population, industrial structure and technological progress are the threshold factors.

Mechanism test

We design a model to study how intermediary effect of population aging affects energy consumption below.

where β_i represent the regression coefficients of corresponding variables. α_i means the fixed effects. The ε_{it} represents a random error term and *i*, *t* refer to regional division and time effect, respectively.

Pooled mean group estimation

The most common panel estimation method is the PMG (pooled mean group) estimator by Pesaran et al. (1999). The PMG estimator is a panel estimation method that allows the long-term coefficients to be homogeneous across groups while the short-term coefficients and error variances to be heterogeneous. This method has several benefits for studying the relationship between population aging and energy consumption in China. First, it can capture the heterogeneity of different regions in China and avoid the bias caused by imposing common coefficients across groups. Second, it can test the long-term equilibrium relationship among variables and estimate the long-term and short-term impacts of population aging on energy consumption. Third, it can handle the cross-sectional dependence and cointegration among variables by using the ARDL (autoregressive distributed lag) model as its framework. Therefore, we use the PMG estimator to analyze the long-term impact of population aging on energy consumption and explore the underlying mechanisms based on panel data from 1997 to 2020 at national and regional levels.

Panel threshold regression model

Our article analyzes the nonlinear characteristics between population aging and energy consumption according to a panel threshold regression model. The model as shown:

$$\ln ec_{it} = \alpha_i + \beta_1 \ln pa_{it} + \sum \beta_i X_{it} + \varepsilon_{it} \quad (4)$$

$$M_{it} = \alpha_i + \beta_1 \ln pa_{it} + \sum \beta_i X_{it} + \varepsilon_{it} \quad (5)$$

$$\ln ec_{it} = \alpha_i + \beta_1 \ln pa_{it} + \beta_2 M_{it} + \sum \beta_i X_{it} + \varepsilon_{it} \quad (6)$$

where *M* refers to intermediary variable. Other variables are the same as Eq. (2).

We also consider some other factors that may influence the relationship between population aging and energy consumption. Jarzebski et al. (2021) pointed out that the world

populations have grown older leading to simultaneously shrinking and ageing populations, which may have different impacts on energy demand and supply across regions and sectors. Ribeiro et al. (2019) analyzed the US data and found that the larger the city, the greater the impact of population or density changes on emissions. Shen et al. (2022) showed that the acceleration of population aging reduced exports and promoted industrial structure upgrading in China. Liang et al. (2023) demonstrated that industrial structure optimization had a significant negative effect on carbon emissions. Institute of Medicine (US) Committee on the Long-Run Macroeconomic Effects of the Aging U.S. Population (2012) suggested that the distribution of population age structure would affect technological progress, which in turn would affect energy consumption and emissions. Gao et al. (2022) confirmed that green technological innovation had a significant inhibitory effect on carbon emissions.

We use the factor decomposition method to decompose the impact on population aging into three important mediating variable effects: scale effect, structural effect, and technology effect as follows:

Scale effect: The measure of the scale effect in this article is examined as population size change.

Structural effect: Given our focus on the impact of population aging on energy consumption, we represent structural effect from a labor perspective using the share of tertiary employees, whereas past literature has typically used industrial structure adjustment.

Technological effect: The measure of technological effect is examined by R&D expenditure level.

Variables and data sources

Dependent variable

Energy consumption is the dependent variable. The *China Provincial Statistical Yearbook* (NBS 2020) provides statistics on energy consumption by province from 1997 to 2020.

Independent variable

Population aging is the independent variable, defined by the rate of people over 65 in the overall population (%). The data on total population and population over 65 years old by province from 1997 to 2020 are obtained from the *China Provincial Statistical Yearbook* (NBS 2020).

Threshold variables

The threshold variables are population, industrial structure, and technological progress, whose impact on energy

consumption have revealed in previous studies. Therefore, population refers to the total population, industrial structure indicates the share of the tertiary employee, technological progress refers to the R&D expenditure.

Control variables

We use economic growth (*gdp*), capital stock (*cs*), industrial structure (*is*), financial development (*fd*), population (*pop*), energy intensity (*ei*) and technological progress (*rd*) as control variables here as they have indicated important impacts on energy consumption. First, in the previous studies on the economic level, Zang et al. (2018) found that both the emissions per unit of GDP and the per-capita energy consumption showed sign of convergence, during the monitoring period. York (2007) revealed that energy consumption increases due to economic growth. Nawaz et al. (2020) found that initially, the improvement of GDP growth increases energy consumption, while after the turning point, GDP has a negative sign with energy consumption. Hanif (2018), Sarwar and Hanif (2018) also found that energy consumption increases and then decreases after reaching a turning point, as the GDP per capita grows. Liu and Hao (2018) found that in China, there is a causal relationship between GDP per capita and renewable energy, with short-term causality running from the former to the latter, and long-term causality in the opposite direction. Thus, to represent the degree of economic growth, we utilize GDP per capita as a control variable. As to the capital stock, Ozcan and Temiz (2022) found human capital stock can increase energy consumption in Türkiye. Here, we consider physical capital stock as a control variable. For industrial structure, Zhao et al., (2022) and Zhang et al. (2020) found that industrial structure upgrading and energy consumption have a significant negative correlation, and energy consumption is positively affected by industrial structure optimization. Since our research focuses on investigating how the aging population influences energy consumption, we select the labor input as a control variable in the industrial structure degree which is expressed as the proportion of labor input in the tertiary industry. Moreover, Sun and Chen (2022) showed a strong correlation between financial development and the reduction of energy consumption. Incorporating the impact of population growth, our model utilizes the ratio of total credit to provincial GDP as a proxy for financial development, and controls for population size as a variable. This approach is consistent with previous studies that have also considered the effect of population on energy consumption (Wang et al. 2017). York (2007) found that under the same other conditions, for every 1% increase in population size, energy consumption is projected to increase by over 2%. Moreover, Liu et al. (2019) show that the energy intensity reduction decreases energy consumption. Finally, R&D expenditure, reflecting technological progress, embodies the

