

**Research Article**



# The Impact of Global Population Aging on Food Production: An Empirical Study Based on Cross-Country Panel Data

Qiaowen Lin<sup>a</sup>, Mengxin Xu<sup>a,\*</sup>

<sup>a</sup>School of Economic and Management, China University of Geosciences, Wuhan 430074, China

\*Corresponding Author: Mengxin Xu

## Abstract:

The stability of food production is crucial for global food security, yet the impact of population aging remains unclear amid the global aging trend. Using 4,094 samples from 162 countries from 1991 to 2020, this study finds that population aging has a significant negative impact on food production. However, this influence shows great heterogeneity in terms of aging level, urbanization level, income level, and geographical location. Specifically, the effect of population aging on food production is not significant in countries with severe aging. However, this negative impact is obvious in countries with other stage of aging. For countries under initial stage of urbanization, the effect of population aging on food production is not significant. However, for countries under other stages of urbanization, such as mature and final stages of urbanization, the negative effect becomes evident. Additionally, in middle-income countries, this effect is not significant. However, in low-income countries, population aging is significantly positively correlated with food production. On the contrary, a significant negative correlation is observed in high-income countries. In Oceania, this effect is not noticeable. In Asia, the Americas and Africa, aging is significantly negatively correlated with food production. However, in European countries, a positive effect is observed. Besides, this study also find that the proportion of agricultural employment and fertilizer use play partial mediating roles in the relationship between population aging and food production. Those findings offer important empirical evidence for global food security and sustainable agricultural development, offering policy insights to mitigate aging's challenges.

**Keywords:** Population aging; Food production; Cross-country panel data; Heterogeneity analysis; Mediating effect;

## Introduction

Food is a fundamental human necessity and an important strategic resource for promoting sustainable social development and maintaining regional security and stability (Liu et al., 2015; Zhao et al., 2017). The stability of food production directly impacts global food security (Prosekov & Ivanova, 2018; Walls et al., 2019). Currently, global population growth is driving a sharp increase in food demand. According to the United Nations' World Population Prospects 2022, the global population is expected to grow from 8 billion to 9.7 billion over the next 30 years, increasing nearly 2 billion people, which presents a significant challenge to food security (United

Nations, 2022). Meanwhile, the State of Food Security and Nutrition in 2023 states that the number of people facing severe food insecurity worldwide has exceeded 345 million, an increase of 210 million compared to 2019 (FAO, 2023).

In the process of population growth, there is the global trend of population aging driven by declining fertility rates and increasing life expectancy (Lutz, Sanderson & Scherbov, 2008). This phenomenon profoundly impacts various sectors such as social life and economic development (Harper, 2014; Bloom et al., 2015; Yu et al., 2018). In fact, population aging has become a common social phenomenon in the

development processes of many countries and is gradually evolving into a global challenge (Peng, 2011; Choi & Shin, 2015). According to the 2023 World Social Report by the United Nations, the global population aged 65 and over is expected to double over the next 30 years, reaching 1.6 billion by 2050, accounting for more than 16% of the world's total population. Agriculture, as a labor-intensive industry, is particularly affected by the significant impacts of population aging (Rigg *et al.*, 2020; Cohen & Greaney, 2023). Aging leads to a reduction in the working-age population, decreased labor productivity, and results in labor shortages and an aging workforce, posing a major challenge to a country's food production (Harper, 2014; Choi & Shin, 2015; Lee & Yuan, 2024).

Regarding the impact of population aging on food production, no consensus has reached. Some studies advocate that population aging reduces the effective supply of agricultural labor, limits the input of agricultural production factors, leads to a decline in labor productivity, and negatively affects food production (Harper, 2014; Rigg *et al.*, 2020; Ren *et al.*, 2023). In addition, older laborers tend to have weaker innovation capabilities and a lower acceptance of new agricultural technologies, which hinders the promotion and application of new technologies, further suppressing agricultural productivity (Ingram & Kirwan, 2011; Burholt & Dobbs, 2012). However, other scholars argue that with the progress of agricultural mechanization, the combination of the rich planting experience accumulated by elderly farmers and mechanized equipment can reduce the need for physical labor, which can, to some extent, compensate for the disadvantages of older labor in terms of physical strength and technical adaptation (Shao *et al.*, 2015; Qiu *et al.*, 2021). Therefore, under certain conditions, population aging may not necessarily have a negative impact on food production (Guo *et al.*, 2015; Yamashita & Hoshino, 2018). Those different views provide some insights for the understanding of the relationship between aging and food production. However, considering the differences in economic development levels, agricultural technology adoption, and labor structure across different countries and regions, the specific impacts of population aging on food production are highly complex and heterogeneous. Therefore, it is of great significance to explore the effects of aging on food production and its heterogeneity from a

