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Assessing the Impact of Rural Population Aging on China's AGTFP: A Mediation and Threshold Effect Analysis

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Abstract: In the context of the increasingly aging rural population in China, this study investigates the implications of this demographic shift on the nation's agricultural green total factor productivity (AGTFP). Utilizing panel data from 30 provinces spanning 2005 to 2019, the AGTFP was quantified employing the slacks-based measure (SBM)-global Malmquist-Luenberger (GML) model. The investigation employed a dynamic panel model, a mediation effect model, and a threshold effect model to elucidate the relationship between rural population aging and AGTFP. Additionally, the potential influence of labor transfer thresholds on this relationship was examined. It was found that: (a) AGTFP in China has exhibited a fluctuating yet ascending trajectory, with an average annual growth rate of 1.55%. The advancement of agricultural green technology has been identified as the primary driver of this growth. (b) The aging rural population significantly and positively influences AGTFP, with notable regional disparities. (c) The positive impact of rural aging on AGTFP has been facilitated through human capital accumulation, land transfer, and agricultural mechanization. (d) This beneficial effect of rural aging on AGTFP is moderated by a single threshold of labor transfer. These findings underscore the complex interplay between demographic trends and agricultural productivity, highlighting the necessity for tailored policies that accommodate the unique characteristics of rural aging in China.

Keywords: Rural population aging; Agricultural green total factor productivity; Slacks-based measure-global Malmquist-Luenberger; Mediation effect; Threshold effect

1. Introduction

As global living conditions improve, life expectancy increases, and fertility rates decline, population aging emerges as a pervasive challenge. This phenomenon is particularly pronounced in China, a nation with a substantial population base. In China's rural regions, the proportion of individuals aged 65 and above has markedly risen, from 7.35% in 2000 to 17.72% in 2020, as a share of the total rural populace. Such demographic shifts are poised to profoundly influence agricultural production, development, and transformation (Ren et al., 2023). Presently, China finds itself at a pivotal juncture, transitioning from traditional to high-quality agriculture. In this context, AGTFP stands as a pivotal metric and foundation for assessing high-quality agricultural progress. Enhancing AGTFP is imperative for fostering high-quality agricultural development (Chen & Gong, 2021; Liu et al., 2020). This study addresses critical queries: How does rural population aging impact the enhancement of AGTFP in Chinese agriculture? What mechanisms underlie this influence? Furthermore, does a threshold effect exist, triggered by the extent of labor transfer, impacting the relationship between rural aging and AGTFP growth? Addressing these questions is of theoretical and practical import, offering a scientific understanding of rural population aging's impacts and propelling high-quality agricultural development. To explore these dynamics, this paper utilizes a dynamic panel model to assess the impact of rural population aging, employs a mediation effect model to uncover underlying mechanisms, and applies a threshold effect model to further investigate these relationships.

The impact of rural population aging on agricultural output and its subsequent response has been a subject of considerable scholarly interest (Huang, 2016; Liu et al., 2023). Research findings on this impact have displayed inconsistency. Several studies posit that rural population aging significantly diminishes agricultural output. The reasoning suggests that aging leads to a decline in the labor force's physical strength and a consequent reduction in agricultural labor supply, directly impacting crop yields and labor productivity (Li et al., 2022; Liu et al., 2023; Jiang et al., 2021). For instance, Dudek & Pawowska (2022) observed that rural population aging hinders the adoption of new technologies and adversely affects agricultural labor productivity. Similarly, Liu et al. (2023), using data from Chinese rural surveys, concluded that rural population aging negatively influences the yield, profitability, and risk tolerance in fruit and vegetable production. Conversely, other studies argue that rural population aging does not necessarily lead to negative, and in some cases, even positive outcomes on agricultural output. This perspective is supported by two main arguments: firstly, the adoption of hiring labor practices and alterations in cropping structure serve as effective responses (Charlton & Taylor, 2016); secondly, the substitution of capital for labor and technological advancements in agriculture are posited to counterbalance the decline in labor productivity due to aging (Han et al., 2023; Huang, 2016; Liao et al., 2019; Qian et al., 2022).

Charlton & Taylor (2016) observed that U.S. farmers, faced with an aging population and labor hiring challenges, are inclined to substitute labor with machinery. This mechanization, however, varies according to different endowment characteristics. Farmers with larger landholdings tend to purchase agricultural machinery, whereas those with smaller landholdings opt for farm machinery socialization services (Qian et al., 2022; Zhang et al., 2017). Furthermore, the impact of rural population aging on agricultural land inheritance or transfer has garnered scholarly attention (Liu et al., 2023; Zou et al., 2018). In several developing countries, including China, where economic and social development is rapid, the younger generation in rural areas shows diminishing interest in small-scale, low-income agricultural production. The question of future land cultivation is increasingly scrutinized by government authorities (Huang, 2016; Teerawichitchainan et al., 2019; Jiang et al., 2021). Studies indicate that in scenarios where future generations are disengaged from agricultural production, older farmers are likely to lease their land to other agricultural entities, such as agricultural leading enterprises, village collectives, and cooperatives (Duesberg et al., 2017; Liu et al., 2023; Szymkowiak & Rhodes-Reese, 2022; Zhong et al., 2023). These new agricultural business entities, compared to the old farmers, possess higher levels of human capital, physical capital, agricultural technology, and larger scales of arable land. Their advantages in human resources, materials, technology, and scale are reflected in the pace and quality of agricultural economic development (Chancellor et al., 2021; Chen & Gong, 2021; Hamid & Wang, 2022; Séogo & Zahonogo, 2023).

It has been observed that the detrimental effects of rural population aging on agricultural output are being mitigated through various adaptive strategies. These include hiring workers, substituting labor with machinery, transferring land, scaling up arable land operations, optimizing agricultural business entities, and accumulating human capital. The culmination of these adaptive measures is evident in technological advancements and enhancements in agricultural total factor productivity (Giorgio et al., 2022; Li et al., 2022; Villacis et al., 2023). Scholarly focus has also been directed toward the influence of rural demographic characteristics on the adoption of agricultural technology or the growth of total factor productivity in agriculture (Pierotti et al., 2022; Tufa et al., 2022). For example, a study utilizing farm household and plot-level data in Malawi by Tufa et al. (2022) revealed that males are significantly more inclined to adopt agricultural technology compared to females, resulting in higher output efficiency. However, it is critical to acknowledge that increases in agricultural technological progress and total factor productivity do not necessarily account for environmental pollution issues arising during agricultural development (Chi, 2022; Fan et al., 2023; Liu et al., 2018). Presently, addressing agricultural land pollution, water pollution, and carbon emissions is paramount. The concept of green total factor productivity in agriculture gains a more comprehensive dimension when it integrates indicators reflecting environmental pollution, alongside traditional growth measures (Dong & Wang, 2023; Fang et al., 2021). In this context, this paper explores the impact of rural population aging on green total factor productivity growth in agriculture and examines the underlying mechanisms. Utilizing provincial-level panel data from China, this study measures China's AGTFP and constructs a dynamic panel model, a mediation effect model, and a threshold effect model. This comprehensive approach aims to scrutinize the influence of rural population aging on AGTFP. The objective is to establish a clear and systematic theoretical framework for analysis, providing decision-making references and policy insights into enhancing AGTFP amidst the deepening of rural population aging.

This paper endeavors to make several contributions to existing literature. Firstly, it aims to investigate the impact of rural population aging on the growth of AGTFP, and quantitatively assesses the direction and magnitude of this impact along with its regional variations in China. This assessment, utilizing provincial panel data, seeks to provide scientific references to deepen the understanding of the effects of rural population aging. Secondly, the mediation effects of agricultural mechanization, land transfer, and human capital accumulation are explored. This exploration aims to unveil the intricate relationship between rural population aging and AGTFP, thereby offering insights into expediting the enhancement of agricultural development quality. This analysis uniquely integrates rural population aging, AGTFP, rural human capital, land transfer, agricultural mechanization, and labor transfer into a singular analytical framework, shedding light on the mechanisms and threshold effects of rural population aging on AGTFP. Additionally, the SBM model in conjunction with the GML productivity index is employed to measure AGTFP.

