

The Impact of Population Aging on China's Carbon Emissions: The Moderating Effect of Green Technology Innovation

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Abstract

China's carbon peaking and carbon neutrality goals are facing the uncertain challenge of population aging. Based on panel data from 30 Chinese provinces from 2015 to 2023, this paper empirically examines the influence of population aging on carbon emissions using a fixed effect model. The following important conclusions are obtained through empirical analysis. First, population aging significantly reduces carbon emissions. Second, green technology innovation plays a significant moderating role, effectively amplifying the carbon-reduction dividend from population aging. Third, the low-carbon effect of population aging exhibits clear heterogeneity. The emission-reduction effect is more pronounced in economically undeveloped regions. Moreover, population aging can curb carbon emissions in low-aging regions, while the increased energy consumption demand of the elderly offsets this effect in deeply aging regions, leading to an insignificant overall impact. Accordingly, this study provides empirical evidence and differentiated policy references for promoting coordinated development of population aging and low-carbon transformation in China.

Keywords: population aging, carbon emissions, green technology innovation, moderating effect, regional heterogeneity

1. Introduction

In the 21st century, global warming has emerged as the foremost international environmental challenge facing humanity (Pan et al., 2021). In response, reducing carbon emissions has

become a central objective of global environmental governance. In December 2015, the 21st Conference of the Parties adopted the Paris Agreement, which aims to limit the rise in global average temperature to well below 2°C above pre-industrial levels, while pursuing efforts to cap the increase at 1.5°C (UNFCCC, 2015). Building on this momentum, as of October 2025, around 145 countries had announced net-zero targets (CAT, 2025). China, as the largest carbon emitter in the world, has set the “dual-carbon goals”: peaking carbon emissions by 2030 and achieving carbon neutrality by 2060 (Shi et al., 2021). This strategy signals a fundamental shift in China’s development paradigm and underscores the urgent need for low-carbon transformation. Although existing policy interventions have largely targeted supply-side sectors such as heavy industry (Zhang et al., 2023), it is also important to recognize that carbon emission trajectories are significantly shaped by demand-side factors, particularly the aging population. According to UN standards, since 2000 China has officially entered an aging society. The seventh census of China in 2021 shows that there are 260 million people aged 60 and above, with a proportion of 18.70%, of which 190 million people are aged 65 and above, with a proportion of 13.50%. Deep aging has become an irreversible force in China’s economic landscape, directly influencing consumption patterns while indirectly exerting pressure on corporate behavior and social development (Li et al., 2024).

Population aging profoundly reshapes both labor supply and consumption patterns, thereby altering the source structure of carbon emissions (Dalton et al., 2008). On the one hand, the ongoing deepening of aging has led to a shrinking labor force and rising labor costs. This trend compels the economic structure to shift from labor-intensive industries toward capital- and technology-intensive sectors, thereby indirectly reducing carbon emissions from industrial production. On the other hand, aging populations drive changes in consumption patterns. Increased demand for residential services, medical care, and daily living amenities shifts energy use from industrial applications to residential heating, electricity consumption, and household activities, thereby creating new sources of carbon emissions (Zhang & Tan, 2016). While population aging may lead to higher carbon emissions through shifts in consumption patterns, green technology innovation, as a fundamental engine of sustainable development, is expected to serve a critical buffering function (Mantaeva et al., 2021). Progress in green technology innovation can counteract the adverse environmental consequences of aging by enhancing energy efficiency and streamlining production processes. Given the distinct influences of population aging and green technology innovation on social production and consumption patterns, a substantial body of literature has examined their individual effects on carbon emissions (Xiang et al., 2023; Yuan et al., 2024). Nevertheless, little attention has been paid to the potential moderating role of green technology innovation in the nexus between aging and carbon emissions. This raises two key questions: how does population aging affect carbon emissions in China? And how does China’s green technology innovation moderate this relationship? Investigating the mechanisms by which population aging affects carbon emissions and clarifying the moderating role of green technology innovation carry significant theoretical and practical implications for scientific and government strategies aimed at achieving low-carbon economic development.

2. Literature Review and Theoretical Hypotheses

2.1 *The Impact of Population Aging on China's Carbon Emissions*

The relationship between population aging and carbon emissions has yielded mixed findings in the literature. Some studies suggest that aging may increase emissions due to rising residential energy demand for heating, healthcare, and daily living (Han et al., 2022). Conversely, a growing body of evidence indicates that aging can contribute to emission reductions through structural transformation and consumption contraction (Li et al., 2023; Xu, 2024; Yu et al., 2023).