influence of technology inputs on energy consumption. Jin and Zhang (2014) found that when the economy embarks on R&D for innovation, fossil energy use will decline along the innovation-led growth path. Gelenbe and Caseau (2015) found that information and communication technologies assist us save much energy. The data of economic growth, capital stock, industrial structure, financial development, population, energy intensity, R&D expenditure are mainly from *China Statistical Yearbook* and *Provincial Statistical Yearbook*, and capital stock are calculated by perpetual inventory method. The specific meaning of control variables is shown in the Table 1 and their descriptive statistic are be shown in Table S1.

Results

Initial diagnostics

We conduct the analysis with initial model diagnostics. First, we develop the cross-sectional independence test and Table S2 below displays it. The result shows that, at 1% statistical level, all variables reject the null hypothesis of cross-sectional independence. Therefore, we need to consider the cross-sectional independence when developing the unit root tests with the CIPS and CADF tests. Table S3 shows the outcomes of CIPS and CADF tests that confirm the absence of unit roots after first-order difference, thus all variables become stationary after first-order difference. This means that we need to consider the application of cointegration test, which is reported in Table S4 with the Kao test. The cointegration test indicates the cointegration of variables, which indicates that all variables have a long run relationship.

Results of pooled mean group estimation

We first adopt the fixed effects model in Table 2 to study how population aging impacts energy consumption, and the result shows that population aging affects energy consumption negatively with the time and region fixed effects. The results with the PMG estimator are also presented in the Table 2, which illustrates the influence of population

Table 2 PMG estimation result

Variables	FE	PMG	
		Short-run coeff	Long-run coeff
<i>lnage</i>	-0.017** (0.007)	-0.004 (0.003)	-0.348*** (0.105)
<i>lngdp</i>	1.016*** (0.016)	1.011*** (0.011)	0.982*** (0.132)
<i>lnis</i>	-0.023*** (0.008)	-0.005 (0.008)	-0.031 (0.049)
<i>lncs</i>	-0.039*** (0.006)	0.017* (0.010)	0.178*** (0.032)
<i>lnfd</i>	-0.039*** (0.013)	-0.004 (0.005)	0.041 (0.078)
<i>lnpop</i>	0.834*** (0.023)	0.762*** (0.135)	0.778*** (0.244)
<i>lnei</i>	0.977*** (0.008)	1.018*** (0.008)	0.816*** (0.047)
<i>lnrd</i>	0.056*** (0.005)	0.002 (0.003)	0.106*** (0.032)
Constants	-6.008*** (0.420)		
Ect			-0.002*** (0.045)

*** indicates significant at 1%, ** indicates significant at 5%, * indicates significant at 10%. Ect refers to error-correction term; standard errors are in parentheses

aging on energy consumption over a long- or short- term. At the 1% statistical level, the error correction term (Ect) is of statistical significance, meaning that in a long-run the adjustment speed can be corrected to reach balance level. The second column of Table 2 shows that a 1% population aging increase triggers to a reduction of 0.004% in energy consumption, however this impact is insignificant. Long-run relationships between population aging and energy consumption show a markedly negative trend, according to the third column of Table 2, which demonstrates that a 1% population aging increase gives rise to a 0.348% decrease in energy consumption. This means that although in the short run, the population aging could not obviously affect energy

Table 1 The definition of control variables

Name	Definition
<i>Gross domestic product per capita (gdp)</i>	GDP per capita (value in the constant price of 2010)
<i>Capital stock (cs)</i>	Capital stock (value in the constant price of 2010)
<i>Labor input (is)</i>	The proportion of labor input in the tertiary industry (%)
<i>Financial development (fd)</i>	The ratio of total credit to provincial GDP (%)
<i>Population (pop)</i>	Total population (value)
<i>Energy intensity (ei)</i>	Energy intensity (value in the constant price of 2010)
<i>Technological progress (rd)</i>	R&D expenditure (value in the constant price of 2010)

consumption, from a long-term viewpoint, low energy consumption is dependent on rising population aging.