The structure of the remainder of the paper is as follows: the second to the third sections detail the measurement of AGTFP in Chinese agriculture. The fourth section discusses the construction of the model. The fifth section presents an analysis and discussion of the empirical results. Finally, the sixth section outlines the conclusions and policy implications.

2. Theoretical Analysis and Hypothesis Formulation

This section presents a theoretical analysis and hypothesis formulation to delve into the impact of rural population aging on AGTFP.

2.1 Impact of Rural Population Aging on AGTFP

It is posited that rural population aging influences the allocation of production factors in agriculture, directly impacting AGTFP. A decline in agricultural labor supply, a direct consequence of rural population aging, leads to labor shortages and increased labor costs. Economic behavior theories suggest that farmers, as rational actors, respond to these labor constraints by substituting labor with capital, technology, and other factors. This substitution fosters a shift in agricultural production methods from labor-intensive to capital and technology-intensive approaches, thereby enhancing agricultural productivity and contributing to AGTFP growth.

Furthermore, the replacement of labor with capital and technology is likely to induce technological advancements in green agricultural practices. These advancements can reduce the reliance on chemical inputs such as fertilizers and pesticides, thereby diminishing agricultural environmental pollution. This, in turn, enhances the environmental and ecological benefits, further bolstering AGTFP. Moreover, rural population aging can lead to the withdrawal of older farmers from agricultural production, necessitating the transfer of land to more efficient producers. This transfer optimizes land factor allocation, improves land productivity, and thus promotes AGTFP growth. Consequently, rural population aging is theorized to trigger a reoptimization of production factors such as labor, physical capital, technology, and chemicals, leading to an increase in AGTFP. Based on these considerations, the following hypothesis is proposed:

Hypothesis 1: Rural population aging exerts a positive effect on AGTFP.

2.2 Theoretical Analysis of Regional Heterogeneity

This section conducts a theoretical analysis to understand the regional disparities in the impact of rural population aging on AGTFP across eastern, central, and western China. These regions exhibit stark differences in economic development levels and labor transfer degrees, necessitating a differentiated analysis. In central and western China, characterized by relatively underdeveloped economies, the levels of urbanization and industrialization are lower. Consequently, the proportion of rural labor transitioning from agricultural to non-agricultural sectors remains minimal. This low degree of labor transfer results in a comparatively abundant agricultural labor force. The slowed migration of rural labor in these regions mitigates the man-land conflict, thereby enhancing land productivity and reducing pressure on rural resources and the environment. This dynamic contributes to the growth of AGTFP. Furthermore, labor migration to industrial sectors spurs agricultural mechanization and boosts agricultural productivity.

The integration of farmers into the modern sector not only facilitates land transfer but also results in knowledge spillovers. Consequently, rural population aging in these regions positively influences AGTFP, contributing to its growth through mechanisms like human capital accumulation, land transfer, and agricultural mechanization. Conversely, in the economically advanced eastern region, a higher degree of labor transfer is observed. The modern sector absorbs a substantial number of agricultural laborers, leading to rural population aging. In this context, the negative impacts of aging on the agricultural and rural system are not entirely offset by the substitution of capital and technological factors. Therefore, in the eastern region, rural population aging does not positively influence AGTFP growth and may even inhibit it. Based on this analysis, the following hypothesis is formulated:

Hypothesis 2: The impact of rural population aging on AGTFP exhibits significant regional heterogeneity. In the central and western regions, rural population aging fosters AGTFP growth, whereas in the eastern region, it inhibits such growth.

2.3 Theoretical Analyses of Mediating Effect

This segment delves into the mechanisms underlying the impact of rural population aging on AGTFP, focusing on three dimensions: human capital accumulation, land transfer, and agricultural mechanization.

2.3.1 The effects of human capital accumulation due to rural population aging

Firstly, it is posited that rural population aging contributes to the accumulation of rural human capital. Research indicates that an aging rural population, characterized by increased life expectancy, enhances the health human capital of agricultural workers. Concurrently, this demographic shift extends educational opportunities for the younger generation, thereby augmenting the total human capital in rural areas. Furthermore, based on the theory of learning by doing, prolonged labor engagement results in accumulated agricultural production experience, enhancing human capital. This experience also generates spillover effects and positive externalities, elevating the per capita rural capital stock. Additionally, the labor supply decrease and labor price increase, consequent to aging, incentivize rural workers to invest more in human capital for higher returns, thus amplifying the accumulation of rural human capital.

Secondly, the accumulation of rural human capital significantly enhances AGTFP. The accumulation of human capital can propel the advancement of green technology in agriculture, thus augmenting AGTFP. Endogenous growth theory suggests that human capital accumulation fosters economic growth by catalyzing technological progress. The enhanced level of rural human capital and per capita capital stock facilitates technological innovation and progress. The accumulation of rural human capital also improves the overall technology absorption capacity of agricultural workers through its spillover effect, thereby promoting AGTFP growth. Additionally, higher levels of human capital in agricultural workers, correlated with superior organizational and management abilities and efficient resource utilization, align with the principles of green agriculture. This alignment improves the efficiency of green resource allocation in agriculture, further boosting AGTFP.

2.3.2 Land transfer effects due to rural population aging

This subsection explores how rural population aging influences the transfer of agricultural land and its subsequent effects on AGTFP. Firstly, an aging rural population, characterized by an increasing old-age labor force and a diminishing young labor force, leads to a shortage of labor for family agricultural production. This shortage often results in the transfer of land through various forms, thereby accelerating rural land transfer. Consequently, rural population aging indirectly facilitates the optimization of land resource allocation among farming households.

Secondly, the transfer of land plays a pivotal role in promoting moderate-scale operations, which in turn enhances the total factor productivity of green agriculture. Farms that acquire transferred land, such as family farms or large professional households, typically possess advanced production equipment and technologies. This endowment favors appropriate scale operations, enabling large-scale intensive production, which reduces the cost and pollution per agricultural product. Furthermore, these entities are generally more inclined to adopt and learn advanced green production technologies, which enhances agricultural output efficiency and environmental benefits, thereby improving AGTFP. The scaling up of operations post-land transfer also improves the efficiency of agricultural resource allocation, including land, capital, and labor. Scientific input ratios and reduced reliance on chemical fertilizers and pesticides enhance green technology efficiency, contributing to the improvement of AGTFP. Additionally, the large-scale operations fostered by land transfer promote specialization and division of labor in agriculture, further enhancing green technology efficiency and AGTFP growth.

2.3.3 Agricultural mechanization effects due to rural population aging

This section assesses how an aging rural population impacts agricultural mechanization and, consequently, AGTFP. Firstly, rural population aging facilitates the enhancement of agricultural mechanization levels. Faced with declining labor supply and rising labor costs, farmers, acting rationally, increasingly adopt agricultural machinery as a substitute for labor. Additionally, they are likely to increase reliance on outsourced agricultural mechanization and socialized agricultural machinery services, mitigating the adverse impacts of labor shortages on agricultural production.

Secondly, elevated levels of agricultural mechanization are instrumental in boosting AGTFP. The progression of agricultural mechanization, characterized by the widespread adoption of agricultural machinery and related technologies, permeates all stages of agricultural production, from plowing to harvesting. This advancement strengthens agriculture's capacity to withstand disasters and risks, thereby enhancing agricultural output potential. Furthermore, increased investment in agricultural machinery spurs a new wave of technological research, development, and innovation, further accelerating agricultural technological progress and, in turn, fostering AGTFP growth. Moreover, agricultural mechanization encourages specialized production and division of labor in agriculture, particularly through cross-regional operation of agricultural machinery, which significantly improves agricultural production efficiency and AGTFP. Additionally, the development of agricultural mechanization generates spatial spillover effects, positively influencing agricultural productivity in adjacent regions and enhancing overall regional agricultural production efficiency. Lastly, agricultural mechanization supports the advancement of eco-friendly agricultural technologies, reducing carbon emissions and environmental pollution, thereby contributing to the growth of AGTFP. In light of the aforementioned analysis, the following hypotheses are proposed:

Hypothesis 3: Rural population aging enhances AGTFP through the effect of human capital accumulation.