On the supply side, existing studies have documented that aging reduces the labor supply, thereby raising labor costs. According to induced innovation hypothesis, this compels labor-intensive industries to substitute labor with technology or capital, thereby facilitating the transition toward technology- and knowledge-intensive industrial structures (Shen et al., 2022). As production factors shift from backward to advanced technologies, carbon emissions are inhibited (Li et al., 2025). Additionally, the development of the elderly care industry, a low-energy-consuming tertiary sector, further supports the decoupling of economic growth from carbon emissions (Wang et al., 2021; Xiao et al., 2019).

On the demand side, evidence suggests that aging suppresses aggregate consumption through multiple channels. At the macro level, increased social pension burdens divert national income from productive investment to non-productive expenditures (e.g., pension, care, and medical services), which suppresses per capita consumption and aggregate social consumption, thereby reducing carbon emissions (Bai & Lei, 2020; Guan et al., 2025). At the micro level, imperfections in China's pension and social security systems lead elderly individuals to reduce daily consumption due to future uncertainty (Zhao & Chen, 2024). Meanwhile, their children also curb current consumption to fulfill maintenance obligations (Chen et al., 2024), and bequest motives further lower the elderly's consumption propensity (Lee & Tan, 2023). Although some studies emphasize the emission-increasing effect of aging through heightened residential energy demand (Shi et al., 2023), the prevailing evidence in the Chinese context suggests that emission-reducing pathways dominate. Based on the above analysis, this paper proposes the following hypothesis:

H1: Population aging tends to reduce carbon emissions, serving as a favorable factor for easing emission pressures in China.

2.2 *The Moderating Effect of Green Technology Innovation*

Green technology innovation constitutes environmentally friendly innovation. It can enhance energy efficiency on the consumption side and facilitate factor substitution on the production side, thereby strengthening the inhibitory effect of aging on regional carbon emissions (Lin & Zhang, 2023; Lu et al., 2023).

On the consumption side, green technological innovation reconfigures consumption patterns in an aging society. Although aging-induced demands, such as medical care and central

heating, exert upward pressure on emissions, GTI reduces the carbon intensity of these demands (Du & Wang, 2011). Technological progress lowers unit energy consumption (Cai, 2024), while the diffusion of smart homes, high-efficiency energy-saving appliances, and green building technologies improves household energy efficiency (Zhou et al., 2024). Thus, technological empowerment accommodates new consumption demands while maximizing aging-related emission reductions.

On the production side, GTI reinforces the technology substitution that drives aging-driven production transformation. Labor scarcity incentivizes firms to increase capital and technology investment, and GTI provides critical support for addressing the shrinking labor supply and rising costs (Lisenkova et al., 2013). Moreover, green technologies upgrade energy-intensive facilities and accelerate the reallocation of resource from labor-intensive industries to low-carbon, capital-intensive, and automated industries (Li et al., 2025). These mechanisms strengthen aging’s positive impact on industrial decarbonization. Accordingly, we propose:

H2: Green technological innovation positively moderates the relationship between population aging and carbon emissions, thereby strengthening the inhibitory impact of aging on carbon emissions.

Based on the above theoretical analysis and literature review, this study proposes a conceptual framework to visualize the logical relationships to be tested. As shown in Figure 1, the framework depicts: (1) the direct effect of population aging on carbon emissions; (2) the moderating role of green technology innovation in this relationship. This framework guides the subsequent empirical design and hypothesis testing.

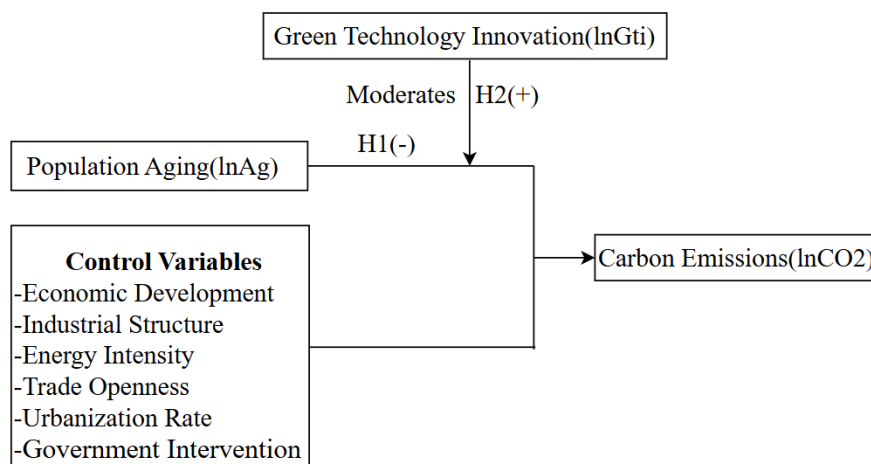


Figure 1. Research Framework

3. Methodology and Variable Selection

3.1 Theoretical Model

This study employs the STIRPAT model and conducts regression analysis using static panel data estimation models to explore the relationship between population aging and carbon