Besides, the outcome shows the role of other control variables on energy consumption. We discover economic development and energy consumption are positively related with the time- and region- fixed effects. The PMG estimator results demonstrate that the economic development significantly and positively affect energy consumption in both long- and short- run at the 1% statistical level. We also find that the proportion of labor input in the tertiary industry and energy consumption are negatively related with the time- and region-fixed effects. However, according to the PMG estimator, the influence of industrial structure on the energy consumption in long-term and short-term is insignificant. We find a negative sign among capital stock and energy consumption with the time and region fixed effects, but the result shows that whether long- or short-term, capital stock has a considerable beneficial impact on energy consumption at the 10% statistical level with the PMG estimator. Financial development and energy consumption have negative correlation with the time and region fixed effects. However, the PMG estimator reveals that neither a long-term nor a short-term evident influence on energy consumption might be expected from the financial development. Moreover, population and energy intensity have positive relationships with energy consumption with the time and region fixed effects respectively, and we find that population has positive long-term and short-term impacts on energy consumption. The outcomes additionally show a positive relation between technological progress and energy consumption, with fixed effects for time and region, while technological progress represents the considerable and positive affect on the energy consumption over a long term but negligible influence on energy consumption over a short term.

Endogeneity test and Robustness test

To address the potential endogeneity problem of population aging, we use the 2SLS method with the lagged value of population aging as an instrumental variable. The results are reported in the first column of Table 3. The coefficient of population aging is still negative and significant at the 1% level, indicating that our main finding is robust to the endogeneity test. The coefficient is slightly larger in magnitude than the PMG estimation, suggesting that the OLS estimation may underestimate the negative effect of population aging on energy consumption.

To further check the robustness of our results, we conduct three additional tests using different methods. First, we use the winsorize method to trim the outliers of the variables at the 5% level. The results are shown in the second column of Table 3. The coefficient of population aging is still negative and significant at the 5% level, and slightly larger than

Table 3 Endogeneity test and Robustness test result

Variable	(1)	(2)	(3)	(4)
<i>lnage</i>	-0.049*** (0.014)	-0.053** (0.026)	-0.005 (0.016)	-0.017** (0.007)
<i>lngdp</i>	1.025*** (0.009)	0.962*** (0.036)	0.994*** (0.035)	1.016*** (0.016)
<i>lnis</i>	-0.029*** (0.010)	-0.042*** (0.018)	-0.017 (0.011)	-0.023*** (0.076)
<i>lncs</i>	0.017*** (0.004)	-0.005 (0.013)	-0.003 (0.009)	-0.039*** (0.006)
<i>lnfd</i>	-0.009 (0.009)	-0.024 (0.029)	-0.103*** (0.020)	-0.039*** (0.013)
<i>lnpop</i>	0.985*** (0.007)	0.738*** (0.056)	0.877*** (0.080)	-0.182*** (0.019)
<i>lnei</i>	0.974*** (0.005)	0.924*** (0.017)	1.009*** (0.011)	0.977*** (0.008)
<i>lnrd</i>	-0.001 (0.004)	0.053*** (0.012)	0.070*** (0.008)	0.056*** (0.005)
Constants	-8.854*** (0.122)	-4.496*** (1.008)	-7.131*** (1.382)	-6.008*** (0.420)

the PMG estimation. This implies that our main result is not driven by extreme observations. Second, we restrict the time window to 2010–2020, which covers the period when China entered into a deeply aging society. The results are presented in the third column of Table 3. The coefficient of population aging becomes insignificant, indicating that the negative effect of population aging on energy consumption may not be evident in the recent decade. This could be due to the fact that China has implemented various policies to cope with the challenges of aging, such as promoting new energy development, improving energy efficiency, and encouraging technological innovation. Third, we use GDP total instead of GDP per capita as a control variable to capture the economic scale effect. The results are reported in the fourth column of Table 3. The coefficient of population aging is still negative and significant at the 5% level, and slightly smaller than the PMG estimation. This suggests that our main result is not sensitive to the choice of economic variable.

Mechanism test

Here we examine the scale effect, structural effect, and technological effect as three views about the mediating effect of population aging on energy consumption. See Table 4 and Fig. 1. First, columns (1), (2) in Table 4 list the result of scale effect. We find that population aging with regression coefficients of -0.097 and -0.095, are negative and significant at the 1% statistical level. Since the overall population decline brought on by population aging, this translates to a negative effect on total energy consumption. Generally, with population aging,

Table 4 Mechanism test results

	<i>lnec</i>	<i>lnpop</i>	<i>lnec</i>	<i>lnis</i>	<i>lnec</i>	<i>lnrd</i>
<i>lnage</i>	-0.097*** (0.013)	-0.095*** (0.013)	-0.018** (0.008)	0.011 (0.042)	-0.034*** (0.008)	-0.292*** (0.062)
<i>lngdp</i>	0.677*** (0.023)	-0.407*** (0.023)	1.014*** (0.016)	0.105 (0.089)	1.059*** (0.017)	0.776*** (0.128)
<i>lncs</i>	-0.077*** (0.011)	-0.045*** (0.014)	-0.039*** (0.006)	-0.018 (0.033)	-0.036*** (0.006)	0.063 (0.049)
<i>lnis</i>	-0.014 (0.014)	0.011 (0.014)			-0.015* (0.008)	0.133** (0.063)
<i>lnfd</i>	-0.170*** (0.022)	-0.157*** (0.022)	-0.040*** (0.013)	0.031 (0.071)	-0.018 (0.014)	0.367*** (0.105)
<i>lnpop</i>			0.832*** (0.024)	0.102 (0.133)	0.871*** (0.026)	0.668*** (0.195)
<i>lnei</i>	0.951*** (0.014)	-0.031** (0.014)	0.975*** (0.008)	0.067 (0.042)	0.992*** (0.008)	0.269*** (0.062)
<i>lnrd</i>	0.082*** (0.009)	0.032*** (0.009)	0.054*** (0.005)	0.060** (0.029)		