Hypothesis 4: Rural population aging boosts AGTFP through the effects of land transfer.

Hypothesis 5: Rural population aging augments AGTFP through the effects of agricultural mechanization.

2.4 Theoretical Analysis of the Threshold Effect

This segment seeks to explore the varying impact of rural population aging on AGTFP under different degrees of labor transfer. Since the implementation of the reform and opening up policy, substantial rural labor migration to urban and non-agricultural sectors has catalyzed China's economic growth and urbanization. Such labor transfers, while accelerating rural aging, also induce shifts in the allocation of agricultural production factors, affecting AGTFP. The examination here delves into whether varying degrees of labor migration modulate the impact of rural aging on AGTFP.

It is hypothesized that, within a certain threshold, rural population aging exerts a positive influence on AGTFP. This positive effect is attributed to the optimization of the rural population structure due to labor outflow. Historically, China's rural areas have been characterized by overpopulation and surplus labor, resulting in limited per capita resource holdings and prominent issues of diminishing marginal land returns. The migration of surplus rural labor, therefore, helps to alleviate the population-land contradiction, enhance land productivity, and reduce the strain on rural resources and the environment, thereby improving AGTFP. Additionally, following the principles of Lewis's dual economy theory, labor transfer enhances the output and capital accumulation of the modern sector, thereby fostering industrial development. This industrial growth, in turn, introduces mechanized production to agriculture, increasing agricultural productivity. Concurrently, the integration of farmers into non-agricultural sectors elevates their income and credit capacity, which encourages further investment in agricultural machinery and facilitates land transfer, both from income and substitution effects.

Initially, it is observed that rural labor migration to urban areas facilitates knowledge spillovers and enhances human capital accumulation, positively contributing to AGTFP. Within certain limits, labor force migration fosters AGTFP growth due to rural population aging. However, crossing a threshold level in agricultural labor transfer alters this dynamic. As industrialization and urbanization accelerate, not only is surplus rural labor transferred, but also labor crucial for agricultural development, leading to a pronounced shortage of rural labor and an intensified aging rural population. This shift may result in a lack of successors in agricultural production. Furthermore, to mitigate the potential reduction in agricultural output and efficiency loss due to aging, farmers may increase the use of chemical inputs like fertilizers and pesticides. This practice exacerbates agricultural surface pollution and generates negative externalities in the rural environment, harming agricultural environmental efficiency. Additionally, the substitution of capital factors such as fertilizers, pesticides, and machinery carries the risk of distortion and mismatch in factor allocation, potentially reducing agroecological efficiency and agricultural output. Thus, beyond a certain level of labor migration, the positive influence of rural population aging on AGTFP may diminish or cease. In light of this analysis, the following hypothesis is proposed:

Hypothesis 6: The positive impact of rural population aging on AGTFP is contingent upon a threshold variable of labor migration. This impact remains significant when the degree of labor migration is below the threshold value but dissipates once the threshold is exceeded.

3. Measuring AGTFP in China

3.1 Research Methodology

The measurement of AGTFP in 30 Chinese provinces (excluding Hong Kong, Macao, Taiwan, and Tibet) for the years 2005 to 2019 is conducted using the SBM model, incorporating unexpected outputs, in conjunction with the GML productivity index.

Initially, each province is considered as a production decision unit with m inputs, s_1 desired outputs, and s_2 undesired outputs. These units are represented by vectors $x \in R^m$, $y \in R^{s_1}$, $b \in R^{s_2}$, and matrices X, Y, and B are defined as $X = [x_1, \dots, x_n] \in R^{m\times n}$, $Y = [y_1, \dots, y_n] \in R^{s_1\times n}$, and $B = [b_1, \dots, b_n] \in R^{s_2\times n}$, where $x_i > 0$, $y_i > 0$, and $b_i > 0$. The production possibility set is denoted as $P = \{(x, y, b) | x \geq X\lambda, y \leq Y\lambda, b \geq B\lambda, \lambda \geq 0\}$, where λ is the weight vector. The returns to scale are variable if $\lambda \geq 0$ and $\sum \lambda = 1$; otherwise, they are constant. Given the characteristics of Chinese agriculture, which typically exhibit constant returns to scale, the SBM model is adapted as follows:

$$\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^+}{y_{r0}} + \sum_{r=1}^{s_2}\frac{s_r^b}{b_{r0}}\right)} \quad (1)$$

$$s.t.\begin{cases} x_0 = X\lambda + s^- \\ y_0 = Y\lambda - s^+ \\ b_0 = B\lambda + s^b \\ s^- \geq 0, s^+ \geq 0, s^b \geq 0, \lambda \geq 0 \end{cases} \quad (2)$$

where, s^-, s^+, and s^b denote slack variables for inputs, desired outputs, and undesired outputs, respectively. The function ρ^* is strictly decreasing in relation to s^-, s^+, and s^b. Efficiency is indicated by $\rho^* = 1$, i.e., when $s^- = s^+ = s^b = 0$, the decision unit is efficient. An efficiency score lower than 1, i.e., $0 \le \rho^* \le 1$, suggests inefficiency, indicating a need for improvement in inputs and outputs.

Subsequently, the GML productivity index is constructed based on the SBM model:

$$GML_t^{t+1} = \frac{1+\overrightarrow{D_0^G}\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\overrightarrow{D_0^G}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)} \tag{3}$$

With constant returns to scale, the GML index is decomposed into the Agricultural Green Technological Efficiency (AGEC) index and the Agricultural Green Technological Progress (AGTC) index:

$$GML = AGEC \times AGTC \tag{4}$$

$$AGEC = \frac{1+\overrightarrow{D_0^t}\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\overrightarrow{D_0^{t+1}}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)} \tag{5}$$

$$AGTC = \frac{\dfrac{1+\overrightarrow{D_0^G}\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\overrightarrow{D_0^t}\left(x^t, y^t, b^t; y^t, -b^t\right)}}{\dfrac{1+\overrightarrow{D_0^G}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)}{1+\overrightarrow{D_0^{t+1}}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)}} \tag{6}$$

Values of GML, AGEC, and AGTC greater than 1 indicate growth in AGTFP, technological progress in green agriculture, and improvement in AGEC, respectively, from t period to $t+1$ period.

3.2 Selection and Processing of Indicators

For the purpose of this research, data from 30 provinces in China, with the exclusion of Hong Kong, Macao, Taiwan, and Tibet, spanning the years 2005-2019, have been utilized. The data sources include the China Rural Statistical Yearbook, China Agricultural Statistics, China Statistical Yearbook, and the statistical yearbooks of each province.

Table 1. Agricultural carbon sources and emission factors

Carbon Source	Carbon Emission Factor
Fertilizer	0.8956 kg-kg^{-1}
Pesticides	4.9341 kg-kg^{-1}
Agro-film	5.18 kg-kg^{-1}
Diesel oil	0.5927 kg-kg^{-1}
Turning the soil	312.6 kg-km^{-2}
Agricultural irrigation	20.476 kg/hm^2

The specific indicators employed in this analysis are as follows:

- Inputs: These comprise various components. Land inputs are gauged using the total sown area of crops. Labor inputs are assessed by the number of individuals employed in the primary sector. Mechanical power inputs are determined through the total power of agricultural machinery. Fertilizer inputs are quantified using the amount of agricultural fertilizer applied. Agricultural film inputs are measured by the amount of agricultural plastic film used. Pesticide inputs are calculated based on the quantity of pesticide utilized. Finally, irrigation inputs are evaluated using the actual effective irrigated area.
- Expected output: The gross output value of agriculture, forestry, animal husbandry, and fishery for each province in the base year of 2005 is selected as a measure of expected output.
- Undesired output: Agricultural carbon emissions represent the undesired output. These emissions are calculated using methodologies from the Intergovernmental Panel on Climate Change (IPCC) study, as follows:

$$AE = \sum AE_i = \sum AT_i \times \delta_i \tag{7}$$

where, AE denotes the total agricultural carbon emissions, AT_i represents the emissions from each carbon source, and δ_i is the emission coefficient for each carbon source. The emission coefficients for various carbon sources in agriculture are detailed in Table 1.