emissions, as well as the moderating effect of GTI. The STIRPAT model is a statistical model for environmental impact assessment developed by Dietz and Rosa (1994). It is rooted in the IPAT identity ($I=P \times A \times T$), introduced by (Ehrlich & Holdren, 1971). While IPAT successfully identifies Population (P), Affluence (A), and Technology (T) as the three pillars driving environmental Impact (I), it functions as a purely mathematical identity. This means it assumes a constant, proportional relationship between variables and does not allow for the inclusion of additional socio-economic factors or the testing of statistical hypotheses.

To address these limitations, Dietz and Rosa (1994) developed the STIRPAT model. The “Stochastic” nature of this model represents a significant theoretical leap. It transforms a rigid identity into a flexible econometric framework capable of estimating the non-proportional and non-linear effects of human drivers on the environment.

The canonical form of the STIRPAT model is expressed as:

$$I = aP^b A^c T^d e$$

Taking natural logarithms for empirical estimation yields:

$$\ln I = \ln(a) + b \ln(P) + c \ln(A) + d \ln(T) + \ln e$$

where I represents environmental impact, P represents population factor, A denotes the wealth effect, T represents the technical level, and a is the model coefficient. Further, b , c , and d are the weight coefficients assigned to each index, and e represents the residual item.

This study extends the model by introducing the old-age dependency ratio to examine the impact of population aging on carbon emissions. The extended STIRPAT model is formulated as follows:

$$\ln CE_{it} = \beta_0 + \beta_1 \ln Ag_{it} + \beta_2 \ln Eco_{it} + \beta_3 \ln Ei_{it} + \beta_4 \ln Str_{it} + \beta_5 \ln Fdi_{it} + \beta_6 \ln Ur_{it} + \beta_7 \ln Gi_{it} + \delta_t + \mu_i + \varepsilon_{it}$$

where the subscripts i and t denote province and year, respectively. CE is represented by carbon emissions; “P” factor is represented by population aging(Ag); “A” factor is denoted by GDP per capital(Eco); “T” factor is denoted by energy intensity(Ei), industrial structure(Str), foreign direct investment level(Fdi), Urbanization rate(Ur) and government intervention(Gi). β_0 denotes constant coefficient; $\beta_i (i=1,2,\dots,7)$ represent the coefficient of variables; μ_i and δ_t denote province and year fixed effects, respectively; and ε_{it} is the idiosyncratic error term.

To test the moderating effect of GTI, the study proposes the extended STIRPAT model with an interaction term:

$$\ln CE_{it} = \beta_0 + \beta_1 \ln Ag_{it} + \beta_2 \ln Gti_{it} + \beta_3 (\ln Ag_{it} \times \ln Gti_{it}) + \beta_4 \ln Eco_{it} + \beta_5 \ln Ei_{it} + \beta_6 \ln Str_{it} + \beta_7 \ln Fdi_{it} + \beta_8 \ln Ur_{it} + \beta_9 \ln Gi_{it} + \delta_t + \mu_i + \varepsilon_{it}$$

where Gti denotes green technology innovation; $\ln Ag_{it} \times \ln Gti_{it}$ denotes the interaction term of population aging and green technology innovation; The meanings of other symbols are the same as those in baseline empirical model.

3.2 Variable Selection

This study uses data from mainland China, covering the period 2015–2023. Tibet is excluded due to severe data missing, inconsistent statistical standards, and substantial heterogeneity in economic structure and population scale, which could generate extreme outliers and biased regression results. Hong Kong, Macau, and Taiwan are also excluded because their statistical standards, accounting systems, and data-collection frequencies differ significantly from those of mainland China, thereby compromising data comparability. With carbon emissions as the dependent variable, population aging as the core independent variable, GTI as a moderating variable, economic development, industrial structure, energy intensity, trade openness, urbanization rate, and government intervention as the control variables, the study explores the relationship between population aging and carbon emissions, as well as the moderating effect of GTI. All the data are from the China Energy Statistical Yearbook, the China Population and Employment Statistics Yearbook, the China National Intellectual Property Administration, and provincial Statistical Yearbooks. All the variables take a log form. The following explains each variable and data.