global perspective.

Unlike previous studies that focus on the micro level, this paper systematically analyzes the impact of population aging on food production from a global perspective using macro data from 162 countries between 1991 and 2020. Population aging is measured by the proportion of individuals aged 65 and above in the total population, while food production and food harvested area are selected as the core dependent variables. This study aims to reveal how aging influences food production through intermediary channels such as the proportion of agricultural labor and agricultural factor inputs. Additionally, it further examines the heterogeneity of these effects across different levels of economic development and geographical locations, offering a comprehensive understanding of the heterogeneous nature of aging's impact. This research not only fills the gap in studies on the global effects of population aging on food production, providing rich theoretical support from a macro perspective, but also offers important empirical evidence for global food security and sustainable agricultural development, thereby providing valuable insights for countries to formulate food production policies to address the challenges of aging.

Compared to previous studies, the main contributions of this research are as follows: First, based on macro data from 162 countries between 1991 and 2020, this study systematically analyzes the impact of population aging on food production from a global perspective, filling a gap in related research at the global level. Secondly, this paper innovatively explores the heterogeneity of aging's impact from four dimensions: aging intensity, urbanization level, income level, and geographical location, providing a new perspective for policy formulation. Thirdly, by incorporating the proportion of agricultural employment and fertilizer input into the analysis framework, it reveals the mediating effect of aging on food production through labor structure and agricultural factor inputs, thereby expanding the research on the mechanisms of aging's impact.

## 2 Literature Review and Theoretical Hypotheses

### 2.1 Literature Review

#### 2.1.1 Factors Affecting Food Production

Food production is influenced by various factors,

including the input of production factors, economic development level, climate conditions, and policy factors (Wang et al., 2018; Liu & Zhou, 2021; Puma, 2019). Regarding the input of production factors, the supply of agricultural labor, along with the input of other production factors such as land, agricultural machinery, and fertilizers and pesticides, all impact food production to some extent (Liu et al., 2022; Meng et al., 2024; Hu & Liu, 2024). The rapid urbanization process has led to a large-scale migration of labor from rural areas to cities (Li et al., 2016), which may result in labor shortages in rural areas, accompanied by aging and feminization of the agricultural labor force, thereby affecting food production (Liu et al., 2019; Liu et al., 2022). Simultaneously, the massive transfer of labor to non-agricultural sectors (Zhang et al., 2023a) has resulted in frequent instances of fallow land, reducing both the quantity and quality of agricultural land, thus threatening food production (Hu & Liu, 2024). In contrast, the development of agricultural mechanization can save the labor required for agricultural activities and promote food production by improving agricultural productivity (Meng et al., 2024). Additionally, the use of production factors such as fertilizers and pesticides, as key components of the agricultural system, can significantly increase food yields when applied in large amounts in agricultural production processes (Alexandrato & Bruinsma, 2012; Carvalho, 2017). However, excessive use of these inputs leads to a range of environmental issues, which are detrimental to sustainable agricultural development and land use, and should be controlled in future agricultural production (Hu & Liu, 2024).

In terms of economic development, it is well acknowledged that GDP per capita is a major factor influencing food production efficiency (Song & Chen, 2019). The increase in GDP per capita has a positive impact on food production. Regions with higher GDP per capita tend to have higher food production efficiency, which is more favorable for food production (Zheng et al., 2022). Furthermore, agricultural labor migration caused by urbanization has also contributed to changes in land use and production efficiency in some areas, potentially affecting food production through technological innovation and economies of scale (Ge et al., 2018; Chen et al., 2023). The

proportion of agricultural value added to GDP represents the degree of agricultural development in a region, and it has a significant positive impact on the efficiency of agricultural land use (Chen et al., 2023).