3.3 Analysis of Measurement Results

Utilizing the SBM model integrated with the GML index, the output-oriented GML productivity index at constant returns to scale was computed for China's agriculture. Maxdea software facilitated this measurement.

The temporal evolution of China's AGTFP was then analyzed in Table 2. It was observed that AGTFP exhibited a fluctuating yet upward trend during 2005-2019. The average AGTFP was calculated at 1.0155, translating to an average annual growth of only 1.55%. Specifically, AGTFP growth was variable from 2005 to 2009; it stabilized between 2009 and 2014; experienced a slight decline in the growth rate during 2014-2015; and then accelerated from 2015-2019, with an average annual growth of 2.89%. This pattern indicates a recent trend towards faster growth in AGTFP. However, it is important to note that the overall level of China's AGTFP is still relatively low, signifying a long journey towards high-quality agricultural development. Further decomposition of AGTFP growth revealed that the primary contributor was agricultural green technology progress. The average value of the green technology progress index stood at 1.0193, with an average annual growth of 1.93%, contributing 124.52% to AGTFP growth. This is attributed to China's consistent focus on agricultural technological innovation and mechanization. Conversely, the agricultural green technical efficiency index averaged at 0.9963, with a growth rate of -0.37%. This indicates that while agricultural technological progress propels AGTFP growth, agricultural green technical efficiency tends to hinder it. Figure 1 illustrates that the trend in China's AGTFP index closely aligns with that of the AGTC index, further substantiating the driver role of green technological progress in AGTFP growth.

Table 2. Green total factor productivity index and its decomposition in Chinese agriculture, 2005-2019

Time	Green Total Factor Productivity Index for Agriculture	Green Technology Efficiency Index	Green Technology Progress Index
2005-2006	1.0082	0.9960	1.0123
2006-2007	1.0000	0.9957	1.0042
2007-2008	1.0092	1.0165	0.9928
2008-2009	0.9991	0.9959	1.0032
2009-2010	1.0030	0.9957	1.0073
2010-2011	1.0060	0.9973	1.0087
2011-2012	1.0098	0.9846	1.0256
2012-2013	1.0185	0.9793	1.0400
2013-2014	1.0187	0.9835	1.0358
2014-2015	1.0132	1.0171	0.9961
2015-2016	1.0277	1.0151	1.0124
2016-2017	1.0273	0.9971	1.0303
2017-2018	1.0432	0.9720	1.0732
2018-2019	1.0336	1.0029	1.0306
National average	1.0155	0.9963	1.0193

Note: The average value is the geometric mean, the same as below.

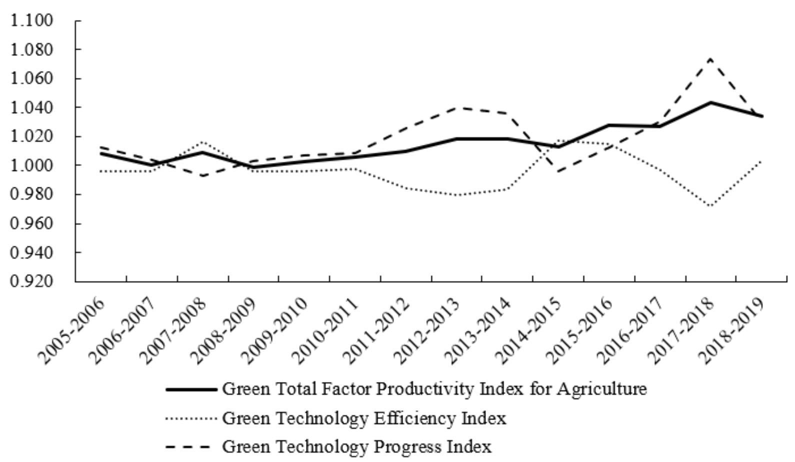

Figure 1. Trend in China's AGTFP index, 2005-2019

An assessment of the spatial variations in China's AGTFP over the period 2005-2019 has been conducted (Table 3). This analysis utilized data to discern interprovincial and regional disparities in AGTFP. At the interprovincial level, it was noted that, with the exception of Shanghai and Inner Mongolia, all other provinces exhibited an increase in AGTFP. Tianjin experienced the most rapid growth, with an average annual increase of 3.27%, followed by Shandong, Hebei, Anhui, and Shanxi. Shandong showed the highest growth in green technical efficiency. However, it was observed that 76.67% of the provinces either had zero or negative growth in green technical efficiency, although all provinces demonstrated positive growth in the green technical progress index. The decline in green technical efficiency in most provinces counterbalances the advances in green technology, suggesting that the primary constraint to AGTFP growth in Chinese agriculture is the stagnation in green technology efficiency. At the regional level, AGTFP growth during 2005-2019 was characterized by the highest rates in the central region, followed by the eastern and western regions, with average annual growth rates of 1.85%, 1.59%, and 1.28%, respectively. The eastern region led in the improvement of green technology efficiency, while the western region showed the fastest progress in green technology. Despite the western region's economic backwardness, the introduction of advanced agricultural technologies facilitated rapid learning and dissemination, leading to swift progress in green technology. However, due to inherent limitations in natural resources, infrastructure deficits, and lower organizational and management levels in western agricultural conditions, improvements in agricultural green technology efficiency were constrained, offsetting some of the benefits of technological progress. Consequently, the western region has experienced the slowest growth in AGTFP.

Table 3. Spatial variations in China's AGTFP (2005-2019)

Provinces	Green Total Factor Productivity Index for Agriculture	Green Technology Efficiency Index	Green Technology Progress Index
Tianjin	1.0327	1.0000	1.0327
Shandong	1.0323	1.0140	1.0180
Hebei	1.0290	1.0070	1.0219
Anhui	1.0231	1.0002	1.0229
Shanxi	1.0230	0.9977	1.0254
Jiangxi	1.0224	1.0044	1.0179
Hubei	1.0213	1.0099	1.0114
Gansu	1.0211	0.9956	1.0256
Guizhou	1.0207	0.9994	1.0213
Yunnan	1.0205	1.0010	1.0195
Fujian	1.0186	1.0074	1.0112
Heilongjiang	1.0180	0.9984	1.0196
Henan	1.0166	0.9980	1.0186
Ningxia	1.0159	0.9736	1.0435
Hunan	1.0156	0.9975	1.0182
Chongqing	1.0155	0.9993	1.0162
Liaoning	1.0153	0.9969	1.0184
Beijing	1.0137	1.0000	1.0137
Jiangsu	1.0131	0.9964	1.0168
Guangdong	1.0123	1.0000	1.0123
Hainan	1.0115	1.0000	1.0115
Guangxi	1.0113	0.9994	1.0119
Shaanxi	1.0113	0.9770	1.0351
Zhejiang	1.0112	0.9970	1.0143
Sichuan	1.0112	0.9918	1.0196
Qinghai	1.0109	1.0000	1.0109
Jilin	1.0083	0.9917	1.0168
Xinjiang	1.0042	0.9860	1.0185
Inner Mongolia	0.9983	0.9670	1.0324
Shanghai	0.9857	0.9826	1.0031
Eastern average	1.0159	1.0001	1.0158
Central average	1.0185	0.9997	1.0189
Western average	1.0128	0.9899	1.0231
National average	1.0155	0.9963	1.0193

The analysis further extends to examining the varying dynamics of AGTFP growth across China's eastern, central, and western regions. In the economically advanced eastern region, the effectiveness of green resource allocation, the sophistication of organization and management, and the degree of marketization in intensive scale operations surpass those in the central and western regions. Consequently, the improvement in green technology efficiency is more rapid in the east. However, given the region's advanced economic and technological status, significant further technological advancements and breakthroughs are challenging, leading to relatively slower progress in green technology. This, in turn, tempers the growth rate of AGTFP in the eastern region. Contrastingly, the central region, though economically trailing behind the eastern region, benefits from a 'catch-up' advantage. Upon the introduction of advanced agricultural green production technologies, rapid dissemination and adoption occur, resulting in a higher green technology progress rate compared to the east. The central region, characterized by its status as a major agricultural province with more abundant agricultural resources, exhibits stronger resource allocation and organizational and management capabilities than the west. This leads to a quicker improvement in green technology efficiency in the central region, making it the region with the fastest AGTFP growth. Moreover, while the eastern region achieves a dual drive of agricultural green technology efficiency and progress, the central and western regions predominantly rely on the singular momentum of green technology progress. Therefore, these regions should not only focus on accelerating agricultural green technology innovation but also on enhancing soft capabilities such as resource allocation efficiency and organizational management. Such improvements are crucial for advancing green technology efficiency and, subsequently, fostering AGTFP growth.