(1) Carbon emission: This study uses fossil consumption CO_2 emissions to assess regional carbon emissions. CO_2 is the most significant component of greenhouse gas, accounting for approximately 90% of total emissions and contributing roughly 60% to the overall greenhouse effect. Following (Li & Zhou, 2019), the study employs the IPCC Inventory Approach to measure CO_2 emissions based on the consumption of eight primary fossil fuel types: coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas, as disclosed by the China Energy Statistical Yearbook. The calculation formula is:

$$CO_2 = \sum_{i=1}^n E_i \times F_i = \sum_{i=1}^8 E_i \times NCV_i \times CC_i \times COF_i \times 44 / 12$$

where CO_2 represents the estimated total carbon emissions (10^4t), while E_i denotes the consumption level of the i -th energy source; F_i represents the carbon emission factor of i -th energy source; NCV_i denotes the average net calorific value of the i -th energy source; CC_i

represents carbon content per unit calorific value of the i -th energy source; COF_i denotes carbon oxidation factor of the i -th energy source; the term $44/12$ refers to the molecular-to-atomic weight ratio of carbon dioxide to carbon, serving as the conversion coefficient in the measurement process. Additionally, $F_i = NCV_i \times CC_i \times COF_i \times 44/12$. The data on average net calorific values of various energy sources are obtained from the appendix of the China Energy Statistical Yearbook, while the data on carbon content per unit calorific value and carbon oxidation rates are derived from the “Guidelines for the Compilation of Provincial Greenhouse Gas Inventories”.

(2) Population aging: This study selects the old-age dependency ratio, representing the aging degree. It refers to (population aged 65 and above)/(population aged 14-64). The indicator explicitly links the elderly population to the working-age population, making it a more indicative measure of labor market pressures (Yang & Wang, 2020).

(3) Green technology innovation: Considering the fact that a patent often begins to generate performance in production well before the formal grant is issued, and patent applications provide a more intuitive and timely reflection of an organization’s innovative activity and output for a given year (Chen et al., 2022), this study utilizes patent application data as the primary proxy to characterize green technological innovation.

(4) Economic growth level: It reflects the level of affluence. Higher affluence leads to higher consumption, which drives up demand for energy-intensive goods like housing and automobiles, thereby increasing carbon emissions (Zhang & Zhang, 2018). The study selects GDP per capita (10^4 RMB per capita) to represent a region’s economic level. To eliminate the impact of price level changes, GDP is deflated using the price level of each province in 2000 as the base price (Wang et al., 2018).

(5) Industrial structure: Among the three industrial sectors, the secondary industry is the sector with the highest energy consumption (Wang & Yan, 2017). According to the three industry classifications, the secondary industry includes mining, manufacturing, production and supply of electricity, gas, and water, and construction. The development of this sector has a direct impact on regional carbon emissions (Zhu et al., 2021). Therefore, in this study, industrial structure is measured by the share of secondary industry value added in GDP.

(6) Energy intensity: It represents the energy consumption required per unit of GDP ((tce/ 10^4 RMB) (Ma & Ogata, 2024; Zhou et al., 2019), which serves as a comprehensive reflection of technological progress, industrial structure, and energy efficiency. All else equal, higher energy intensity indicates a greater reliance on energy for production, which typically correlates with elevated carbon emissions (Tao et al., 2024). Consequently, the research controls the variable.

(7) Trade openness degree: trade openness can influence carbon emissions via factor agglomeration, industrial change, and innovation dynamics (Wang & Zhang, 2021). In this study, trade openness is proxied by the ratio of foreign direct investment (converted at the

average exchange rate) to regional GDP.

(8) Urbanization rate: Urbanization rate is measured as the ratio of urban population to total population. As a key dimension of social development, urbanization exerts a notable influence on carbon emission intensity (Yao et al., 2023). A higher urbanization rate reflects more advanced urban socioeconomic development. The scale effect of population agglomeration within cities expands the scope of local industrial activities, thereby amplifying the environmental impacts of economic production.

(9) Government intervention: Local governments affect regional carbon emissions by administratively regulating economic development and factor allocation. As policy implementation depends on adequate fiscal support, we measure the level of government intervention by the ratio of local fiscal expenditure to GDP.

4. Empirical Analysis Process

4.1 Descriptive Statistics

Table 1 reports the descriptive statistics of the main variables used in this study. The sample comprises 270 observations. All variables are transformed to natural logarithms to mitigate heteroscedasticity and facilitate the interpretation of elasticities. From Table 1, no extreme outliers are detected. Among the key variables, green technology innovation (lnGti) exhibits the largest regional heterogeneity, while industrial structure (lnStr) shows the least. Carbon emissions (lnCO2) have a moderate regional variation. Most variables display approximately symmetric distributions. However, energy intensity (lnEi) is slightly right-skewed, suggesting that a few regions have notably higher energy intensity.