In terms of climate conditions, frequent extreme weather events pose a major threat to global food production (Augsburger, 2013; Zhang et al., 2023b). Extreme rainfall in the past two decades has reduced rice yields in China by one-twelfth, presenting a serious threat to national food security (Fu et al., 2023). Regarding policy and institutional factors, the abolition of agricultural taxes and the implementation of agricultural subsidy policies have increased food planting areas and food production by influencing land leasing prices and farmers' agricultural production decisions. These policies have also enhanced farmers' income from crop cultivation, incentivizing them to engage in food production (Yi et al., 2015; Lin & Huang, 2021).

### 2.1.2 Population Aging and Food Production

There is no consensus among scholars regarding the impact of population aging on food production. Most scholars believe that population aging negatively affects food production (Choi & Shin, 2015; Rigg et al., 2020; Liu et al., 2023). On one hand, population aging reduces the effective supply of labor and the input of agricultural production factors, leading to a decline in labor productivity, which poses a threat to food security (Harper, 2014; Rigg et al., 2020; Ren et al., 2023). As the degree of aging intensifies, the physical capacity of the labor force gradually declines (Lee & Yuan, 2024). Given the physical limitations, elderly laborers may choose to reduce the scale of food production or even abandon agricultural activities, leading to the abandonment of arable land, which threatens food production (Jansuwan & Zander, 2021). On the other hand, elderly laborers, due to a lack of innovation capacity, also have a lower acceptance of new agricultural technologies, which hinders the development and adoption of new agricultural techniques and is detrimental to food production (Ingram & Kirwan, 2011; Burholt & Dobbs, 2012).

However, some scholars argue that compared to younger laborers, elderly laborers possess more time on agricultural labor and richer experience. With the advancement of agricultural

mechanization, population aging may not have a negative impact on food production (Guo et al., 2015; Yamashita & Hoshino, 2018). The accumulation of agricultural experience by elderly farmers and the application of agricultural mechanization can reduce the physical labor required for agricultural production. This suggests that agricultural mechanization and planting experience can somewhat offset the disadvantages of elderly laborers' human capital (Shao et al., 2015; Qiu et al., 2021). Additionally, some scholars hold an optimistic view regarding the impact of population aging on food production. Some indicates that rural population aging in China has not had a negative impact on food security, and the application of artificial intelligence plays a positive moderating role in mitigating the effects of aging on food security. Therefore, there is no need to be overly pessimistic about the inevitable process of population aging (Lee et al., 2024).

In conclusion, there is no unified conclusion regarding the impact of population aging on food production. Most research on the effects of aging on food production has been limited to micro-level analyses using provincial, county, and household-level data. In contrast, this paper focuses on macro-level global data and conducts a cross-country comparative study, filling the gap in macro data analysis. By utilizing empirical data from multiple countries, this study provides a more comprehensive understanding of the impact of population aging on food production, offering a new perspective for further research on the issue. Furthermore, this global perspective helps to identify both the differences and commonalities in how countries respond to the impact of aging on food production, providing valuable references for policy making.

## 2.2 Theoretical Hypothesis

### 2.2.1 Negative Relationship between Population Aging and Food Production

On one hand, aging reduces the physical strength and overall health of the labor force (Harper, 2014; Lee & Yuan, 2024), thereby decreasing the supply of agricultural labor and adversely affecting food production (Liu et al., 2023). As individuals age, the decline in physiological functions weakens the labor capacity and efficiency of farmers engaged in food production

activities (Harper, 2014; Bloom et al., 2015; Choi & Shin, 2015). Specifically, due to physical limitations, elderly laborers struggle to perform labor-intensive tasks in critical stages of food production (Rigg et al., 2020). Moreover, these physiological changes cause elderly laborers to reduce their working time and decrease output levels, which negatively impacts food production (Bloom et al., 2015; Liu et al., 2023). On the other hand, elderly laborers often exhibit lower learning abilities and adaptability when confronted with new technologies and equipment (Burholt & Dobbs, 2012). They are generally more accustomed to traditional agricultural practices that are inefficient and resource-intensive, which cannot meet the demands of modern agriculture for high efficiency (Guo & Zhang, 2023; Wang et al., 2024). Furthermore, they often lack interest or understanding of complex new technologies, such as smart farming, which slows the adoption of such technologies and hampers improvements in agricultural productivity (Ingram & Kirwan, 2011). Based on this, the following hypothesis is proposed:

Hypothesis 1: Population aging has a negative impact on food production.

### 2.2.2 Mediating Effect

As the degree of aging increases, elderly individuals in rural areas, due to physical limitations and skill restrictions, find it difficult to integrate into urban labor markets, and continuing agricultural production becomes their primary means of livelihood (Wang et al., 2020). Moreover, due to the underdeveloped rural pension system, many elderly individuals cannot rely on social security or savings for subsistence, and are thus forced to continue working in agriculture, increasing the proportion of agricultural employment (Gutiérrez et al., 2016; Carolan, 2018). Additionally, the strong emotional attachment and identity of rural elderly individuals to the land makes them more inclined to remain in agricultural production (Conway et al., 2016), further increasing the share of elderly workers in the agricultural labor force. Although the proportion of agricultural laborers increases due to aging, this group's labor efficiency is limited, making it difficult to support large-scale food production (Harper, 2014; Choi & Shin, 2015). Elderly workers, due to physical and health constraints, typically reduce their cultivated areas

or decrease the intensity of their farming, which negatively affects food production (Shao et al., 2015; Jansuwan & Zander, 2021). As a result, despite the increase in the proportion of agricultural labor, the actual contribution of this group to food production is limited, or even declines, leading to a scenario where the "proportion of labor increases while output decreases." Furthermore, as aging deepens, elderly laborers gradually reduce the scale of planting or the intensity of farming due to physical limitations (Shao et al., 2015; Jansuwan & Zander, 2021). In this situation, as cultivated areas shrink, the demand for agricultural inputs, such as fertilizers and pesticides, decreases, leading to a decline in overall agricultural investment and weakening the stability of food output (Ren et al., 2023). Based on this, the following hypothesis is proposed:

Hypothesis 2: Population aging may influence food production by affecting the proportion of agricultural employment and the input of production factors such as fertilizers.

### 2.2.3 Heterogeneity

The impact of population aging on food production shows significant differences across regions with varying levels of urbanization (Lee et al., 2021; Hou et al., 2022). With the development of urbanization and industrialization, a large amount of high-quality arable land is being occupied, and the low profitability of agricultural production combined with the higher income in non-agricultural employment leads to the

migration of a significant portion of rural labor (Li et al., 2016; Liu et al., 2022). Compared to regions with low levels of urbanization, areas with higher urbanization will experience a greater impact on food production (Liu et al., 2021). Moreover, the geographical conditions of different regions including climate, terrain, soil directly influence agricultural practices, thus resulting in varying effects on food production (Ji et al., 2017; Li et al., 2019; Niu et al., 2024). Additionally, differences in income levels can also affect the extent of the impact of population aging on food production (Xie et al., 2021; Zheng et al., 2022). In regions with higher income levels, farmers are more likely to rely on alternative economic sources, reducing their dependence on agriculture (Gutiérrez et al., 2016). Elderly laborers are more likely to withdraw from agricultural production, further negatively affecting food production (Jansuwan & Zander, 2021). Based on this, the following hypothesis is proposed:

Hypothesis 3: The impact of population aging on food production significantly varies across different levels of urbanization, regions, and income levels.