4. Modeling

4.1 Model Construction

4.1.1 Dynamic panel modeling

To explore the impact of rural population aging on AGTFP, a dynamic panel model, informed by the preceding theoretical analysis, is developed:

$$agtf\ p_{i,t} = \alpha + Bold_{i,t} + \eta X_{i,t} + \mu_i + \varepsilon_{i,t} \tag{8}$$

where, i represents the region, t the year, and $agtfp$ AGTFP. The constant term is denoted by α, while old represents rural population aging. The term X comprises a series of control variables, encompassing the disaster rate, openness to the outside world, agricultural structure, industrialization, and others. The variable μ reflects individual fixed effects, and ε is the random error term.

Acknowledging the continuity characteristic of AGTFP, a model incorporating the first-order lag term of AGTFP is established, based on Eq. (8):

$$agtf\ p_{i,t} = \alpha + \beta_0\ agtfp_{i,t-1} + \beta_1 old_{i,t} + \varpi X_{i,t} + \mu_i + \varepsilon_{i,t} \tag{9}$$

where, $agtfp_{i,t-1}$ signifies the first-order lag term of AGTFP, with other variables consistent with Eq. (8). Given the presence of endogeneity, the two-step SYS-GMM method is employed for the estimation of Eq. (9).

4.1.2 Mediation effect modeling

To ascertain if human capital accumulation, land transfer, and agricultural mechanization significantly mediate the relationship between rural population aging and AGTFP, a mediation effect model is constructed:

$$agtf\ p_{i,t} = \omega_{10} + \omega_{11} old_{i,t} + \omega_{12} X_{i,t} + \mu_i + \varepsilon_{i,t} \tag{10}$$

$$M_{i,t} = \omega_{20} + \omega_{21} old_{i,t} + \omega_{22} X_{i,t} + \mu_i + \varepsilon_{i,t} \tag{11}$$

$$agtf\ \mathrm{p}_{i,t} = \omega_{30} + \omega_{31} old_{i,t} + \omega_{32} M_{i,t} + \omega_{33} X_{i,t} + \mu_i + \varepsilon_{i,t} \tag{12}$$

where, $M_{i,t}$ denotes the mediating variables, including agricultural mechanization (*pmachine*), land transfer (*ptransfer*), and human capital accumulation (*education*). The stepwise regression method is applied to test the mediating effects, and the bootstrap method is utilized for further verification.

4.1.3 Threshold effect modeling

Investigating whether the impact of rural population aging on AGTFP is influenced by the threshold variable of labor migration, a panel threshold model is structured, drawing upon Hansen's approach:

$$agtf\ p_{i,t} = \phi_0 + \gamma_1 old_{i,t} I\left(q_{i,t} \le \tau\right) + \gamma_{2old} I\left(q_{i,t} > \tau\right) + \theta X_{i,t} + u_i + e_{i,t} \tag{13}$$

To accommodate potential multiple thresholds, a multi-threshold panel model is also formulated:

$$agtf\ p_{i,t} = \phi_0 + \gamma_1\ \mathrm{old}_{i,t} I\left(q_{i,t} \le \tau_1\right) + \gamma_2\ \mathrm{old}_{i,t} I\left(\tau_1 < q_{i,t} \le \tau_2\right) + \cdots + \gamma_n\ \mathrm{old}_{i,t} I\left(\tau_{n-1} < q_{i,t} \le \tau_n\right) + \gamma_{n+1}\ \mathrm{old}_{i,t} I\left(q_{i,t} > \tau_n\right) + \theta X_{i,t} + u_i + e_{i,t} \tag{14}$$

where, $q_{i,t}$ represents the threshold variable, τ the threshold value, and $I(\cdot)$ the indicator function, where $I = 1$ is applied if the condition in parentheses is satisfied, and $I = 0$ otherwise.

4.2 Data Sources and Variable Selection

4.2.1 Data sources

The research utilizes panel data from 30 provinces in China, excluding Hong Kong, Macao, Taiwan, and Tibet, for the period from 2005 to 2019. The sources of this data include the China Rural Statistical Yearbook, the China Demographic Statistical Yearbook, the China Population and Employment Statistical Yearbook, the China Statistical Yearbook, and the China Rural Business Management Statistical Yearbook, in addition to the statistical yearbooks of each individual province. In instances of missing data, specifically regarding areas of crop damage in certain provinces, linear interpolation methods were employed to estimate and fill in the missing values.

Table 4. Descriptive statistics of variables

Variable Type	Variable Name	Average Value	(Statistics) Standard Deviation	Minimum Value	Maximum Value
Explanatory variable	AGTFP	1.0747	0.1217	0.7880	1.5688
Core explanatory variable	Rural population aging	0.1080	0.0317	0.0502	0.2293
	Agricultural mechanization	1408.5560	1061.5710	0.4225	5508.5760
Intermediary variable	Land transfer	569.5393	852.8112	0.0326	5679.8900
	Human capital accumulation	7.6260	0.6364	5.4494	9.6974
Threshold variable	Labor force transfer	0.3617	0.1479	0.0296	0.6944
	Disaster rate	0.2042	0.1468	0.0059	0.9356
	Economic opening rate	0.3146	0.3665	0.0128	1.7113
Control variable	Agricultural structure	0.5101	0.0886	0.3223	0.7851
	Industrialization	0.4311	0.0822	0.1599	0.6196

4.2.2 Selection of variables

The following variables were selected for analysis:

- Explained variable: AGTFP (*agtfp*). The GML index, initially a chained index (previous year = 100), has been transformed into a cumulative growth index, using 2005 as the base year (2005 = 100), to reflect cumulative changes in AGTFP.
- Core explanatory variable: Rural population aging (*old*) is quantified as the proportion of the rural population aged over 65 to the total rural population.
- Mediating variables: Human capital accumulation (*education*) is measured as average years of education, with different education levels assigned specific years. Land Transfer (*ptransfer*) is represented by the per capita family contracted arable land transfer total area (mu/person). Agricultural mechanization (*pmachine*) is gauged using the total power of agricultural machinery per capita (kW/person).
- Threshold variable: Labor transfer (*labortransfer*). Following Mathieu-Clarke law and Lewis's dual economy theory, the proportion of the agricultural labor force in the total labor force is utilized as a proxy for labor force transfer. The declining trend in the proportion of the agricultural labor force, relative to the total labor force, is posited to mirror the broader trend of labor migration within China. Consequently, it is adjudged more appropriate to utilize the proportion of the agricultural labor force as a proxy variable to represent labor migration. The metric for the agricultural labor force is thus expressed in terms of employment figures within the primary industry, while the total labor force is quantified by the cumulative employment numbers in the tertiary industry.
- Control variables: Disaster rate (*Disaster*), calculated as the proportion of crop-affected area to the total sown area of crops. Agricultural Structure (*planting*), measured by the proportion of the planting industry's output value to the total output value of agriculture, forestry, animal husbandry, and fishery. Industrialization (*industry*), represented by the proportion of the value added of the secondary industry to the regional GDP. Economic opening rate (*open*), indicated by the proportion of each province's total import and export value to its GDP, adjusted by the annual average exchange rate of RMB against the US dollar. Financial support for agriculture (*finance*), expressed as the proportion of financial expenditure on agriculture to total financial expenditure. Income distribution (*distribution*), measured by the ratio of urban residents' disposable income per capita to rural residents' disposable income per capita.