*** indicates significant at 1%, ** indicates significant at 5%, * indicates significant at 10%

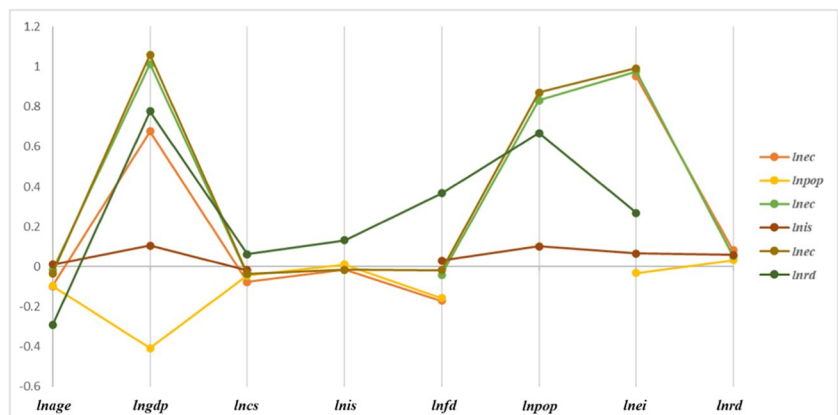
the population mortality rate increases, and the birth rate decreases, thereby decreasing the population size. The total amount of energy consumption of declines as the population grows smaller. Therefore, the scale effect mediates the negative correlation between population aging and energy consumption. As to structural effect, columns (3), (4) in Table 4 prove that population aging has a considerably negative correlation with energy consumption at the 5% statistical level, whereas it has a significantly positive correlation with industrial structure. This demonstrates that population aging is significantly beneficial to decrease of energy consumption but promotes the upgrading of industrial structure inapparently. Thus, invalidation of structure effect is embodied. The columns (5) and (6) are used to test the technological effect. We find that at the 1% statistical level, the regression coefficient of population aging on technological progress is significantly negative. This is because that

older people are less dynamic in the innovation process and has insufficient capacity of receiving new knowledge, which is not beneficial for technological innovation. Moreover, the technological progress and energy consumption are highly positively correlated. Thus, our result proves that population aging decreases energy consumption mainly by affecting technological progress. In conclusion, the effect of population aging on energy consumption embodies a prominent mediating effect, with valid scale effect and technological effect, even if the structural effect is insignificant.

Nonlinear effect analysis

Here the panel threshold regression model with three threshold variables, population, industrial structure, and technological progress are utilized to examine the nonlinear link between population aging and energy

Fig. 1 Mechanism test results



consumption. In order to access the significance of each threshold value, the LR statistic is firstly developed. The statistical significance of the second threshold values for population size is higher than 0.05 and the first threshold values for technological advancement have statistical significance that is greater than 0.01. However, the first, second and third thresholds for industrial structure are all not statistically significant. These indicate a relationship between two threshold variables that population size and technological progress, and nonlinear effect of population aging on energy consumption (see Table S5). The population aging coefficient below the first threshold has obvious negative impact on the energy consumption, presented in Table 5. Population aging has a negative effect on energy consumption when the population size value reaches the first threshold. However, with the continuous increase of population, the negative effect of population aging on the energy consumption declines again when the value of population size above the second threshold. This indicates that the population size has the greatest impact on energy usage when it is over the first threshold number but below the second threshold. Moreover, the population aging negatively affects the energy consumption with low technological progress level. When the technological progress level exceeds the first threshold, the energy consumption is insignificantly impacted by population aging.

This means that the impact of population on energy consumption begins to disappear when technological progress level reaches a threshold level.

In summary, we can conclude via the panel threshold that the decrease impact of population aging on energy consumption are nonlinear. The impact of population aging on the energy consumption has a U-shape relationships with the population. Technological progress also affected the nonlinear effect of population aging on the energy consumption. As technological improvement, the impact of population aging on energy consumption becomes insignificant.