Table 1. Variable descriptive statistics

Variables	N	Mean	SD	Min	Median	Max
lnCO2	270	10.47	0.762	8.611	10.42	11.99
lnAg	270	-1.764	0.265	-2.341	-1.762	-1.184
lnGti	270	8.510	1.187	5.303	8.569	10.94
lnEco	270	11.07	0.425	10.20	11.01	12.29
lnStr	270	-0.985	0.236	-1.903	-0.933	-0.614
lnEi	270	-0.541	0.560	-1.796	-0.629	0.774
lnFDI	270	-1.817	0.948	-4.883	-1.974	0.0399
lnUr	270	-0.473	0.162	-0.846	-0.487	-0.111
lnGi	270	-1.444	0.371	-2.238	-1.482	-0.442

4.2 Correlation Analysis

To preliminarily assess the direction and strength of bivariate relationships and to detect potential multicollinearity among independent variables, the correlation analysis is conducted. These results provide initial validation for the theoretical framework and guide subsequent multivariate regression. The correlation matrix (Table 2) reveals several high correlations among independent variables, most notably, green technology innovation (lnGti) is highly correlated with both government intervention (lnGi) and energy intensity (lnEi), suggesting potential multicollinearity concerns.

Table 2. Correlation of the Variables

	lnCO2	lnAg	lnGti	lnEco	lnStr	lnEi	lnFDI	lnUr	lnGi
lnCO2	1								
lnAg	0.212***	1							
lnGti	0.398***	0.503***	1						
lnEco	0.041	0.396***	0.685***	1					
lnStr	0.534***	-0.031	0.026	-0.228***	1				
lnEi	0.172***	-0.422***	-0.732***	-0.604***	0.297***	1			
lnFDI	0.118**	0.220**	0.693***	0.673***	-0.265***	-0.647***	1		
lnUr	0.006	0.308***	0.517***	0.865***	-0.279***	-0.387***	0.686***	1	
lnGi	-0.460***	-0.417***	-0.830***	-0.569***	-0.242***	0.661***	-0.663***	-0.405***	1

4.3 VIF Test

The correlation analysis reveals strong correlations among some explanatory variables, which may lead to multicollinearity and compromise the efficiency and stability of subsequent regression estimates. To systematically evaluate this issue, this study computes the variance inflation factor (VIF) for all variables. It is generally accepted that a VIF value below 10 indicates no serious multicollinearity problem. The test results (Table 3) show that the VIF values of all variables are less than 10, with an average VIF of 4.61, indicating that there is no serious multicollinearity and the model specification is reasonable.

Table 3. VIF Test Result

Variable	VIF	1/VIF
lnEco	7.05	0.141781
lnUr	6.66	0.150213
lnGi	5.75	0.174012
lnGti	5.00	0.200162
lnFDI	4.50	0.222137
lnEi	3.96	0.252321
lnStr	2.42	0.413610
lnAg	1.56	0.640614
Mean VIF	4.61	

4.4 Hausman Test

To determine the appropriate panel data model specification, the Hausman test is performed to choose between the fixed-effects (FE) and random-effects (RE) specifications. As shown in Table 4, the χ^2 statistic is 16.72 with a p-value of 0.0104, which strongly rejects the null hypothesis that the random-effects estimator is consistent. Therefore, the fixed-effects model (FEM) is selected for the baseline regression.

Table 4. Hausman Test Result

Test method	χ^2 Statistic	p-value
Hausman Test	16.72	0.0104

4.5 Regression Results and Analysis

Before conducting the regression analysis, this paper performs the Pesaran cross-sectional dependence test and the modified Wald heteroskedasticity test. The results indicate significant cross-sectional dependence ($CD = 3.24$, $p = 0.0012$) and heteroskedasticity ($\chi^2 = 3743.18$,

$p = 0.0000$). To address these issues, all regressions are estimated using the Driscoll-Kraay standard errors, which are robust to cross-sectional dependence, heteroskedasticity, and serial correlation. Table 5 reports the regression results.

Column (1) presents a parsimonious specification including only the aging variable. The coefficient of $\ln Ag$ is -0.2612 and significant at the 5% level, indicating a negative correlation between population aging and carbon emissions when control variables are omitted. However, this result may be subject to omitted-variable bias, as it does not account for other key factors that influence emissions.

Column (2) introduces the full set of control variables. The coefficient for $\ln Ag$ becomes -0.2248 and is significant at the 5% level. Economically, this means that a 1% increase in population aging is associated with a 0.2248% reduction in carbon emissions, *ceteris paribus*. This finding demonstrates that, after controlling for economic development, industrial structure, energy intensity, and other confounding factors, population aging significantly curbs carbon emissions, providing strong support for Hypothesis H1.