## 3 Modeling and Data Description

### 3.1 Modeling

To examine the impact of population aging on food production and its heterogeneity, a two-way fixed effects model is used. The specific model is as follows:

$$\ln GY_{it} = \alpha_0 + \alpha_1 AG_{it} + \alpha_j Controls_{it} + \mu_k + \vartheta_t + \varepsilon_{it} \quad (1)$$

Where  $i$  represents the country,  $t$  represents the year.  $\ln GY_{it}$  denotes the food production level of country  $i$  in year  $t$ , and  $AG_{it}$  indicates the degree of aging in country  $i$  in year  $t$ .  $Controls$  represents a set of control variables.  $\mu_k$  and  $\vartheta_t$  represent country-specific and time-specific fixed effects, respectively, controlling for unobserved factors that may influence food production at the individual country and time levels.  $\varepsilon_{it}$  is the random error term.

To improve the accuracy of the model estimation, standard errors are clustered at the country level. On one hand, this helps address potential heteroscedasticity in the model and avoids bias in traditional standard error estimates due to

heterogeneity, enhancing the precision of the estimates. On the other hand, by capturing the within-country correlation of disturbance terms across different years, clustering robust standard errors can correct for bias resulting from intra-country correlation, ensuring the robustness and validity of the hypothesis tests. This also enhances the consistency of the standard error estimates and provides more reliable statistical inferences for the empirical study (Yang et al., 2023).

### 3.2 Variable Selection

#### 3.2.1 Dependent Variable

Cereals are the main food crops, accounting for a large portion of total food production globally

(FAO, 2021). Therefore, cereal production can more accurately reflect the overall food production level (Ray et al., 2013). To ensure the comparability and consistency of cross-country panel data, this study uses cereal production (*GY*) as the core dependent variable and measures food production levels using cereal yield data provided by the World Bank. In addition, to minimize the impact of heteroscedasticity on the model estimation, the food production variable is transformed into its natural logarithm to enhance the robustness of the estimates.

### 3.2.2 Independent Variable

The core independent variable in this study is the level of population aging (*AG*). Taking reference of the research of Zhang & Xia (2020) and Wang & Wang (2021), this study uses the proportion of the population aged 65 and above to total population as an indicator to measure the degree of population aging in a country. This indicator effectively reflects the aging trend of the population structure and is one of the commonly used methods in current academic research to measure aging levels.

### 3.2.3 Control Variables

Based on relevant studies (Liu et al., 2019; Song & Chen, 2019; Fu et al., 2023) and considering data availability, this study examines key factors affecting food production from three dimensions: labor, economic, and climate factors. Firstly, regarding labor, both population aging and feminization significantly influence food production (Liu et al., 2019; Lee & Yuan, 2024). Therefore, gender structure and life expectancy are selected as control variables for labor factors. Gender structure is measured by the gender ratio (the ratio of the male population to the female population), which is used to explore gender differences in the labor force, especially the impact of feminization on food production. Life expectancy reflects the aging trend, representing the number of years a newborn is expected to live under current mortality patterns, and is used to assess the potential impact of population aging on food production. Secondly, in terms of economic factors, GDP level and urbanization rate are crucial determinants of food production (Song & Chen, 2019; Hu & Liu, 2024). Accordingly, this study selects GDP level, urbanization rate, and labor productivity in agriculture as control

variables. GDP level is measured by GDP per capita, reflecting the level of economic development. Urbanization rate is measured as the proportion of the urban population to the total population, reflecting the potential impact of urban-rural structural changes on food production. Labor productivity in agriculture is represented by the value-added per agricultural worker as a percentage of GDP, serving as a key indicator of agricultural labor productivity and the level of agricultural modernization, which affects food production. Finally, climate conditions also significantly influence food production (Augsburger, 2013; Fu et al., 2023). Therefore, this study selects average rainfall as a key indicator for climate factors. Specifically, the average rainfall in a country refers to the average annual precipitation depth over multiple years, reflecting the influence of climate conditions on food production. To reduce the impact of data volatility on estimation results, the study applies logarithmic transformations to GDP per capita and average rainfall.

### 3.2.4 Mediating Variables

Building on the theoretical analysis, this study further selects the proportion of agricultural employment and fertilizer input as mediating variables, examining their mediating effects between population aging and food production. The proportion of agricultural employment, which is the percentage of workers in the agricultural sector relative to total employment, is an important indicator of the allocation of labor resources in agriculture and reflects the impact of agricultural labor supply on food production. Fertilizer input is measured by the amount of fertilizer used per hectare of arable land. Given the distribution characteristics of the data, the fertilizer input variable is log-transformed.

