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Does Population Aging Affect Carbon Emission Intensity by Regulating Labor Allocation?

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Abstract: Carbon emission is the focus of global climate change concerns. Population aging changes the level of labor structure, which directly affects the industry adjustment and will also have a long-term impact on carbon emissions. Uncovering the complex association among population aging, labor allocation, and CO_2 emission is crucial for developing effective policies for low-carbon and sustainable development in China. Therefore, this study aims to analyze whether population aging contributes to reducing carbon emission intensity by regulating labor allocation. Based on provincial panel data from 2000 to 2019, the Systematic Generalized Method of Moments (Systematic GMM) model and the Bias Corrected Least Squares Estimation with Nonsymmetric Dependence Structure (Bias Corrected LSDV) model are adopted in this study. The results show that nationwide as a whole, population aging objectively inhibits human capital accumulation and, to some extent, weakens its positive carbon emission reduction effect. Meanwhile, population aging helps to mitigate the increase in carbon emissions caused by the capital-labor endowment structure. Due to the dual impact of aging and population migration, the emission reduction effect of human capital accumulation is significant in the East. The brain drain in the central and western regions further inhibits the positive effect of regional human capital accumulation. Promoting the rationalization of population mobility nationwide, reducing the brain drain in less developed regions, and directing capital into technology-intensive industrial sectors are the core keys to achieving optimal labor allocation in an aging society. This will help China meet its carbon neutrality target on schedule.

Keywords: population aging; labor allocation; carbon emission reduction; human capital; capital-labor ratio

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1. Introduction

Global warming is one of the most severe problems facing the world, and it has become a global consensus to promote energy saving and emission reduction. To maintain the hope of achieving the 1.5 °C targets for temperature rise control, the Glasgow Climate Pact (COP26) is a key collective effort to speed up the industrial transition to achieve net-zero emissions by 2050. This is a crucial step in line with Sustainable Development Goals (SDGs) after initiating the Kyoto Protocol and Paris Agreement for climate change control [1]. China is the world's largest carbon emitter, accounting for more than 30% of global CO_2 emissions yearly [2]. In 2021, China's carbon emissions reach 11.47 billion tons, double that of the US (5 billion tons) and four times that of the EU (2.79 billion tons) (Data source: ourworldindata.org (accessed on 7 June 2023)). To achieve the goal of carbon neutrality, China started to strengthen carbon intensity control during the 11th Five-Year Plan, and by 2020 carbon emissions of 10,000 Yuan GDP have been reduced by 46.8% compared to 2005 [3]. The emission control target will be gradually improved during the 14th Five-Year Plan to fully ensure the achievement of the 3060 strategic goals [4]. Optimizing industrial structure, improving resource allocation efficiency of production factors, and improving low-carbon technology innovation has become critical tasks for China's sustainable development [5,6].

All of the above are inseparable from the demographic labor force. Since 2000, China has entered into an aging society. By 2021, the proportion of the population aged 65 and above has reached 14.2%. Deep aging has become an inevitable trend affecting China's economic development [7].

The impact of population aging on China's labor allocation and carbon emissions cannot be ignored. First, China's manufacturing industry is mainly labour-intensive [8]. With the deepening of the aging trend, China has changed from an oversupply of labor to an undersupply of labor [7,9]. The rise in labor costs has caused China's traditional manufacturing industry to lose a large amount of cheap labor [10,11]. This means that China's "demographic dividend" has become unsustainable. To achieve healthy and sustainable development, China's economy must break away from its dependence on labor-intensive and energy-intensive industries [12]. Second, the improved quality of the labor force due to increased years of education per capita is a qualitative demographic dividend [13]. With further upgrading the industrial structure, the innovation advantage brought by human capital accumulation will continue to grow and eventually replace the industrial dominance of the quantitative demographic dividend [14]. Therefore, future high-quality growth will depend on human capital accumulation and technological innovation capability [15,16].

Rational allocation of the labor force in quantity and quality is essential in promoting industrial structure upgrading [17,18]. Human capital accumulation directly determines the quality of the labor force, while the relative input quantity of capital and labor within the industrial sectors reflects the quantitative structure of labor allocation. Population aging may affect the labor allocation from the above two aspects [19]. The impact of population aging on human capital is twofold: first, the increase in older people in an aging society is bound to increase the share of social pensions, which will inevitably crowd out other social welfare inputs, including education inputs [20], which has a negative effect on the accumulation of human capital [21].

The aging age structure also objectively accelerates the shift from quantity to quality of labor factor endowment [22–24]. The immediate problem caused by aging is the decline of the young working population and the disappearance of the quantitative advantage of labor [25]. With the extension of life expectancy, people will increase the return on their investment in education, such as delaying their entry into the labor market to get an education or improving their labor productivity by getting some skills training [26–28], thus complementing total social human capital.

In terms of the quantitative structure of labor allocation, the reduction in the quantity of the age-appropriate workforce may also lead to changes in the input structure of productive factors within the industrial sectors [29]. To find substitutes for the labor force, firms tend to increase their input of capital factors [30,31], the direct result of which is a decrease in the share of traditional labor-intensive industries and an acceleration of the upgrading and transformation to technology-intensive industries in the economy.

The moderating effect of aging on labor allocation will further have a ripple reaction with the adjustment of industrial structure. First, the accumulation of human capital can significantly promote green technological innovation. The innovation level of a region is closely related to the scale of talent. The accumulation of human capital, i.e., the increase of education per capita, is crucial for expanding talent capacity. Increasing educational attainment per capita and rising workforce quality will not only promote labor productivity [32], but also are conducive to the advanced transformation of the industrial structure [33]. When the aging of society deepens, on the one hand, the heavy pension burden will crowd out part of the investment in education and hinder human capital accumulation. On the other hand, the long-term work experience and knowledge accumulation of older workers can compensate for the decline in overall social labor productivity to a certain extent [34] and generate knowledge spillover effects to supplement human capital [35], maintaining sustainable industrial development.

However, it cannot be ignored that regular interprovincial population migration also occurs during the aging process in China [36,37]. In the past two decades, China's interprovincial population migration has been mainly from the central and western regions and the northeastern region to the eastern coastal region [38]. Regional development imbalance and wage income disparity are the underlying causal factors of interprovincial migration [38,39]. Since the willingness to migrate older people will gradually decrease with age, the main interprovincial migration group is the working-age population [40,41]. On the one hand, for the emigrating regions, the migration of the population is usually dominated by the outflow of labor and talent, which may inhibit the accumulation of local human capital, resulting in a lack of basis for technological innovation [42,43].