Table 5. Main Tests of Regression

	(1)	(2)
	$\ln CO_2$	$\ln CO_2$
$\ln Ag$	-0.2547^{**} (-2.8119)	-0.2248^{**} (-2.9390)
$\ln Eco$		0.8719^{***} (6.8724)
$\ln Str$		0.5830^{***} (5.0249)
$\ln Ei$		0.6776^{***} (7.8116)
$\ln FDI$		0.0161 (1.0838)
$\ln Ur$		0.3239^{***} (4.4966)
$\ln Gi$		0.0621^{**} (2.4793)
_cons	9.8835^{***} (54.7943)	1.6102 (1.0831)
N	270	270
adj. R^2	0.3845	0.7353

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.6 Moderating Effect of Green Technology Innovation

To examine the moderating role of green technology innovation ($\ln Gti$), we introduce an interaction term between population aging and green technology innovation. Table 6 reports the results of the test for the moderating effect. The interaction term is -0.0617 and significant at the 1% level. This negative coefficient indicates that green technology innovation plays a reinforcing moderating role: higher levels of green technology innovation strengthen the emission-reducing effect of population aging. Thus, Hypothesis H2 is supported.

Table 6. Moderating Effect of Green Technology Innovation

	lnCO2
lnAg	-0.2365** (-2.6868)
lnGti	-0.0586*** (-4.5176)
lnAg × lnGti	-0.0617*** (-3.5700)
Control Variables	YES
Time Effect	YES
Province Effect	YES
_cons	1.9315 (0.9984)
<i>N</i>	270
adj. <i>R</i> ²	0.7489

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 2 further visualizes this moderating effect, building on the findings from Table 6. The plot shows the marginal effect of lnAg on lnCO2 at different levels of lnGti. The 95% confidence intervals are also presented. As shown in the figure, the marginal effect of lnAg is negative across all levels of lnGti, and it becomes significantly more negative as lnGti increases. Specifically, the effect is not statistically significant when lnGti is low, but becomes significantly negative once lnGti exceeds a certain level. This confirms that green technology innovation plays a key role in activating and amplifying the carbon-reduction effect of population aging.

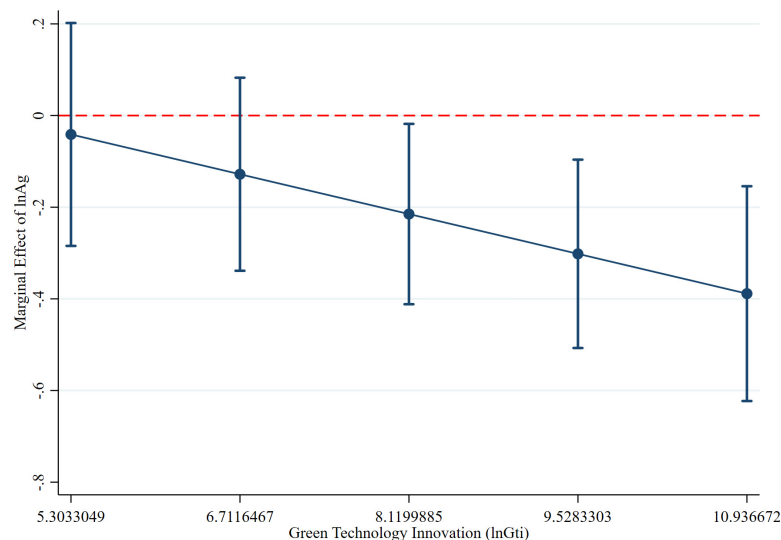


Figure 2. Marginal Effect of Population Aging on Carbon Emissions

Note: The vertical bars represent 95% confidence intervals. The effect is statistically significant when the confidence interval does not cross the zero line.

4.7 Robustness Tests

4.7.1 Endogeneity Test

To address endogeneity concerns, this study employs the 2SLS method using the first lag of $\ln Ag$ as an instrumental variable. Table 7 reports the test results. The Durbin-Wu-Hausman test rejects the exogeneity null at the 10% significance level, confirming endogeneity in the core explanatory variable and justifying the use of the 2SLS approach. The Kleibergen-Paap rk LM statistic rejects underidentification, while the Kleibergen-Paap rk Wald F statistic rejects weak instruments, verifying the validity of the instrumental variable. The regression results show that aging continues to have a significant negative effect on carbon emissions, supporting the robustness of the core findings.