Discussion

Role of technological progress

In the panel threshold model and mechanism test, R&D expenditure is regarded as the representative data to describe the level of technological progress from the perspective of technological input. However, several other presentative data collected are also representative, including the number of green patents granted and the amount of R&D personnel. In this section, these technological variables are discussed to deepen the technological effect on the association among population aging and energy consumption. Table 5 shows

Table 5 Panel threshold regression results

Variables	Coefficients	Variables	Coefficients
<i>lngdp</i>	0.759*** (0.023)	<i>lngdp</i>	1.075*** (0.013)
<i>lncs</i>	0.028*** (0.007)	<i>lncs</i>	-0.004 (0.004)
<i>lnis</i>	0.035*** (0.013)	<i>lnis</i>	-0.017** (0.008)
<i>lnfd</i>	-0.067*** (0.019)	<i>lnfd</i>	0.020** (0.010)
<i>lnei</i>	0.992*** (0.011)	<i>lnpop</i>	0.899*** (0.019)
<i>lnrd</i>	0.105*** (0.009)	<i>lnei</i>	0.991*** (0.006)
<i>lnage (lnpop < 15.778)</i>	-0.120*** (0.023)	<i>lnage(lnrd < 5.229)</i>	-0.021*** (0.006)
<i>lnage (15.778 < lnpop < 16.494)</i>	-0.161*** (0.013)	<i>lnage (lnrd > 5.229)</i>	-0.001 (0.007)
<i>lnage (16.494 < lnpop < 16.778)</i>	-0.120*** (0.012)		
<i>lnage (c > 16.778)</i>	-0.046*** (0.011)		
Constant	7.573*** (0.056)	Constant	-7.311*** (0.318)

*** indicates significant at 1%, ** indicates significant at 5%, * indicates significant at 10%

the threshold effect test result. According to the result of number of green patents granted and R&D personnel, both test statistics for the single are significant at 1%, which result means that the impact of population aging on energy consumption is significantly influenced by the number of green patents granted and R&D personnel at a single threshold. This is consistent with the R&D expenditure threshold effect test result, confirming the nonlinear impact of population aging on energy consumption.

Furthermore, Table S6 and Table 6 list the estimated results of the threshold effect model. When the number of green patents granted under 8.418, the regression coefficient of population aging is -0.026 and significant at the 1% level. The result reveals that there is unquestionably a substantial impact of the number of green patents granted on the execution effect of population aging. However, when the number of green patents granted over 8.418, the regression coefficient of population aging drops to -0.014, but it is still significant at the level of 1%, which implies that as the number of green patents granted increases, the impact of number of green patents granted on the execution effect of population aging decreases. As for R&D personnel, the population aging regression coefficient is -0.023 and is significant at the 1% level, when the value of R&D personnel is under 2.932. This indicates the certainly significant relationships between R&D personnel and the enforcement of population aging. Nevertheless, with the rise of R&D personnel that exceeds 2.932, the regression coefficient of population aging is nearly 0. Based on these result, R&D personnel obviously affects the impact of population aging when its

level is relatively low. However, the influence turns indistinct with the increase of R&D personnel.

At last, in order to further study technological effect, Table 7 shows mechanism test results. In the first and second columns in Table 7, technological effect is examined by number of green patents granted. The regression coefficient of population aging on energy consumption is negative and significant at the level of 1%, whereas the regression coefficient of patents granted on the number of green patents granted is negative and not significant. The result means that population aging is significantly beneficial to decrease

Table 7 Mechanism test results

	<i>lnec</i>	<i>lnrd1</i>	<i>lnec</i>	<i>lnrd2</i>
<i>lnage</i>	-0.034*** (0.008)	-0.161 (0.112)	-0.034*** (0.008)	-0.365*** (0.000)
<i>lngdp</i>	1.059*** (0.017)	1.675*** (0.232)	1.059*** (0.017)	0.457*** (0.163)
<i>lncs</i>	-0.036*** (0.006)	0.324*** (0.090)	-0.036*** (0.006)	0.106** (0.063)
<i>lnis</i>	-0.015* (0.008)	0.134 (0.115)	-0.015* (0.008)	0.278*** (0.081)
<i>lnfd</i>	-0.018 (0.014)	0.890*** (0.190)	-0.018 (0.014)	0.094 (0.134)
<i>lnpop</i>	0.871*** (0.026)	1.489*** (0.000)	0.871*** (0.026)	0.962*** (0.249)
<i>lnei</i>	0.992*** (0.008)	0.266** (0.113)	0.992*** (0.008)	0.194** (0.079)

Table 6 Panel threshold regression results

Variables	Threshold (Number of green patents granted)	Variables	Coefficient (R&D personnel)
<i>lngdp</i>	1.084*** (0.013)	<i>lngdp</i>	1.076*** (0.013)
<i>lncs</i>	-0.010** (0.004)	<i>lncs</i>	-0.005 (0.004)
<i>lnis</i>	-0.015* (0.008)	<i>lnis</i>	-0.016** (0.008)
<i>lnfd</i>	0.026** (0.011)	<i>lnfd</i>	0.024** (0.010)
<i>lnpop</i>	0.930*** (0.019)	<i>lnpop</i>	0.908*** (0.019)
<i>lnei</i>	1.001*** (0.006)	<i>lnei</i>	0.993*** (0.006)
<i>lnage(c < 8.418)</i>	-0.026*** (0.007)	<i>lnage (c < 2.932)</i>	-0.023*** (0.006)
<i>lnage (c > 8.418)</i>	-0.014** (0.007)	<i>lnage (c > 2.932)</i>	-0.004 (0.007)

*** indicates significant at 1%, ** indicates significant at 5%, * indicates significant at 10%

of energy consumption but inapparently decline number of green patents granted. Besides, technological effect is assessed by R&D personnel in the fifth and sixth columns of Table 7. The regression coefficients of population aging are both negative and significant at the level of 1%, whose values are -0.034 and -0.365 respectively. The result proves that population aging decreases energy consumption and it also triggers the drop of R&D personal. Thus, the technological effect is negative and established. The reason in the previous section clearly explains this result: population aging has reduced the capacity for technological progress, hence slowing down the investment in green innovation and leading to the decrease in R&D personnel. In summary, the technological effect is clearly valid regardless of which representative variable is chosen.