The statistical characteristics of these variables are summarized in Table 4.

5. Empirical Analysis

5.1 Panel Data Tests

To address the issue of heteroscedasticity, logarithmic transformation was applied to the variables *pmachine*, *ptransfer*, and *education*. Additionally, to eliminate the risk of pseudoregression, panel unit root tests and multiple covariance tests were conducted for each variable. A range of methods, including the Levin, Lin & Chu (LLC), Im, Pesaran & Shin (IPS), Fisher-Augmented Dickey-Fuller (Fisher-ADF), and Fisher-Phillips-Perron (Fisher-PP) tests, were employed to assess the stationarity of each variable. A variable was deemed stationary if it passed at least two of these tests simultaneously. The results indicated that all variables were stationary, having passed the LLC, Fisher-ADF, and Fisher-PP tests at the 1% significance level. Furthermore, the variance inflation factor (VIF) for each variable was examined to rule out multicollinearity concerns. The VIF values ranged between 1.34 and 4.98, with the maximum VIF of 4.98 significantly below the threshold of 10. This confirms the absence of multicollinearity issues in the data set.

5.2 Benchmark Regression

5.2.1 Benchmark regression results

The estimation of Eq. (9) was carried out using the two-step System-Gaussian Mixture Model (SYS-GMM) method, and the results are presented in Table 5. This table also includes the outcomes of the fixed effects (FE) estimation and the mixed ordinary least squares (OLS) estimation for comparison. The results from column (1) of Table 5 reveal that the p-value for the AR (1) test is 0.012, rejecting the null hypothesis, and the p-value for the AR (2) test is 0.774, supporting the null hypothesis. This indicates the absence of autocorrelation in the model and suggests that the endogeneity problem has been addressed effectively. Furthermore, the Hansen test results confirm the validity of the instrumental variables, including lagged terms of *agtfp*, *planting*, *open*, *disaster*, and industry variables. The consistency and validity of the two-step SYS-GMM estimates are further corroborated when comparing these results to the FE estimation in column (2) and the mixed OLS estimation in column (3). The estimated value of the first-order lag term of *agtfp* in the SYS-GMM (1.071) lies between the FE estimation (0.966) and the OLS estimation (1.077), implying robustness and validity of the SYS-GMM estimation. The significance of the first-order lagged term of *agtfp* indicates that current period's AGTFP is influenced by the previous period's AGTFP.

Using the SYS-GMM estimation results, the estimated coefficient of rural population aging is 0.283, significant at the 1% level. This suggests that rural population aging significantly and positively impacts AGTFP, thereby confirming Hypothesis 1.

Table 5. Estimated results of the impact of rural population aging on AGTFP

Variant	**Two-Step SYS-GMM (1)**	**FE (2)**	**OL Sm (3)**	**FE (4)**
L.agtfp	1.071***	0.966***	1.077***	
	(0.044)	(0.034)	(0.023)	
old	0.283***	0.418***	0.046	2.095***
	(0.108)	(0.134)	(0.070)	(0.534)
disaster	-0.025	-0.045**	-0.037**	-0.136***
	(0.021)	(0.021)	(0.016)	(0.040)
open	0.002	0.019	-0.013**	0.037
	(0.021)	(0.018)	(0.006)	(0.107)
planting	0.117*	0.022	0.003	-0.130
	(0.063)	(0.049)	(0.022)	(0.198)
industry	0.004	-0.128**	-0.015	-0.709***
	(0.067)	(0.049)	(0.024)	(0.216)
Constant term (math.)	-0.147*	0.055	-0.053*	1.236***
	(0.079)	(0.053)	(0.030)	(0.146)
N	420	420	420	450
Adj-R^2		0.906	0.935	0.499 4
Wald value/F value	280152.4	630.5	885.0	18.49
p value for AR (1) test	0.012			
p value for AR (2) test	0.774			
Hansen's test p value	1.000			

Note: Standard errors are in parentheses and *, ** and *** represent 10%, 5% and 1% significance levels, respectively. Same as below.

5.2.2 Robustness tests

To further substantiate the robustness of the findings, two additional tests were conducted. Firstly, an alternative measure for the core explanatory variable, rural population aging, was employed. Instead of the original metric, the elderly population dependency ratio was used, defined as the ratio of the rural population aged 65 and over to the population aged 15-64. The two-step SYS-GMM method's estimation results, presented in column (1) of Table 6, successfully passed the AR (1) and AR (2) tests, as well as the Hansen test, indicating the model's freedom from autocorrelation and endogeneity issues. The significance of the first-order lagged term of *agtfp*, with an estimated coefficient of 1.071, further validates the robustness and reliability of the two-step SYS-GMM method. The elderly population dependency ratio's estimated coefficient of 0.140, significant at the 5% level, corroborates the positive influence of rural population aging on AGTFP, reinforcing the initial results.

Secondly, the one-step SYS-GMM estimation was applied to address the potential downward bias in the asymptotic standard error of the two-step SYS-GMM estimator in finite samples. The results, shown in column (4) of Table 6, passed the AR (1), AR (2), and Hansen tests, with the estimated coefficients on rural population aging remaining positive and significant at the 5% level. The estimated coefficient of the first-order lagged term of *agtfp* (1.057) falls between the FE estimate (0.966) and the OLS estimate (1.077), underscoring the robustness of the one-step SYS-GMM estimation. These findings further substantiate the significant positive impact of rural population aging on AGTFP.

Table 6. Robustness tests

Variant	Two-Step SYS-GMM	FE	OLS	One-Step SYS-GMM
	(1)	(2)	(3)	(4)
L.agtfp	1.071***	0.991***	1.081***	1.057***
	(0.048)	(0.029)	(0.021)	(0.032)
old	0.140**	0.024	0.002	0.308***
	(0.070)	(0.020)	(0.013)	(0.112)
disaster	-0.025	-0.054**	-0.039**	-0.018
	(0.023)	(0.022)	(0.015)	(0.021)
open	-0.005	0.020	-0.012**	-0.011
	(0.016)	(0.016)	(0.006)	(0.009)
planting	-0.028	0.029	0.003	0.082***
	(0.108)	(0.049)	(0.021)	(0.029)
industry	-0.013	-0.210***	-0.015	-0.003
	(0.040)	(0.051)	(0.024)	(0.027)
Constant term (math.)	-0.054	0.104*	-0.052*	-0.110***
	(0.067)	(0.054)	(0.030)	(0.039)
N	420	420	420	420
Adj-R^2		0.904	0.935	
Wald value/F value	466 978.0	682.3	824.5	387530.55
p value for AR (1) test	0.007			0.011
p value for AR (2) test	0.658			0.757
Hansen's test p value	1.000			1.000

5.3 Heterogeneity Analysis

Table 7. Regional differences in the impact of rural population aging on AGTFP

Variant	(1) Eastern Part	(2) Central Region	(3) Western Region
L.agtfp	1.600***	0.982***	1.026***
	(0.002)	(0.045)	(0.039)
old	-0.401*	0.455*	0.429*
	(0.214)	(0.252)	(0.241)
disaster	0.080***	-0.048***	-0.068***
	(0.024)	(0.017)	(0.025)
open	-0.011	-0.016	-0.066
	(0.028)	(0.095)	(0.092)
planting	0.359***	-0.046	-0.003
	(0.129)	(0.050)	(0.102)
industry	0.505***	-0.085	-0.121
	(0.141)	(0.065)	(0.153)
N	154	112	154
Number of provinces	11	8	11

To investigate the heterogeneity in the impact of rural population aging on AGTFP across different regions, the Least Squares Dummy Variable Corrected (LSDVC) method was employed, considering the dynamic long panel data structure (N<T) of the subregional dataset. The results, as depicted in Table 7, elucidate significant regional disparities. In the eastern region, the estimated coefficient of rural population aging is -0.401, which is significant at the 10% level. This indicates that rural population aging negatively impacts AGTFP in the eastern region. Conversely, in the central and western regions, the coefficients are 0.455 and 0.429, respectively, both significant at the 10% level. These positive coefficients suggest that rural population aging in the central and western regions contributes positively to AGTFP. Therefore, the analysis reveals substantial regional heterogeneity in the effects of rural population aging on AGTFP, confirming Hypothesis 3.