On the other hand, the rise in the resident population in the in-migration area can alleviate the degree of aging [44]. The continuous in-migration of the population provides labor security for the upgrading of local industrial structure, and the concentration of talents is more conducive to the scale effect of human capital accumulation [45], thus reducing the marginal cost of green technology innovation [46]. Therefore, population migration has diametrically opposite effects on human capital accumulation and green technology innovation in and out-migration locations. Along with the impact of aging, the number of age-appropriate labor forces decreases, and the social creativity of the aging population is weaker, making society less economically dynamic [25]. For less developed regions, the lack of innovation leads to a rigid industrial structure with no suitable employment positions available for talented people, which can intensify the brain drain [47]. Developed regions have a stronger talent attraction due to higher wages and quality of life services [38]. So, under the dual effect of aging and population migration, the gap in human capital scale and industrial structure among regions will be further widened.

Second, aging makes social labor factors scarce, leading to a change in the relative quantity between capital and labor factors, and this change also facilitates the low carbonization of the industrial structure. Technological innovation always saves productive factors with higher relative prices [48]. When the price per unit of employment rises due to labor scarcity, firms expand the amount of capital investment to replace labor [49]. However, the substitution of capital for labor is limited, and when the marginal utility of capital investment starts to diminish, firms will adopt technological innovation to increase productivity [50]. Labor scarcity forces firms to expand their investment in innovation and thus increase labor efficiency [51]. The experience of developed countries shows that the negative impact caused by the lack of labor supply can be compensated by the application of artificial intelligence and automation technologies [52,53].

Existing studies on the impact of population aging on labor allocation are sufficient, and the population's age structure is well documented as a non-negligible factor influencing carbon emission. Shift in the age composition have contributed to rising carbon emissions [54], mainly because of the rise in older people, leading to increased consumption of natural gas and electricity, causing more CO_2 emissions [55]. For carbon emission intensity, some scholars suggest that the proportion of the elderly population may have an inverted U-shaped effect on per capita CO_2 emissions [56]. And in terms of labor allocation, improving labor quality is proven to be conducive to technological innovation [16], reducing the carbon intensity of the production process [57]. The change in the structure of factor inputs also contributes to carbon emission reduction by improving energy efficiency [58]. However, there is a gap in the comprehensive analysis of the transmission mechanism among population aging, labor force allocation and carbon emission intensity. The existing mechanism analyses focus on how aging affects industrial carbon emissions through changing labor quantity or production efficiency [59,60]. Simultaneous analysis of whether regulating labor allocation by aging in quantitative and qualitative perspectives contributes to reducing carbon emission intensity is lacking. Therefore, in this research, we propose constructing an econometric model to verify whether population aging drives low-carbon economic growth by regulating labor allocation by changing human capital accumulation and capital-labor ratio and further enriching the connotation of carbon emission reduction.

2. Materials and Methods

2.1. Model Setting

Since the effects of population aging and labor force allocation on carbon intensity may yield exactly opposite conclusions in different regions and at different times, two-way fixed-effects models (with individual fixed effects and time-fixed effects) using panel data can effectively fix the impact of regional and temporal differences, leading to more definitive conclusions [61]. However, there is a time-lag effect in the adjustment of economic production activities and the implementation of policies [62], so the industrial carbon emissions in the current period of the region may be correlated with the previous. This study further constructs a dynamic panel model to consider this effect. To eliminate the endogeneity issue caused by the lag term, this study uses a Systematic Generalized Method of Moments (Systematic GMM) approach [63] to estimate the dynamic panel model. The baseline model is designed as follows:

$$CEI_{it} = \alpha_0 + \alpha_1 age_{it} + \alpha_2 hc_{it} + \alpha_3 cl_{it} + \beta_k X_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (1)$$

where CEI is carbon emission intensity, which is a region's per capita CO_2 emission. age is population aging, hc is human capital stock, and cl is capital-labor factor endowment structure. X represents a set of control variables, including industrial structure upgrading index (TS), per capita gross regional product (pgdp), foreign direct investment (FDI), technological innovation (tech), and urbanization level (urz). α_0 is the constant term, μ_i is the individual fixed effect of different regions; η_t is the year fixed effect, ε_{it} is the stochastic error.

To examine whether there is a synergistic mechanism between population aging and labor force allocation, two interaction terms, age×hc and age×cl, are added to the benchmark model to test the influence mechanism. The form is as follows:

$$CEI_{it} = \alpha_0 + \alpha_1 age_{it} + \alpha_2 hc_{it} + \alpha_3 cl_{it} + \lambda_1 age_{it} * hc_{it} + \lambda_2 age_{it} * cl_{it} + \beta_k X_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (2)$$

2.2. Variable Description

2.2.1. Explained Variables

Carbon emission intensity (CEI) is the ratio of total regional CO_2 emissions to year-end population. We use the method recommended by IPCC to estimate CO_2 emission from energy consumption (except electricity):

$$CO_{2j} = E_j \times G_j \times A_j \times B_j \times \frac{44}{12} \quad (3)$$

where CO_{2j} is the CO_2 emission of the j energy, E_j is the consumption of the j energy (including coal, coke, oil, crude oil, gasoline, diesel oil, kerosene, fuel oil, liquefied petroleum gas, and natural gas), G_j is the net calorific value of the j energy, A_j is the CO_2 emission coefficient, B_j is the carbon oxidation factor.

Because electricity does not cause emissions, the CO_2 emitted mainly comes from burning coal in thermal power generation. The formula for calculating the CO_2 emissions from electric power is as follows:

$$CO_{2e} = T_E \times R \times T_C \times E_C \times K_C \quad (4)$$

In the formula, CO_{2e} is the CO_2 emission of electricity consumption, T_E is the total electricity consumption; R is the ratio of thermal power generation to total power; T_C is the conversion standard coal coefficient of thermal power; E_C is the default emission coefficient of coal; K_C is the calorific value of coal.

As shown in Figure 1, the per capita carbon emission at China's provincial level has an increasing trend from 2000 to 2019. The per capita carbon emission intensity of Xinjiang, Inner Mongolia and Qinghai is extremely high, related to the resident population and industrial structure. Excluding these three provinces, the carbon emission intensity of economically developed coastal regions is significantly higher than that of inland regions, showing a descending trend from east to middle to west.