A comparison with other studies

One of the main contributions of our study is that we examine the long-term impact of population aging on energy consumption in China using the PMG estimation and explore the underlying mechanisms based on mediating effects and threshold effects models. Previous studies on this topic have either ignored these aspects or used different methods and data sources that have yielded inconsistent results. For example, Han et al. (PNAS 2022) used age-period-cohort detrended analysis to estimate age and generational effects based on China's urban household survey data from 1992 to 2015. They found that both the elderly and younger generations tended to be energy-intensive consumers, resulting in higher energy consumption in this aging society. However, they did not consider the mediating effects of scale, structural, and technological factors or the nonlinear effects of population size and technological progress on the relationship between population aging and energy consumption. (Li et al. 2018) used panel data from 30 provinces in China from 1999 to 2014 and applied a panel threshold regression model to investigate the nonlinear relationship between population aging and household energy consumption. They found an inverted U-shaped curve between population aging and household energy consumption, which was influenced by income level and urbanization rate. However, they did not examine the long-term impact of population aging on energy consumption or the mediating mechanisms behind it.

Also, our findings are consistent with some previous studies (e.g., O'Neill et al. 2012; Guo et al. 2016; Wei et al. 2018; Hu et al. 2020; Yu et al. 2022) that suggest a negative correlation between population aging and energy consumption, like Yu et al. (2022) who indicated that elderly households have relatively lower indirect CO₂ emissions, but differ from others (e.g., Menz and Welsch 2012; Huang et al. 2019; Yang et al. 2015; Li et al. 2018; Balsalobre-Lorente et al. 2021) that suggest a positive, nonmonotonic,

or insignificant correlation. Han et al. (2022) suggest that the elderly generations consume more energy, using age-period-cohort. This discovery focuses on the perspective of household consumption, without considering the impact of aging on energy consumption through other means. Our study also provides more insights into the mechanisms and nonlinearities behind the relationship between population aging and energy consumption in China.

Policy implications

Our finding led to the following policy recommendation from three angles. Firstly, the policy recommendations for upgrading of energy industry. On the basis of PMG estimation results, as China's population aging increases, there will be vacancies in future energy consumption demand. Given the domestic carbon neutral policies, the market share of traditional energy will decrease. Therefore, Chinese government are suggested to strive to promote the development of energy industry from rapid expansion to high-quality development. In the past the energy industry only focused on energy supply, while the energy industry in the context of aging should lay emphasis on energy distribution, cost reduction and efficiency improvement. For energy distribution, a more complete energy supply system can be established in areas such as residential and elderly care products, while in some other industries, the expectation of energy consumption reduction should be well prepared to face the challenges of aging more confidently. In terms of cost reduction and efficiency improvement, the energy sector should lower the cost of energy supply. This can be achieved through digitalization to reduce the costs of labor and energy waste, as well as through the transformation from traditional energy to new energy to decline carbon emissions and thus reduce economic externalities cost.

Secondly, the policy recommendations for encouraging green technological progress in energy conservation and emission reduction. According to PMG estimation results, energy consumption should be driven by technological progress. However, technological progress is the cornerstone of social development, and it is unreasonable and unrealistic to slow down technological progress to reduce energy consumption. Therefore, we suggest that the Chinese government should launch more aggressive green technology incentive policies. Especially in an aging society, according to the mechanism test results, aging reduces the ability of technological progress. Thus, to support the steady advancement of green technology and realize the goal of reducing energy consumption, government intervention is needed.

Thirdly, the policy recommendations for energy-saving potential. In light of the PMG estimation results, the aging population will reduce China's energy consumption demand.

Therefore, when formulating local energy-saving targets, the current and expected proportions of aging population in the local area are expected to be referred by government to better estimate the local energy-saving potential and increase the intensity of energy conservation efforts.

Limitation and future guidelines

Our study also has some limitations and directions for future research. First, we only focused on the aggregate level of energy consumption, without distinguishing different types of energy sources or sectors. Future studies could explore how population aging affects the structure and quality of energy consumption in China. Moreover, we only considered three mediating mechanisms (scale, structural, and technological effects) and three threshold variables (population size, industrial structure, and technological progress) in our analysis. Future studies could incorporate other factors that may influence the relationship between population aging and energy consumption, such as consumption patterns, environmental awareness, institutional arrangements, or cultural values. Finally, our analysis only focuses on China, which may limit the generalizability of our findings to other countries or regions. Future studies could conduct comparative or cross-country analyses to explore how population aging affects energy consumption in different contexts.