5.4 Mediating Effect Test

The examination of mediating effects commenced with the first-step estimation, the results of which are illustrated in column (4) of Table 5. The estimated value of rural population aging was found to be significantly positive at the 1% level, with a coefficient of 2.095. This outcome suggests a substantial total effect of rural population aging on AGTFP. The second step of the mediation effect test, whose results are detailed in Table 8, focused on the influence of rural population aging on the three mediating variables: agricultural mechanization, land transfer, and human capital accumulation. The findings reveal that rural population aging significantly enhances agricultural mechanization, facilitates land transfer, and boosts human capital accumulation, with all effects being significant at least at the 5% level. These results underscore the critical role of rural population aging in promoting key aspects of agricultural development.

The final stage of the mediation effects test is presented in Table 9, showing the results of the third estimation step. These results reveal that the coefficients of the impact of agricultural mechanization, land transfer, and human capital accumulation on AGTFP are all significantly positive at the 1% level. This, in conjunction with the second step estimation results from Table 7, confirms the existence of mediation effects. Specifically, the shares of agricultural mechanization, land transfer, and human capital accumulation in the total effect are calculated to be 3.52%, 13.62%, and 17.51%, respectively.

Furthermore, the 95% confidence intervals obtained from the bootstrap test for agricultural mechanization, land transfer, and human capital accumulation are [0.000557, 0.158549], [0.140454, 0.448209], and [0.183897, 0.596952], respectively. None of these intervals include zero, signifying that the bootstrap tests are successfully passed. Consequently, it can be concluded that rural population aging positively influences AGTFP growth through these three mechanisms: agricultural mechanization, land transfer, and human capital accumulation.

Table 8. Effects of rural population aging on mediating variables

Variant	(1) *lnpmachine*	(2) *lnptransfer*	(3) *lneducation*
old	24.458***	45.123***	0.730**
	(5.286)	(8.550)	(0.348)
disaster	-0.387	-1.960**	-0.118***
	(0.896)	(0.925)	(0.021)
open	0.780	0.101	-0.094***
	(0.499)	(0.685)	(0.013)
planting	-4.342	-5.747**	0.088
	(2.888)	(2.737)	(0.093)
industry	-3.368	-4.763	0.064
	(2.390)	(3.214)	(0.128)
Constant term (math.)	7.324***	5.491*	1.930***
	(2.431)	(2.825)	(0.102)
Individual fixed effect	YES	YES	YES
N	450	450	450
Adj-R^2	0.0676	0.2251	0.3959
F value	21.48	30.01	115.09

5.5 Threshold Effect Test

An analysis was conducted to determine the threshold effects of labor force transfer on the impact of rural population aging on AGTFP. The results, presented in Table 10, indicate the presence of a single threshold effect. The threshold value is identified at 0.0333, with a P value of 0.0000, significant at the 1% level. In contrast, the tests for double and triple thresholds do not exhibit statistical significance.

Table 9. Mechanism test of rural population aging affecting AGTFP

Variant	(1) *agtfp*	(2) *agtfp*	(3) *agtfp*
old	1.728^{***}	1.810^{***}	2.021^{***}
	(0.448)	(0.530)	(0.535)
lnpmachine			0.003^{***}
			(0.001)
lnptransfer		0.006^{***}	
		(0.002)	
lneducation	0.502^{***}		
	(0.168)		
disaster	-0.076^{**}	-0.123^{***}	-0.135^{***}
	(0.035)	(0.037)	(0.040)
open	0.084	0.036	0.035
	(0.111)	(0.104)	(0.107)
planting	-0.174	-0.094	-0.117
	(0.211)	(0.198)	(0.197)
industry	-0.741^{***}	-0.679^{***}	-0.699^{***}
	(0.215)	(0.214)	(0.216)
Constant term (math.)	0.267	1.202^{***}	1.214^{***}
	(0.442)	(0.152)	(0.147)
Individual fixed effect	YES	YES	YES
N	450	450	450
Adj-R^2	0.530 5	0.515	0.501 7
F value	20.27	20.75	19.87

Table 10. Significance tests and confidence intervals for threshold effect (1)

Modeling	F Value	P Value	Threshold Value			Threshold Value	95% Confidence Interval
			10%	5%	1%		
Single threshold	79.21	0.0000	38.3725	43.6690	56.1018	0.0333	[0.0328, 0.0333]
Double threshold	36.44	0.1300	37.8670	48.2935	58.2292	-	-
Triple threshold	18.93	0.5467	34.9510	42.5163	56.6193	-	-

The regression results, shown in column (1) of Table 11, further elucidate these findings. In this study, the proportion of the agricultural labor force to the total number of employed persons is used as a proxy for the degree of labor transfer. Therefore, a lower proportion implies a higher degree of labor transfer. The regression reveals that when the proportion of the agricultural labor force exceeds 0.0333, indicating a lower degree of labor transfer, rural population aging significantly boosts AGTFP, with an estimated coefficient of 2.124. Conversely, when this proportion falls below 0.0333, signaling a higher degree of labor transfer, the impact of rural population aging on AGTFP is positive but not statistically significant, as indicated by an estimated coefficient of 0.450. This shift from a significant to an insignificant coefficient, coupled with a decrease in the coefficient's magnitude, suggests that the driving effect of rural population aging on AGTFP diminishes once the threshold of labor transfer is exceeded. Consequently, Hypothesis 5, which posits the existence of a threshold effect in the relationship between rural population aging and AGTFP, is supported.

To bolster the robustness of these findings, several additional tests were performed:

- Inclusion of control variables: To account for potential omitted variable bias, control variables like financial support for agriculture (*finance*) and income distribution (*distribution*) were incorporated into the model. This step was taken to ensure that the threshold effect test results remained consistent, even after adjusting for these additional factors.
- Addressing endogeneity in threshold variables: Recognizing the potential endogeneity of the threshold variable, the model was re-estimated using the lag of two periods of labor force transfer as a new threshold variable.
- Application of moving average treatment: To reduce the volatility inherent in annual data, the sample data underwent a moving average treatment with a period of three years. This treatment was applied before conducting the panel threshold regression.

Table 11. Threshold model estimation results

Variant	(1)	(2)	(3)	(4)
	agtfp	*agtfp*	*agtfp*	*agtfp*
$old \cdot 1(q_{i,t} \leq \tau)$	0.450	0.110	0.192	0.145
	(0.327)	(0.338)	(0.296)	(0.322)
$old \cdot 1(q_{i,t} > \tau)$	2.124***	1.750***	2.038***	2.187***
	(0.227)	(0.249)	(0.239)	(0.267)
disaster	-0.126***	-0.090***	-0.125***	-0.176***
	(0.028)	(0.030)	(0.029)	(0.042)
open	-0.003	-0.013	-0.000	-0.016
	(0.031)	(0.031)	(0.036)	(0.031)
planting	-0.169*	-0.226**	-0.157	-0.456***
	(0.102)	(0.101)	(0.104)	(0.110)
industry	-0.770***	-0.738***	-0.887***	-0.761***
	(0.112)	(0.111)	(0.119)	(0.113)
finance		-0.141		
		(0.133)		
distribution		-0.086***		
		(0.023)		
Constant term	1.292***	1.595***	1.349***	1.504***
	(0.087)	(0.120)	(0.090)	(0.094)
N	450	450	390	390
Number of provinces	30	30	30	30
Adj-R^2	0.520	0.533	0.574	0.589
F value	86.84	68.77	93.22	98.70

Note: The -0.000 in the table is the result of rounding, not the actual value of 0.