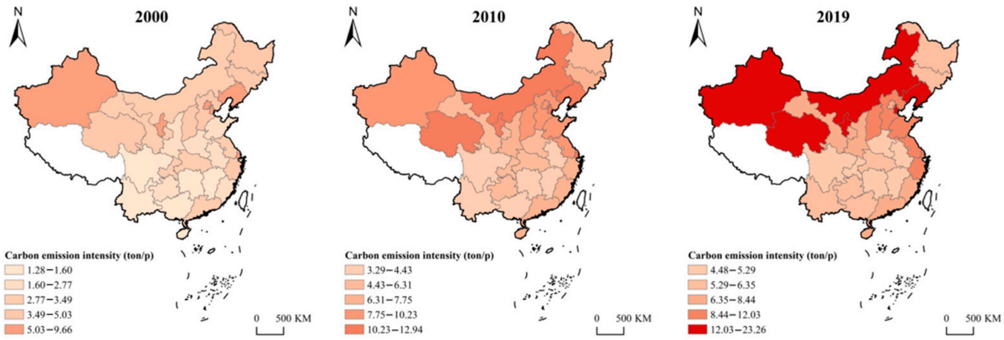

Figure 1. The carbon emission intensity of 30 provinces in China.

2.2.2. Core Explanatory Variables

Population aging (age): The elderly dependency ratio is chosen to measure the degree of aging. The elderly dependency ratio is expressed as the proportion of the population aged 65 and over to the working-age population (15–64 years). As shown in Figure 2, China's population aging is on an overall upward trend.

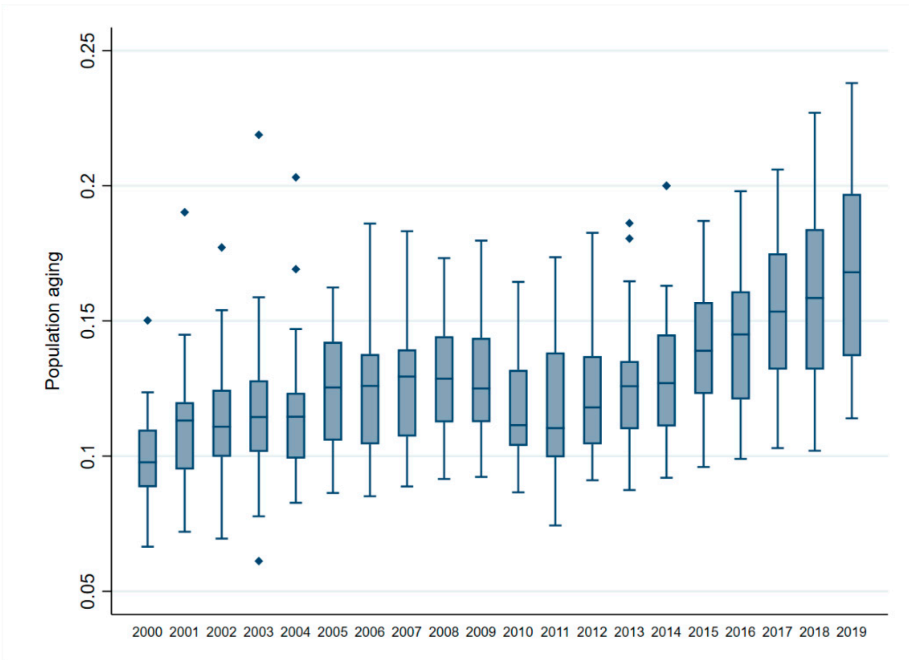

Figure 2. Box diagram of China's population aging degree from 2000 to 2019.

Labor allocation: labor allocation is specifically represented by the human capital (hc) and the capital-labor factor endowment structure (cl). Human capital (hc) is measured by the years of schooling per capita in the region. Human capital accumulation reflects the improvement in the overall quality of the labor force, which is the knowledge base for promoting technological innovation in enterprises. The capital-labor factor endowment structure (cl) is the capital labor ratio, measured by the ratio of fixed capital stock to regional employment, where the fixed capital stock is calculated using the perpetual inventory method [64]. The formula is as follows:

$$K_t = K_{t-1}(1 - \eta_t) + {}^{I_t}\!/_{P_t} \quad (5)$$

K_t and K_{t-1} represent the fixed capital stock of t period and t−1 period. For the base period capital stock of provinces in 2000, we use the ratio of the actual capital formation of each province in 2001 to the sum of the average depreciation rate and the average investment growth rate from 1953 to 1957 to estimate [65]. η_t represents the depreciation rate of period t, In this study, the capital depreciation rate of all regions is 10.96% [65]. I_t represents the investment amount of fixed assets. P_t represents the fixed assets investment price index. The capital-labor ratio reflects the resource allocation structure of industrial production. Rising capital investment is likely to have both a technology-driven effect and an increase in energy consumption.

2.2.3. Control Variables

Industrial structure upgrading index (iup): The growth rate of the tertiary industry, mainly the information service industry, exceeds that of the secondary industry, is an essential indicator of industrial structure upgrading. Based on this, this research adopts the ratio of the output value of the tertiary industry to the output value of the secondary industry as the index of industrial structure upgrading. This measure can reflect the service orientation of the economic structure. If the iup value is on the rise, it means that the industrial structure is upgrading.

Gross regional product per capita (pgdp): The actual GDP of each region is divided by the total population to obtain the value of GDP per capita for that region, and the data is obtained from the local statistical yearbooks of previous years. GDP per capita reflects the level of the economic output of a region. On the one hand, a higher level of output depends to a certain extent on a large amount of energy consumption, which is not conducive to carbon emission reduction. On the other hand, economically developed regions have stronger environmental regulations, and people have higher requirements for environmental quality. Local governments and enterprises will invest more intensively in improving production methods and resource utilization efficiency.

Foreign direct investment (fdi): In this paper, the total import and export of goods by foreign-invested enterprises are selected as the proxy variable of FDI, according to the "pollution halo" theory [66]. FDI not only has a technology spillover effect but also brings advanced management experience to local enterprises, which is conducive to improving the production efficiency of local enterprises, thus saving energy. However, the "pollution sanctuary" hypothesis suggests that [67], due to the more stringent environmental regulations in developed countries, FDI often leads to the transfer of energy-intensive and high-polluting industries to China, leading to an increase in local energy consumption and pollution emissions.