Conclusions

We examined how population aging affects China's energy consumption and explored the underlying mechanisms and nonlinear effects of this relationship. Using panel data from 1997 to 2020, we applied pooled mean group estimation, panel threshold regression, and mediating effect analysis to test our hypotheses. We found that population aging has a negative impact on energy consumption in China in the long run, mainly through scale and technological effects. We also found that population size and technological progress moderate the nonlinear effect of population aging on energy consumption, with a U-shaped relationship between population size and energy consumption, and a diminishing effect of population aging as technological progress increases.

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Author's contributions All authors contributed to the study conception and design. Specific contributions for each author are below.

Yuehan Yu: Conceptualization, Data curation, Formal analysis, Methodology, Software, Investigation, Writing-original draft.

Hao Feng: Conceptualization, Methodology, Writing-review, Editing, Supervision.

Rong Yuan: Data curation, Formal analysis, Methodology.

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Data availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request. All data generated or analyzed during this study are included in this published article.

Declarations

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Consent to publish Not applicable.

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References

- Balsalobre-Lorente D, Sinha A, Driha OM et al (2021) Assessing the impacts of ageing and natural resource extraction on carbon emissions: A proposed policy framework for European economies. *J Clean Prod* 296:126470
- Breusch TS, Pagan AR (1980) The lagrange multiplier test and its applications to model specification in econometrics. *Rev Econ Stud* 47(1):239. <https://doi.org/10.2307/2297111>
- Dalton M, O'Neill B, Prskawetz A et al (2008) Population aging and future carbon emissions in the United States. *Energy Econ* 30:642–675
- Danish, Zhang JW, Hassan ST et al (2019) Toward achieving environmental sustainability target in Organization for Economic Cooperation and Development countries: The role of real income, research and development, and transport infrastructure. *Sustain Dev* 28(1):83–90
- Danish, Hassan ST (2022) Investigating the interaction effect of urbanization and natural resources on environmental sustainability in Pakistan. *International J Environ Sci Technol* 1–8. <https://doi.org/10.1007/s13762-022-04497-x>
- Fan J, Zhou L, Zhang Y et al (2021) How does population aging affect household carbon emissions? Evidence from Chinese urban and rural areas. *Energy Econ* 100:105356
- Gao P, Wang Y, Zou Y, Su X, Che X, Yang X (2022) Green technology innovation and carbon emissions nexus in China: Does industrial structure upgrading matter? *Front Psychol* 13:951172
- Gelenbe E, Caseau Y (2015) The impact of information technology on energy consumption and carbon emissions[J]. *Ubiquity* 2015(June):1–15. <https://doi.org/10.1145/2755977>
- Guo W, Sun T, Dai H (2016) Effect of Population Structure Change on Carbon Emission in China. *Sustainability* 8(3):225