Table 7. Endogeneity test

	(1) first $\ln Ag$	(2) 2sls $\ln CO_2$
L. $\ln Ag$	0.5313*** (7.8519)	
$\ln Ag$		-0.3697** (-2.3352)
Control Variables	YES	YES
Time Effect	YES	YES
Province Effect	YES	YES
N	240	240
R ²		0.6996
Endogeneity test(DWH) $\chi^2(1)$ (P-val)		2.944(0.0862)
Kleibergen-Paap rk LM statistic(P-val)		10.52(0.0012)
Kleibergen-Paap rk Wald F statistic		61.65
Stock-Yogo critical values(10%)		16.38

4.7.2 Alternative Measurement for Dependent and Independent Variables

To verify the robustness of the core findings, this study conducts a robustness check by replacing the measurement methods of the core independent and dependent variables. Specifically, it replaces the logarithmic of the old-age dependency ratio ($\ln Ag$) with the logarithmic of the aging rate measured by the proportion of the population aged 65 and above ($\ln Ag_rate$) as the core explanatory variable, and substitutes the logarithmic of total carbon emissions ($\ln CO_2$) with the logarithmic of carbon emissions per unit GDP ($\ln CO_2_GDP$) for the dependent variable. Table 8 reports the measurement results.

The core main effect is robust: regardless of the measurement methods used, the negative impact of population aging on carbon emissions remains significant. This indicates that the core conclusion that population aging significantly inhibits carbon emission growth is unaffected by the choice of variable measurement methods and is highly reliable.

The moderating effect is robust: The coefficient of the interaction term between green technology innovation and population aging is consistently significantly negative. This proves that green technology innovation significantly strengthens the inhibitory effect of population aging on carbon emissions. The conclusion regarding the moderating effect is consistent and robust.

Table 8. Alternative Measurement for Dependent and Independent Variables

	(1) lnCO2	(2) lnCO2	(3) lnCO2 GDP	(4) lnCO2 GDP
lnAg_rate	-0.2608** (-2.7092)	-0.2847** (-2.5271)		
lnGti		-0.0557** (-4.3093)		-0.0774*** (-4.9054)
lnAg_rate×lnGti		-0.0744** (-3.9974)		
lnAg			-0.0654* (-1.9921)	-0.0789 (-1.5900)
lnAg×lnGti				-0.0669*** (-3.8372)
Control Variables	YES	YES	YES	YES
Time Effect	YES	YES	YES	YES
Province Effect	YES	YES	YES	YES
_cons	1.3055 (0.8556)	1.5891 (0.8053)	3.4981** (2.8621)	3.7556** (2.7676)
<i>N</i>	270	270	270	270
adj. <i>R</i> ²	0.7326	0.7469	0.9233	0.9291

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.7.3 Dynamic Panel Estimation with System GMM

To further verify the reliability of the empirical conclusions and alleviate potential endogeneity bias, while capturing the time-dependent characteristics of carbon emissions, this paper constructs a dynamic panel regression model and adopts the system GMM method for robustness testing.

The corresponding estimation results are shown in Table 9. The coefficient on the lagged carbon emissions variable is significantly positive, indicating that carbon emissions exhibit clear path dependence, and that it is reasonable to introduce dynamic lag terms into the model. After incorporating the lagged term of the explained variable and correcting endogeneity problems, the core explanatory variable, population aging, still shows a significant negative impact on carbon emissions, consistent with the benchmark model's regression results.

Although the interaction term fails to pass the significance test, its coefficient sign is consistent with previous research results and still reflects a directional moderating effect. In addition, the Arellano-Bond sequence correlation test and the Hansen overidentification test both meet the empirical requirements, indicating that the dynamic panel model specification is reasonable and the selection of instrumental variables is effective.

The above dynamic regression results fully support the core research conclusion that population aging can significantly curb carbon emissions.

Table 9. Dynamic Panel Estimation with System GMM

Variable	GMM
L.lnCO2	0.8570*** (10.2856)
lnAg	-0.1806** (-2.4399)
lnGti	-0.1175 (-1.5575)
lnAg×lnGti	-0.0244 (-1.0741)
Control Variables	YES
Time Effect	YES
Province Effect	—
_cons	0.8656 (0.6261)
<i>N</i>	240
Number of instruments	30
AR(1) (p-value)	0.001
AR(2) (p-value)	0.598
Hansen test (p-value)	0.808

z statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Province fixed effects are eliminated in the system GMM estimation. AR(1) and AR(2) are Arellano-Bond tests for first- and second-order serial correlation in the first-differenced residuals. The Hansen test is the overidentification test for the validity of instrument variables.

4.8 Heterogeneity Analysis

To explore the heterogeneous effects of population aging on carbon emissions, this paper conducts subsample regressions by economic development level and degree of population aging, with results presented in Table 10.