The results obtained from these robustness checks, as illustrated in Table 11, align with the initial estimation outcomes. This consistency reinforces the conclusion that rural population aging significantly influences AGTFP, with the degree of labor force transfer serving as a crucial threshold factor. The research conclusions are thus affirmed to be robust and reliable.

Tables 12-14 present the results of further robustness tests for the threshold effect, incorporating additional control variables, new threshold variables, and moving average treatments, respectively.

Table 12. Tests of significance and confidence intervals for threshold effect with additional control variables (2)

Modeling	F Value	P Value	Threshold Value			Threshold Value	95% Confidence interval
			10%	5%	1%		
Single threshold	79.51	0.0000	39.1581	42.9826	55.1135	0.0333	[0.0328, 0.0333]
Double threshold	36.73	0.1133	37.3444	42.0977	54.3551	-	-
Triple threshold	17.66	0.6733	41.2380	46.3759	59.9990	-	-

Table 13. Tests of significance and confidence intervals for threshold effects after with new threshold variables (3)

Modeling	F Value	P Value	Threshold Value			Threshold Value	95% Confidence Interval
			10%	5%	1%		
Single threshold	113.30	0.0000	37.9550	43.3054	56.5253	0.0370	[0.0340, 0.0391]
Double threshold	20.59	0.4367	98.8534	122.2445	168.5107	-	-
Triple threshold	15.68	0.7267	44.8900	54.1533	78.4477	-	-

Table 14. Significance tests and confidence intervals for threshold effects after moving average treatment (4)

Modeling	F Value	P Value	Threshold Value			Threshold Value	95% Confidence Interval
			10%	5%	1%		
Single threshold	115.82	0.003 3	49.9818	65.4664	102.3549	0.0345	[0.0333, 0.0362]
Double threshold	25.93	0.470 0	65.6739	83.1560	123.8999	-	-
Triple threshold	20.35	0.523 3	42.1612	57.0486	92.9720	-	-

6. Conclusions and Policy Implications

Employing the SBM-GML productivity index, this study has measured AGTFP across 30 Chinese provinces from 2005 to 2019. The investigation focused on the influence of rural population aging on AGTFP, its mechanisms, and the potential threshold effect of labor force transfer. The following conclusions have been drawn:

(a) Throughout 2005-2019, AGTFP in China exhibited a fluctuating upward trend, averaging an annual growth rate of 1.55%. The primary driver of this growth was identified as progress in agricultural green technology, though the efficiency of this technology was found to impede overall progress. Consequently, it is evident that the pathway to high-quality agricultural development in China requires considerable advancement.

(b) Regression analyses, utilizing both one-step and two-step SYS-GMM methods and substituting core explanatory variables with the elderly population dependency ratio, consistently reveal a significant positive impact of rural population aging on AGTFP.

(c) A distinct regional heterogeneity is observed in the effects of rural population aging on AGTFP. In the central and western regions, aging is positively driving AGTFP growth, whereas, in the eastern region, it appears to dampen AGTFP growth.

(d) Mediation effects analysis indicates that rural population aging fosters AGTFP growth through mechanisms such as human capital accumulation, land transfer, and agricultural mechanization, contributing 17.51%, 13.62%, and 3.52% to the total effect, respectively.

(e) Threshold effect examination demonstrates that the beneficial impact of rural population aging on AGTFP is subject to a single labor force transfer threshold. Specifically, when the proportion of the agricultural labor force exceeds 0.0333, indicating a lower degree of labor transfer, rural aging significantly boosts AGTFP. Conversely, when this proportion falls below 0.0333, the positive impact diminishes. Robustness checks, incorporating additional control variables, alternative threshold variables, and moving average treatments, corroborate these findings.

This study's findings lead to the following policy recommendations:

Firstly, an adaptive and flexible response to the aging rural population is essential. The influence of rural population aging on AGTFP is multifaceted and uncertain. Hence, it is vital to objectively approach the aging phenomenon, avoiding excessive preoccupation with its potential negative impacts on agricultural production. The effect of rural aging needs to be contextualized, varying across regions and degrees of labor transfer. In instances where rural aging positively influences AGTFP, it is crucial to harness this situation and capitalize on the opportunities presented by aging to enhance AGTFP. Conversely, in cases where rural aging hampers AGTFP, reliance on scientific and technological advances and institutional reforms becomes imperative. Relevant authorities are advised to monitor the dynamics of rural aging accurately and devise flexible strategies that cater to specific temporal and locational needs, thereby fostering the sustained growth of China's AGTFP.

Secondly, prudent foresight and scientific mitigation strategies for the aging crisis are recommended. While rural population aging has been a driver of AGTFP growth over the past decade, this trend might not persist indefinitely. The impact of rural aging on AGTFP exhibits both threshold and lag effects, and over the long term, the negative consequences are likely to become more pronounced. With increasing rural aging and accelerated agricultural labor transfer, challenges such as rural support and the dwindling number of successors in agricultural production could hinder AGTFP growth. Governmental bodies should anticipate and prepare for these eventualities, enhancing the rural old-age security system and advancing the rural pension system. Additionally, the promotion of comprehensive family planning policies, including "two-child" and "three-child" options, should be actively pursued.

Thirdly, the enhancement of human capital accumulation, the facilitation of land transfer, and the advancement of agricultural mechanization are imperative. Investment in rural human capital must be escalated, establishing mechanisms that encourage skilled professionals to contribute to rural revitalization and thereby foster rural human capital growth. Concurrently, adherence to land transfer policies is vital to advocate moderate-scale agricultural operations. The role of the market in land transfer should be harnessed, along with leveraging modern technologies such as the Internet and big data to construct platforms for agricultural land transfer. Moreover, the promotion of agricultural mechanization is crucial for the modernization of agriculture. The implementation of agricultural machinery subsidy policies and the development of an agricultural machinery socialized service system are recommended. Additionally, investment in agricultural mechanization research should be intensified to provide technical support for mechanization and modernization.

Fourthly, reliance on scientific and technological progress and institutional innovation is essential for further liberating the agricultural labor force. The current trend of labor transfer, coupled with rural population aging, has been instrumental in augmenting AGTFP. However, as labor transfer intensifies, the positive impact of rural aging may diminish, potentially impeding agricultural productivity. Hence, China faces the challenge of balancing rural labor transfer with aging population concerns. It is essential to pivot towards agricultural methods that are less labor-intensive and more focused on capital and technology. This shift will not only boost AGTFP but also facilitate the transition of labor from agricultural to non-agricultural sectors, thereby promoting a high-quality economic structural transformation.

Fifthly, the coordination of regionally balanced development tailored to local conditions is paramount. The impact of rural population aging on AGTFP in China exhibits regional disparities, necessitating differentiated policy foci in various regions. In the eastern region, it is imperative to deepen the reform of the rural pension insurance system, enhancing the government's financial contribution and basic livelihood support for the elderly. Additionally, amplifying green technological innovation in agriculture, optimizing the allocation of green resources, and spearheading a national revolution in agricultural green productivity are crucial. For the central region, the enhancement of a multi-level social security system and the advancement of the rural pension insurance system are essential. Increasing investments in agricultural technology research and development and fostering technical exchanges with the eastern region are also recommended. In the western region, achieving comprehensive pension insurance coverage for rural residents is necessary. Introducing and assimilating advanced green agricultural production techniques and fully promoting agricultural mechanization, particularly machinery suited for complex terrain, is vital. Furthermore, encouraging college graduates to seek employment in the west to augment human capital accumulation and strengthening interactions with the eastern and central regions to boost agricultural openness and cooperation are essential for fostering high-quality agricultural development.

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Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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