Technological innovation (tech): measured by the number of local annual patent applications granted and data from the statistical yearbooks of previous years. The improvement of energy use efficiency depends on the production methods and technologies, while the increase in the level of innovation is the primary driver for the upgrading of production technologies [68]. Technological innovation is a direct and effective way to improve the efficiency of resource use, thus reducing carbon emissions per unit of output.

Urbanization level (urz): calculated by the proportion of the urban population to the total population. Urbanization is considered an important social development factor affecting the intensity of carbon emissions [69]. An increase in population urbanization implies a deeper degree of urban socio-economic development. The scale effect of population agglomeration within the city results in a larger local industrial structure and a more significant environmental effect from economic production activities.

This study uses panel data from 30 Chinese provinces from 2000–2019 for the econometric analysis. Raw data of all variables are obtained from the official statistical yearbooks of China published in previous years. For CEI, the energy consumption data are from China Energy Statistical Yearbook, and the calculation parameters are from IPCC. Data on the year-end population are collected from China Regional Economic Statistics Yearbook. For age, data on the elderly dependency ratio are from China Statistical Yearbook. For hc, Data on years of schooling per capita are collected from China Labor Statistics Yearbook. For cl, the data for the calculation of fixed capital stock are from China Statistical Yearbook, and labor and employment data are from the statistical yearbook of each province. All raw data of control variables (iup, pgdp, fdi, tech, urz) are collected from China Statistical Yearbook. The descriptive analysis of the main variables is shown in Table 1.

Table 1. Descriptive Statistics.

Variable	Definition	Unit	Obs	Mean	Std. Dev.	Min	Max
CEI	Carbon emission intensity	Tons/person	600	6.889	3.720	1.278	23.26
age	Elderly dependency ratio	/	600	0.128	0.031	0.061	0.238
hc	Human capital	year	600	9.198	1.322	6.089	13.901
cl	Capital labor ratio	/	600	11.602	9.793	0.71	56.234
iup	Industrial structure upgrading index	/	600	1.014	0.541	0.494	5.169
pgdp	Gross regional product per capita	Thousand yuan/person	600	9.936	5.362	2.645	29.662
fdi	Foreign direct investment	Billion dollar	600	43.534	96.993	0.004	592.071
tech	Technological innovation	Thousand	600	28.024.	56.789	0.07	527.39
urz	Urbanization level	%	600	51.179	15.191	23.3	89.6

3. Results

3.1. Panel Stability Test

Since the number of individuals in the sample of this study is 30 (N = 30) and the length of time is 20 (T = 20), it belongs to short panel data. The HT test is used to test the stationarity of each variable.

As shown in Table 2, the concomitant probability of the first-order difference values of all nine variables is 0.0000, which passes the 1% significance test, so the original hypothesis (the series is non-stationary and panels contain unit roots) is rejected. The first-order difference sequences of the variables are all stationary and integrated of order one I(1). According to cointegration theory, when the variables have the same order sequence, there may be a cointegration relationship among the variables.

Table 2. HT unit root test for panel data.

Variables	Horizontal Sequence	First Order Differential Sequence
CEI	0.8538 (0.4512)	−0.0864 *** (0.0000)
age	0.6909 *** (0.0000)	−0.2790 *** (0.0000)
hc	0.7065 *** (0.0000)	−0.2532 *** (0.0000)
cl	0.9563 (0.9999)	0.4973 *** (0.0000)
iup	0.9510 (0.9997)	0.1109 *** (0.0000)
pgdp	0.9613 (0.9999)	0.1920 *** (0.0000)
fdi	0.9339 (0.9978)	−0.0654 *** (0.0000)
tech	0.8481 (0.3688)	0.0407 *** (0.0000)
urz	0.9543 (0.9998)	0.2480 *** (0.0000)

Note: *** indicates the significance at the 1% level.

3.2. Cointegration Test

The previous section tested the stationarity of the panel data, and the results showed that the variables are integrated into the order I(1). This section further tests the cointegration relationship among the variables using the Kao test, and the results are shown in Table 3.

Table 3. Panel Cointegration Test.

	Statistic	*p*-Value
Modified Dickey-Fuller t	−1.4281	0.0766
Dickey-Fuller t	−2.4516	0.0071
Augmented Dickey-Fuller t	−2.2304	0.0129
Unadjusted modified Dickey-Fuller t	−1.4211	0.0776
Unadjusted Dickey-Fuller t	−2.4476	0.0072

The *p*-values corresponding to the five test statistics are all less than 0.1, meaning the original hypothesis of "no cointegration relationship" can be rejected at the 10% level. The cointegration relationship holds, indicating a stable equilibrium relationship between CEI, age, hc, cl, iup, pgdp, fdi, tech and urz in the long run. So, the original series can be used for panel model regression.

3.3. Multicollinearity Test

This section judges whether there is multicollinearity among the explanatory variables by calculating the correlation coefficients and variance inflation factors among the explanatory variables.

As shown in Table 4, the correlation coefficients among the variables are less than 0.75, except for three groups of variables (urz and hc, urz and cl, urz and pgdp). The results of the VIF test (see Table 5) shows that the mean value of the VIF is 5.01. Except for urz, the VIF values of all the variables are also less than 10. So there is no multicollinearity among the explanatory variables.

Table 4. Correlation coefficient matrix.

Variables	Age	hc	cl	iup	pgdp	fdi	tech	urz
age	1.000							
hc	0.366	1.000						
cl	0.415	0.708	1.000					
iup	0.197	0.513	0.346	1.000				
pgdp	0.295	0.763	0.626	0.377	1.000			
fdi	0.526	0.592	0.455	0.176	0.738	1.000		
tech	0.628	0.641	0.619	0.223	0.589	0.695	1.000	
urz	0.389	0.859	0.806	0.426	0.884	0.674	0.620	1.000

Table 5. Variance inflation factors test.

Variable	VIF	1/VIF
age	1.85	0.5393
hc	5.50	0.1819
cl	4.80	0.2082
iup	1.50	0.6645
pgdp	6.49	0.1540
fdi	5.22	0.1915
tech	4.45	0.2248
urz	10.22	0.0978
Mean VIF	5.01	

3.4. Benchmark Results and Carbon Reduction Mechanism Verification

This research constructs a two-way fixed-effects model containing individual and time effects and a random-effects model for regression. According to the Hausman test, the results show that the fixed-effects model is more applicable. Considering the possible endogeneity of the explanatory variable, we select the two-step system GMM model for comparative analysis. The lagged term of carbon emission intensity is chosen as the instrumental variable, and the rest are exogenous variables. In the following section, we mainly consider the coefficients of the system GMM model.