1. Heterogeneity by Economic Development Level

The sample is divided into high- and low-economic-development groups based on the median of per capita GDP. Column (1) and (2) both show that population aging significantly inhibits carbon emissions in economically developed and less developed regions. Notably, the magnitude of the coefficient is larger in the low-income group, indicating that the emission-reduction effect of aging is stronger in economically underdeveloped regions. This heterogeneity arises perhaps because underdeveloped regions, which are still dominated by labor-intensive high-carbon industries, see a more pronounced decline in high-carbon production activities as the population ages. Meanwhile, developed regions, with their more advanced industrial structures and green technologies, have already realized significant emission reductions, leaving less room for aging to deliver additional emission-reduction gains.

2. Heterogeneity by Population Aging Degree

Following the internationally recognized threshold of 14% for an aged society, the sample is split into high-aging and low-aging groups. Column (3) shows that aging has no significant impact on carbon emissions in deeply aging regions. Column (4) shows that population aging exerts a negative and marginally significant effect on carbon emissions in regions at the early

stage of aging. This pattern indicates that the emission-reduction effect of aging is weak and unstable across different aging stages. At the early stage of aging, demographic shifts are accompanied by initial efficiency gains and a reduction in high-carbon production activities, which generate a weak inhibitory effect on carbon emissions. However, this effect is not strong enough to reach conventional significance levels. In high-aging regions, the potential emission-reduction effect of aging is offset by newly generated energy consumption demand, such as rising medical care and residential heating needs, leading to an insignificant overall effect.

Table 10. Heterogeneity Analysis

	(1) High GDP	(2) Low GDP	(3) High aging	(4) Low aging
lnAg	-0.1953** (-2.6333)	-0.2730*** (-3.6830)	0.1370 (1.1248)	-0.2230 (-1.8176)
Control variables	YES	YES	YES	YES
Time Effect	YES	YES	YES	YES
Province Effect	YES	YES	YES	YES
Cons	3.5227** (2.4833)	-0.0990 (-0.0642)	8.9015*** (5.5369)	-1.0346 (-0.8824)
<i>N</i>	135	135	83	187
adj. <i>R</i> ²	0.7839	0.7646	0.4117	0.8280

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Conclusions

Using 2015–2023 panel data from 30 Chinese provinces, this study investigates how population aging affects carbon emissions, along with the moderating role of green technology innovation and regional heterogeneity characteristics. Multiple endogeneity and robustness tests verify the validity of the results. First, population aging significantly inhibits carbon emissions. After controlling for socioeconomic and energy-related factors, a 1% increase in aging reduces carbon emissions by 0.2248%. This core negative effect remains robust across 2SLS, variable substitution, and system GMM tests. Second, green technology innovation positively reinforces the aging-induced carbon mitigation effect. The significant negative interaction term and marginal effect results confirm that advanced green innovation effectively amplifies the low-carbon dividend of population aging. Third, the mitigation effect presents evident heterogeneity. Aging exerts a stronger emission-reduction effect in economically undeveloped regions. Moreover, aging curbs emissions in low-aging regions, while increased elderly energy demand offsets such benefits in deeply aging regions, leading to an insignificant overall effect. This study clarifies the causal relationship, moderating mechanism, and heterogeneous boundaries between population aging and carbon emissions. It enriches relevant literature on demographic transition and low-carbon development and provides empirical evidence for China’s differentiated regional low-carbon governance amid population aging and green transformation.

These results suggest policymakers need context-specific strategies to link demographic

changes, economic development, and carbon mitigation. First, address heterogeneous aging impacts across regions. Deeply aging regions need proactive measures, including industrial upgrading and support for green innovation, to counter rising energy demand from elderly care services. Less aged regions should seize the opportunity to embed low-carbon principles into urban planning and consumption patterns before aging-driven energy pressures escalate. Second, strengthen green technology innovation as a catalyst for emission reduction. Targeted incentives such as R&D subsidies for aging-friendly green technologies, cross-regional innovation platforms, and market mechanisms like carbon pricing can amplify the synergy between aging and low-carbon transitions, especially in regions with weak innovation capacity. Third, advance inclusive energy transition strategies. Balance structural transformation with energy efficiency improvements, ensuring policies do not disproportionately burden elderly households. Expand access to affordable clean energy, promote residential energy retrofits, and align social protection schemes with low-carbon goals to support both aging populations and decarbonization efforts.

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Author contributions

Xuke Li was responsible for study design and manuscript drafting. Dr. Ema revised the manuscript. Zhilin Chen was responsible for data collection. All authors read and approved the final manuscript.

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Obtained.

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Data sharing statement

No additional data are available.

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