- Guo L, Song Y, Zhao S et al (2022) Dynamic Linkage between Aging, Mechanizations and Carbon Emissions from Agricultural Production. *Int J Environ Res Public Health* 19(10):6191
- Han X, Wei C, Cao GY (2022) Aging, generational shifts, and energy consumption in urban China. *Proc Natl Acad Sci* 119(37):e2210853119. <https://doi.org/10.1073/pnas.2210853119>
- Hanif I (2018) Economics-energy-environment nexus in Latin America and the Caribbean. *Energy* 141:170–178
- Hu J, Wang M, Cheng Z, Yang ZS (2020) Impact of marginal and intergenerational effects on carbon emissions from household energy consumption in China. *J Clean Prod*:273123022. <https://doi.org/10.1016/j.jclepro.2020.123022>
- Huang Y, Shigetomi Y, Chapman A et al (2019) Uncovering Household Carbon Footprint Drivers in an Aging, Shrinking Society. *Energies* 12(19):3745
- Institute of Medicine (US) Committee on the Long-Run Macroeconomic Effects of the Aging U.S. Population (2012) *Aging and the Macroeconomy: Long-Term Implications of an Older Population*. Washington (DC): National Academies Press (US); 2012 Dec 10. 6, Aging, Productivity, and Innovation
- Jarzebski MP, Elmqvist T, Gasparatos A et al (2021) Ageing and population shrinking: implications for sustainability in the urban century. *Npj Urban Sustain* 1:17
- Jin W, Zhang ZX (2014) Quo vadis? Energy consumption and technological innovation[J]. Crawford School of Public Policy, The Australian National University, CCEP Working Paper 1412. <https://doi.org/10.2139/ssrn.2731398>
- Kao C (2000) Spurious regression and residual-based tests for cointegration in panel data. *J Econ* 90(1):1–44
- Kim J, Lim H, Jo H-H (2020) Do Aging and Low Fertility Reduce Carbon Emissions in Korea? Evidence from IPAT Augmented EKC Analysis. *Int J Environ Res Public Health* 17(8):2972
- Li W, Qi X, Zhao X (2018) Impact of population aging on carbon emission in China: A panel data analysis. *Sustainability* 10(7):2458. <https://doi.org/10.3390/su10072458>
- Liang L, Huang C, Hu Z (2023) Industrial structure optimization, population agglomeration, and carbon emissions—Empirical evidence from 30 provinces in China. *Front Environ Sci* 10:1078319
- Liddle B (2013) Impact of population, age structure, and urbanization on carbon emissions/energy consumption: evidence from macro-level, cross-country analyses[J]. *Popul Environ* 35:1–2
- Liu Y, Hao Y (2018) The dynamic links between CO2 emissions, energy consumption and economic development in the countries along “the Belt and Road.” *Sci Total Environ* 645:674–683
- Liu H, Wang C, Tian M et al (2019) Analysis of regional difference decomposition of changes in energy consumption in China during 1995–2015. *Energy* 171:1139–1149
- Menz T, Welsch H (2012) Population aging and carbon emissions in OECD countries: Accounting for life-cycle and cohort effects. *Energy Econ* 34:842–849
- Nawaz MA, Hussain MS, Kamran HW et al (2020) Trilemma association of energy consumption, carbon emission, and economic growth of BRICS and OECD regions: quantile regression estimation. *Environ Sci Pollut Res* 28:16014–16028
- NBS (2020) China provincial statistical. Yearbook China Statistics Press
- O’Neill BC, Liddle B, Jiang L et al (2012) Demographic change and carbon dioxide emissions. *Lancet* 380:157–164
- Ozcan B, Temiz M (2022) An empirical investigation between renewable energy consumption, globalization and human capital: A dynamic auto-regressive distributive lag simulation[J]. *Renew Energy* 193:195–203
- Pedroni P (1999) Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors. *Oxford Bull Econ Stat* 61:653–670
- Pesaran MH (2004) General diagnostic tests for cross section dependence in panels. *Cambridge Working Papers in Economics* 69(7):1240
- Pesaran MH, Shin Y, Smith RP (1999) Pooled mean group estimation of dynamic heterogeneous panels. *J Am Stat Assoc* 94(446):621–634
- Ribeiro HV, Rybski D, Kropp JP (2019) Effects of changing population or density on urban carbon dioxide emissions. *Nat Commun* 10:3204
- Sarwar A, Hanif U (2018) Pakistan’s electricity demand analysis 1975–2016. *Empir Econ Rev* 1
- Shen X, Liang J, Cao J, Wang Z (2022) How Population Aging Affects Industrial Structure Upgrading: Evidence from China. *Int J Environ Res Public Health* 19:16093
- Sun H, Chen F (2022) The impact of green finance on China’s regional energy consumption structure based on system GMM. *Resour Policy* 76:102588
- Tang HY, Zhang JQ, Fan F, Wang ZW (2022) High-speed rail, urban form, and regional innovation: a time-varying difference-in-differences approach. *Technol Anal Strateg Manag*:1–15
- Tarazkar MH, Dehbidi NK, Ozturk I et al (2020) The impact of age structure on carbon emission in the Middle East: the panel autoregressive distributed lag approach. *Environ Sci Pollut Res* 28:33722–33734
- Wang Q, Wang L (2021) The nonlinear effects of population aging, industrial structure, and urbanization on carbon emissions: A panel threshold regression analysis of 137 countries. *J Clean Prod* 287:125381
- Wang Y, Kang Y, Wang J et al (2017) Panel estimation for the impacts of population-related factors on CO2 emissions: A regional analysis in China. *Ecol Ind* 78:322–330
- Wei L, Liu Z (2022) Spatial heterogeneity of demographic structure effects on urban carbon emissions. *Environ Impact Assess Rev* 95:106790
- Wei T, Zhu Q, Glomsrød S (2018) Ageing Impact on the Economy and Emissions in China: A Global Computable General Equilibrium Analysis. *Energies* 11:1–2
- 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
- Yang Y, Zhao T, Wang Y et al (2015) Research on impacts of population-related factors on carbon emissions in Beijing from 1984 to 2012. *Environ Impact Assess Rev* 55:45–53
- York R (2007) Demographic trends and energy consumption in European Union Nations, 1960–2025. *Soc Sci Res* 36:855–872
- Yu M, Bo M, Rong Li (2022) Analysis of China’s urban household indirect carbon emissions drivers under the background of population aging[J]. *Struct Chang Econ Dyn* 60:114–125
- Zang Z, Zou X, Song Q et al (2018) Analysis of the global carbon dioxide emissions from 2003 to 2015: convergence trends and regional contributions. *Carbon Manag* 9(1):45–55
- 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
- Zhang F, Deng X, Phillips F et al (2020) Impacts of industrial structure and technical progress on carbon emission intensity: Evidence from 281 cities in China. *Technol Forecast Soc Chang* 154:119949

- Zhang J, Tang H, Bao M (2023) Can environmental protection policies promote regional innovation efficiency: a difference-in-differences approach with continuous treatment. *Environ Sci Pollut Res* 30(1):1357–1373
- Zhao J, Jiang Q, Dong X et al (2022) How does industrial structure adjustment reduce CO2 emissions? Spatial and mediation effects analysis for China. *Energy Econ* 105:105704
- Zheng H, Long Y, Wood R et al (2022) Author Correction: Ageing society in developed countries challenges carbon mitigation. *Nat Clim Chang* 12:593–593

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