For the core explanatory variables, the results of model (1)–(3) in Table 6 shows that age is negatively correlated with CEI, indicating that population aging contributes to the reduction of regional carbon emission intensity. The coefficient of the lagged term L.CEI is significantly positive, which proves that the carbon emission intensity of the previous period has a positive effect on the carbon emission intensity of the current year. It is related to the time lag of the adjustment of economic production activities and policy implementation. The coefficient of hc in the model (3) of Table 6 is significantly negative, indicating that the accumulation of human capital contributes to the low carbon development after eliminating the effect of the previous period CEI. The capital-labor ratio (cl) enhances CEI, so the increase of capital input in the production process leads to more carbon emissions.

Table 6. Baseline regression results.

	(1)	**(2)**	**(3)**
	FE	**RE**	**System GMM**
L.CEI			0.4845 ***
			(0.0404)
age	−0.1803 ***	−0.2290 ***	−0.0314 *
	(0.0590)	(0.0574)	(0.0186)
hc	0.4231 **	0.4962 ***	−0.1060 **
	(0.1901)	(0.1838)	(0.0517)
cl	0.0892 *	0.1371 ***	0.2130 ***
	(0.0456)	(0.0443)	(0.0247)
iup	−0.2860 ***	−0.2527 ***	−0.0760 ***
	(0.0304)	(0.0277)	(0.0158)
pgdp	0.1996 **	0.2568 ***	0.2152 ***
	(0.0782)	(0.0756)	(0.0411)
fdi	−0.0156	−0.0178 *	0.0198 ***
	(0.0096)	(0.0092)	(0.0050)
tech	−0.0475 **	−0.0624 ***	−0.0599 ***
	(0.0219)	(0.0197)	(0.0080)
urz	0.2555 **	0.2947 ***	0.1224
	(0.1130)	(0.1098)	(0.0836)
_cons	−2.1057 ***	−2.9409 ***	−1.4025 ***
	(0.6764)	(0.5971)	(0.3908)
Hausman test	$p = 0.0002$		
AR(1)			0.0354
AR(2)			0.8765
Sargan test			0.7511
N	600	600	540
R^2	0.8828	0.8819	

Note: ***, **, and * indicate the significance at the 1%, 5%, and 10% levels.

For the control variables, as shown in model (3) in Table 6, the coefficients of iup, tech are significantly negative, while the coefficients of pgdp, fdi, and urz are positive. Industrial structure upgrading and technological innovation are essential factors for carbon emission reduction. Because the main feature of the advanced industrial structure is the transformation of capital-intensive industries to technology-intensive industries, the reliance on energy inputs is greatly reduced. And technological innovation is the core endogenous driving force for energy saving and emission reduction.

As for the verification of the mechanism by which aging affects carbon intensity by regulating labor allocation, the coefficient of age×hc (as shown in model (3) in Table 7) is significantly positive after eliminating the endogenous factors, i.e., the trend of population aging weakens the inhibitory effect of human capital on carbon emission intensity. The coefficient of age×cl is significantly negative (see Table 7), meaning that population aging helps to mitigate the carbon emission effect from capital substitution for labor allocation. The possible reason is that population aging promotes the conversion of capital inputs to low-carbon technology R&D.

Table 7. Empirical Results on the Effects of Population Aging and Labor Allocation on Carbon Emission Intensity.

	(1)	(2)	(3)
	FE	**RE**	**System GMM**
L.CEI			0.4535 ***
			(0.0381)
age	−0.4605 ***	−0.5398 ***	−0.3071 ***
	(0.1509)	(0.1458)	(0.0784)
hc	0.2570	0.2856	−0.3718 ***
	(0.2173)	(0.2107)	(0.0820)
cl	0.1662 ***	0.1913 ***	0.2900 ***
	(0.0526)	(0.0522)	(0.0293)
age×hc	0.2706 **	0.2740 **	0.2852 ***
	(0.1159)	(0.1130)	(0.0760)
age×cl	−0.0450 ***	−0.0255	−0.0434 ***
	(0.0168)	(0.0157)	(0.0112)
iup	−0.2920 ***	−0.2537 ***	−0.0540 ***
	(0.0303)	(0.0278)	(0.0162)
pgdp	0.1185	0.2211 ***	0.1646 ***
	(0.0842)	(0.0790)	(0.0512)
fdi	−0.0210 **	−0.0237 **	0.0156 ***
	(0.0103)	(0.0098)	(0.0049)
tech	−0.0443 **	−0.0571 ***	−0.0526 ***
	(0.0219)	(0.0199)	(0.0078)
urz	0.0883	0.2101 *	0.0254
	(0.1315)	(0.1249)	(0.1012)
_cons	−1.2949	−2.8205 ***	−0.9674 **
	(0.7945)	(0.6663)	(0.4153)
Hausman test	p = 0.0000		
AR(1)			0.0448
AR(2)			0.8672
Sargan test			0.7650
N	600	600	540
R^2	0.8565	0.8832	

Note: ***, **, and * indicate the significance at the 1%, 5%, and 10% levels.

3.5. Robustness Test

To test the robustness of the estimation results of the baseline regression, the models in Table 7 are re-estimated in this section by replacing the measures of the explanatory and core explanatory variables, respectively. First, CO_2 emissions per unit of economic output are used instead of CO_2 emissions per capita to represent carbon emission intensity. Then this section chooses to replace the measure of population aging by using the ratio of the population aged 65 years or older to the total population at the end of the year in each province. The results of the fixed-effects model, random-effects model, and Systematic GMM model are shown in Table 8. The estimation results of the main explanatory variables remain consistent with the results in Table 7, where age still significantly negatively affects CEI. After controlling for endogeneity, the coefficients of hc remained significantly negative, and there is a significant positive relationship between cl and CEI. The results of the mechanism test of aging on labor allocation (age×hc, age×cl) also remain stable in Table 7. Therefore, the robustness test confirms that the results of the baseline regression and carbon reduction mechanism are reliable.

Table 8. Robustness test.

	Replace the Interpreted Variable CEI			Replace Explanatory Variable Age		
	FE	RE	System GMM	FE	RE	System GMM
	(1)	(2)	(3)	(4)	(5)	(6)
L.CEI			0.8998 ***			0.4153 ***
			(0.0356)			(0.0401)
age	−0.4605 ***	−0.5398 ***	−0.2785 ***	−0.4894 ***	−0.5815 ***	−0.2430 ***
	(0.1509)	(0.1458)	(0.1015)	(0.1526)	(0.1466)	(0.0918)
hc	0.2570	0.2856	−0.2212 *	0.2937	0.3237	−0.3475 ***
	(0.2173)	(0.2107)	(0.1161)	(0.2141)	(0.2085)	(0.1225)
cl	0.1662 ***	0.1913 ***	0.2286 ***	0.1783 ***	0.2019 ***	0.2968 ***
	(0.0527)	(0.0522)	(0.0593)	(0.0524)	(0.0519)	(0.0311)
age×hc	0.2706 **	0.2740 **	0.3015 ***	0.3820 **	0.4032 ***	0.3387 ***
	(0.1159)	(0.1130)	(0.0874)	(0.1556)	(0.1522)	(0.1108)
age×cl	−0.0450 ***	−0.0255	−0.0650 ***	−0.0716 ***	−0.0444 **	−0.0638 ***
	(0.0168)	(0.0157)	(0.0155)	(0.0221)	(0.0207)	(0.0142)
iup	−0.2920 ***	−0.2537 ***	−0.0181	−0.2936 ***	−0.2545 ***	−0.0587 ***
	(0.0303)	(0.0278)	(0.0244)	(0.0302)	(0.0279)	(0.0152)
pgdp	−0.8815 ***	−0.7789 ***	−0.8653 ***	0.1062	0.2192 ***	0.1910 ***
	(0.0842)	(0.0790)	(0.0526)	(0.0844)	(0.0793)	(0.0492)
fdi	−0.0210 **	−0.0237 **	−0.0214 ***	−0.0215 **	−0.0244 **	0.0148 ***
	(0.0103)	(0.0098)	(0.0051)	(0.0104)	(0.0098)	(0.0056)
tech	−0.0443 **	−0.0571 ***	−0.0548 ***	−0.0444 **	−0.0565 ***	−0.0446 ***
	(0.0219)	(0.0199)	(0.0131)	(0.0219)	(0.0198)	(0.0092)
ur	0.0884	0.2101 *	0.3173	0.0577	0.1941	0.0470
	(0.1315)	(0.1249)	(0.3595)	(0.1319)	(0.1251)	(0.1018)
_cons	5.6128 ***	4.0873 ***	6.5308 ***	−1.3881 *	−3.1374 ***	−1.2438 ***
	(0.7945)	(0.6663)	(1.0471)	(0.8288)	(0.7035)	(0.4494)
Hausman test	p = 0.0006			p = 0.0000		
AR(1)			0.0147			0.0525
AR(2)			0.7342			0.8502
Sargan test			0.9827			0.7823
N	600	600	540	600	600	540
R^2	0.7672	0.7645		0.8851	0.8837	

Note: ***, **, and * indicate the significance at the 1%, 5%, and 10% levels.

3.6. Regional Heterogeneity Test

To analyze whether there is regional heterogeneity in the mechanism of the influence of population aging and labor force allocation on carbon emission intensity, this section divides the sample provinces into three regions: eastern, central, and western regions. Because the three subsamples are long panel data (The number of individuals N is smaller than the number of periods T), the long-time sequence contains more information and has intra-group solid autocorrelation [70], it is necessary to consider heteroskedasticity and autocorrelation of error terms, so the feasible generalized least squares (FGLS) estimation is adopted to analyze the regional influence mechanism [70]. Since the Systematic GMM model is not applicable to long panel data [71], this study uses the Bias Corrected Least Squares Estimation with Nonsymmetric Dependence Structure (Bias Corrected LSDV) method to estimate the dynamic long panel model [72].

The results in Table 9 show significant regional differences in the effect of human capital accumulation (hc) on carbon emission intensity. In model (1) and model (2), the coefficients of hc are significantly negative, which indicates that only in the eastern region does human capital accumulation plays a role in carbon emission reduction.

In terms of carbon reduction mechanisms, the coefficients of age×hc are positive in all three regions (as shown in models (2), (4), and (6) in Table 9), implying that the constraint of aging on the carbon reduction effect of human capital accumulation is nationally widespread. The coefficients of age×cl are significantly negative in all three subsamples (as shown in models (2), (4) and (6) in Table 9), suggesting that aging objectively mitigates the carbon emission effect of the structural shift in factors of production, i.e., the substitution of capital for labor.

Table 9. Regional heterogeneity test results.

	Eastern Region		Central Region		Western Region	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
L.CEI		0.8146 ***		0.8096 ***		0.7622 ***
		(0.0437)		(0.0669)		(0.0507)
age	−0.4522 **	−0.2656	−0.0139	0.2577	−0.1058	−0.0652
	(0.1927)	(0.2042)	(0.2688)	(0.2798)	(0.1460)	(0.1211)
hc	−0.7371 **	−0.5268 *	0.0101	0.3821	−0.0022	0.1174
	(0.3377)	(0.3115)	(0.4226)	(0.4333)	(0.1799)	(0.1504)
cl	0.2335 **	0.0235	0.4558 ***	0.0804	0.3408 ***	0.0500
	(0.0951)	(0.0678)	(0.0965)	(0.0735)	(0.0751)	(0.0563)
age×hc	0.4111 ***	0.2127	0.0728	0.1923	0.1084	0.0092
	(0.1350)	(0.1404)	(0.2834)	(0.2452)	(0.1377)	(0.1088)
age×cl	−0.0653 ***	−0.0221 *	−0.1067 ***	−0.0728 ***	−0.1208 ***	−0.0261 *
	(0.0205)	(0.0128)	(0.0364)	(0.0243)	(0.0247)	(0.0155)
Control variables	Y	Y	Y	Y	Y	Y
N	220	209	180	171	200	190
R^2	0.9491		0.9294		0.9749	

Note: ***, **, and * indicate the significance at the 1%, 5%, and 10% levels.

4. Discussion

4.1. Synergy of Population Aging Trend and Carbon Reduction Targets

Since China entered the "aging" society later than developed countries, the aging of China is dominated by the "low elderly" [37,73]. When the population aging is at a low level, the overall mature working-age population is still relatively large, but the increase in the number of older workers will create a sense of crisis for enterprises to improve productivity due to the potential increase in employment costs [34]. At the same time, with the deepening of aging, social consumption tendency is gradually focused on the medical technology industry and consumer service sectors [74,75], which is conducive to promoting the optimization and upgrading of industrial structure. Thus, population aging will form a positive effect on regional carbon emission reduction.

4.2. Differentiation of the Contribution of Changes in the Quantity and Quality of the Labor Force Allocation to CEI

This research shows that human capital accumulation can play a role in reducing carbon emissions intensity. Because the increase in the level of education of individuals is more conducive to the diffusion of technological knowledge [33] and makes the productive skills of the labor force more specialized [28]. Moreover, the mastery of professional technology allows workers to have a higher awareness of environmental protection, and it can help them translate the theory of sustainability into production practice [35]. That is conducive to optimizing the allocation efficiency of production factors and promoting the R&D and application of clean production technologies.

For the regional Heterogeneity, human capital accumulation is significantly negatively correlated with CEI only in the eastern region (see model (2) in Table 9). This is partly since the talent education and technology R&D capability of the eastern region is in the leading position in China [33]. Compared with the central and western regions, the technology-intensive industries in the eastern region are larger, and the scale effect of increasing capital investment in technology research and development is obvious. The marginal cost of low-carbon process innovation is relatively lower, which can motivate enterprises to develop environmentally friendly technology rather than simply increasing energy inputs. On the other hand, as shown in Figure 3, this result is related to the brain drain in less developed regions in the context of the aging trend. The eastern regions are among the major population in-migration areas [38,39], and the corresponding talent concentration effect is more prominent, with human capital inputs can effectively being converted into innovative technological outputs [46].

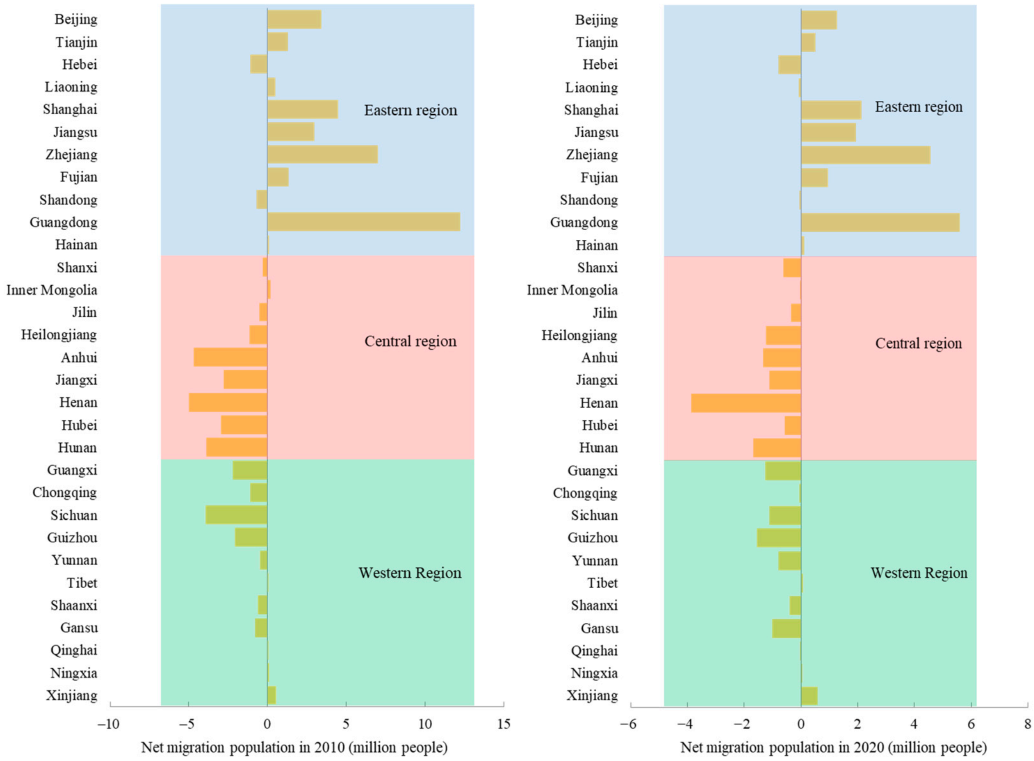

Figure 3. The net migration of the provincial population in China from 2010 to 2020.

On the contrary, the central and western regions are generally experiencing a net out-migration of the population, resulting in a serious brain drain [47]. Human capital accumulation cannot be used locally, so the investment in education cannot be transformed into a local green growth engine [43]. As human capital flows from the central and western regions to the eastern regions, the imbalance of sustainable development between regions is aggravated.

The structure of capital-labor endowment reflects the change in the quantity of labor, but its rise brings an increase in CEI. This is related to the fact that producers will replace labor with capital to reduce production costs, and the increase in capital input is usually accompanied by a rise in energy input [76]. Currently, China's industrial R&D level lags behind developed countries, and most capital-intensive industries rely on energy consumption to some extent [77]. The growth in the capital-labor ratio leads to an increase in the energy intensity of the industrial sectors, which becomes a barrier to developing a low-carbon economy.

4.3. Aging Limits the Emission Abatement Effect of Human Capital Accumulation

In China, the phenomenon of "aging" and "childlessness" coexist, and the number of older people rises while the growth of the youth population slows down [78]. Human capital accumulation is the driver of technological innovation, and the lower education level of the elderly weakens its contribution to low-carbon economic growth. The increase in the proportion of elderly also has a crowding-out effect on household human capital investment [19]. Influenced by the family planning policy in the 1980s, simultaneously taking up elderly support and child-rearing has become a major burden for young and middle-aged families in China [79]. As the aging trend deepens, the increased burden of elderly care will inevitably crowd out investment in education for the next generation [20], affecting the sustainable accumulation of human capital [21].

The advantage of the older workforce lies in the accumulated work experience and professional skills knowledge, while our findings show that this experience accumulation has not been effectively linked to low-carbon technological innovation. Even though aging may force firms to exploit their technological innovation potential to mitigate the negative impact of labor shortage, the accumulation of knowledge has not yet formed a mature scale effect, which to some extent, slows down the positive effect of social human capital.

4.4. Aging Mitigates Carbon Emissions Caused by Changes in the Capital-Labor Ratio

The rise in the capital-labor ratio is the use of other production factor inputs by firms to compensate for the labor gap. The gradual aging of the workforce force companies to use capital and technology factors to replace labor factors [31]. Labour-intensive industries are gradually transformed into capital and technology-intensive industries. Meanwhile, due to the endogenous needs of older people, the demand for high technology-level tertiary industries related to medical, health and life services will rise [74]. Thus, from both the supply and demand side, the aging population will help drive capital into technology-intensive industries to replace labor-intensive industries, decreasing the share of energy-dependent industries and thus curbing the growth of carbon emissions.

The eastern region benefits from its developed and complete industrial system [33]. In the context of the decline of labor-intensive industries, upgrading the demand structure of aging consumption and the local technological advantages make enterprises more inclined to inject capital into technology-intensive industries and consumer services. The central region's geographical advantages and mineral reserves make raw material processing and equipment manufacturing the dominant local industries [80]. When the number of laborers decreases, it is not conducive to the expansion of these labor-intensive industries. For the Western region, it has an exceptional development orientation. The western region is rich in natural and biodiversity resources, so the national strategy restricts industry over-expansion. With the decline of labor-intensive industries, capital investment is concentrated in the tertiary and high-end technology industries under the guidance of local policy [81]. This industrial transformation is conducive to low-carbon sustainable development.

4.5. Other Important Factors Affecting Carbon Emission Intensity

The advanced industrial structure is the main content of industrial upgrading. The growth of technology-intensive industries has knowledge spillover effects, which can feed the development of downstream industries and realize the upgrading of production processes [82]. The tertiary industry gradually eliminates the excess capacity of the former secondary industry, which helps to reduce unnecessary industrial pollution emissions.

The results of this study show that technological innovation is also a major factor contributing to the reduction of CEI. While reducing the marginal cost of products, the activities of technological innovation can stimulate more low-carbon clean technologies and their practical application [51], decreasing the energy consumption and carbon emissions per unit of output value in production. It can attenuate the negative impact of various production activities on the natural environment.

The significant positive correlation between gross regional product per capita and carbon emission intensity (see the model (3) in Table 7) means that China has not yet been able to break away from the crude economic growth, the scale of clean production is relatively limited, and carbon emissions from economic and social activities are still serious. Although the economy of the developed regions is gradually shifting to intensive economic growth driven by technological progress, the share of traditional industries that rely on high energy consumption remains high within the broader region [58]. The characteristics of resource endowments limit the industrial transformation of less developed regions [76], leading to constraints on low-carbon economic development.

This study supports that the environmental impact of FDI in China is more inclined to the "pollution sanctuary" effect. Since the intensity of environmental regulations in China is relatively lax, developed regions tend to transfer their industries with high resource dependence and low technological safety to China [67], resulting in pollution migration. Although foreign investment has a technology spillover effect, it is insufficient to compensate for the increased pollution intensity caused by the industrial transfer. Our research also shows that urbanization fails to drive carbon reduction, which is consistent with the results of related studies [83,84].

4.6. Policy Implications

This study shows a ripple effect among population aging, labor allocation and carbon emissions intensity. Population aging is not conducive to the carbon emission reduction effect of human capital accumulation. Therefore, the government should encourage enterprises and individuals to strengthen vocational education, rehire retired workers with high education, and fully exploit the technical potential of older workers [85]. It is also necessary to rationally allocate educational resources to reduce the cost of raising children. Although China has implemented the "two-child" policy, government departments still need to complement it with subsidies to reduce the burden on young and middle-aged families [78]. It is also urgent to raise the average income level of residents through industrial transformation and increased social welfare spending, which will help to relieve the pressure on families to support older people and educate their children. Suppose the accumulated knowledge and experience of older people can be reasonably combined with the young population's learning ability and advanced ideas. In that case, the sustainable development of the economy will be significantly enhanced.

GDP per capita, urbanization rate and foreign direct investment are strongly positively correlated with CEI. Therefore, the government still needs to actively promote the advanced transformation of industrial structure and promptly eliminate the backward production capacity of secondary industry, to reduce the carbon emission intensity per unit of output. In the process of population urbanization, the expansion of the production scale brought by the growing consumption demand is inevitable. It is necessary to improve the green consumption concept of residents and guide low-carbon green products into the consumption market with preferential policies or subsidies. The current FDI is not conducive to CEI reduction. The Chinese government needs to raise the entry threshold for foreign investment and screen foreign enterprises by strict environmental standards to prevent the transfer of pollution from developed countries. Local enterprises should also learn from the advanced clean production technologies of foreign companies to reduce the carbon emission rate of their products.

For the heterogeneity of economic development among regions, the virtuous cycle between human capital accumulation and low-carbon development exists only in developed eastern regions. It is essential to alleviate the brain drain from less developed regions. In central and western regions, tax breaks and subsidies for home purchase and residence are needed to enhance the willingness of high-end talents to reside locally [86]. In addition, there is a necessity for the government to guide the transition from labor-intensive industries to technology-intensive industries in the context of population aging. Green credit has been proven that is an important tool to guide green economic development through financial means [87]. Less developed regions should actively use this policy to encourage the conversion of corporate capital inputs into low-carbon technological outputs.

4.7. Limitations and Prospects

This study does have some limitations. Firstly, due to data limitations, it is unable to refine the gap between the number of older and younger workers within industrial sectors. Further quantification of specific labor numbers in different age groups is needed to clarify their impact on low-carbon growth. Secondly, this study fails to discuss the effect of different levels of aging because of data missing. Significant differences in personal abilities and lifestyle habits between older and younger seniors can lead to uncertainty in their impact on economic development. Therefore, expanding the dataset to refine the impact of different age groups of older people on social resource allocation and sustainable development is an important direction for future research.

5. Conclusions

This study analyzes the effects of population aging and labor force allocation on carbon emission intensity. The main findings are: (1) Population aging negatively correlates with regional carbon emission intensity. Human capital accumulation is an essential favorable factor for regional carbon emission reduction, and the rise of the capital-labor ratio intensifies energy consumption. (2) Population aging has a ripple effect on carbon emission intensity by regulating labor force allocation. The growth in the number of elderly hinders the carbon emission reduction effect of human capital accumulation but helps to promote capital investment in technology-intensive industries and improve energy utilization. (3) Human capital accumulation has a significant carbon-reducing effect only in the eastern region. Due to the dual effect of the aging trend and population migration, the brain drain in less developed regions is exacerbated, resulting in human capital accumulation in central and western regions that cannot form a virtuous cycle with local, sustainable development.

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