## 3.3 Data Sources and Processing

### 3.3.1 Data Sources

The core dependent variable (food production, *GY*), core independent variable (population aging level, *AG*), control variables, and mediating variables in this study all come from the World Bank Database. This database offers advantages such as global coverage, high data consistency, and strict standardization processes. Firstly, the World Bank Database provides consistent indicator definitions and data collection standards

for countries worldwide, ensuring the feasibility of cross-country comparative studies and the reliability of the data. Secondly, as an internationally authoritative organization, the World Bank has stringent standards and procedures for data collection, review, and publication, ensuring high-quality and authoritative data. Using data from the World Bank Database significantly reduces the risk of measurement errors and data biases, ensuring the reliability of the research findings, enhancing the interpretability and robustness of the models, and providing strong support for the credibility of the study results.

### 3.3.2 Data Preprocessing

①Data Download. Annual data for each variable was obtained from the World Bank Database. The core variables include food production (dependent variable), population aging level (core independent variable), proportion of agricultural employment and fertilizer input (mediating variables), as well as other control variables. The time range for the data is from 1991 to 2020, covering multiple countries globally, ensuring

sufficient time span and geographical coverage.

②Data Merging. A preliminary check was conducted on the downloaded data to ensure consistent country and year codes. Then, the data sets for different variables were merged using country and year as matching codes, ensuring that all variables corresponded consistently within the same time point and country. ③Missing Data Treatment. After data merging, missing data was addressed. For countries or years where key variables could not be obtained, relevant records were excluded to ensure data completeness and the robustness of model analysis. Additionally, the distribution of missing values was carefully examined, and observations that could not be reasonably imputed or completed were removed at this stage. ④Final Data. After merging, handling missing values, and data cleaning, a dataset covering 162 countries from 1991 to 2020 was finalized, resulting in a total of 4,094 observations.

## 4 Results

### 4.1 Descriptive Statistics

**Table1 Descriptive statistics**

| Variable             | Variable name | Variable definition  | Unit | N    | Mean (std. dev.)  | Min   | Max    |
|----------------------|---------------|--|------|------|-------------------|-------|--------|
| Dependent variable   | InGY          | World Bank cereal production is used as grain production data  | t    | 4094 | 14.129<br>(2.824) | 1.609 | 20.242 |
|                      | InGA          | World Bank cereal harvested area is used as data on grain harvested area   | ha   | 4094 | 13.225<br>(2.821) | 2.197 | 18.453 |
| Independent variable | AG            | The proportion of a country's population over the age of 65  | /    | 4094 | 0.075<br>(0.055)  | 0.002 | 0.296  |
|                      | EDR           | The proportion of a country's population aged 65 and over to the population aged 15-64   | /    | 4094 | 0.118<br>(0.081)  | 0.002 | 0.506  |
| Control variable     | Gender        | The proportion of total male population to total female population   | /    | 4094 | 1.007<br>(0.180)  | 0.822 | 3.275  |
|                      | LE            | Life expectancy at birth is the number of years a newborn is likely to live, assuming that mortality patterns at birth remain the same throughout life | Year | 4094 | 68.792<br>(9.407) | 37    | 85     |
|                      | InGDP         | GDP per capita of a country  | USD  | 4094 | 8.142<br>(1.597)  | 3.172 | 11.725 |
|                      | Urban         | Proportion of urban  | /    | 4094 | 0.553             | 0.055 | 1      |

|                       |              |   |       |      |                  |       |       |
|-----------------------|--------------|---|-------|------|------------------|-------|-------|
|                       |              | population to total population  |       |      | (0.226)          |       |       |
|                       | AAV          | Agriculture, forestry, and fisheries, value added per worker (% of GDP)       | /     | 4094 | 0.129<br>(0.118) | 0.001 | 0.790 |
|                       | lnRainfall   | The long-term average depth of annual precipitation within a country          | mm    | 4094 | 6.719<br>(0.920) | 2.950 | 8.084 |
| Instrumental variable | Death        | The average number of deaths per 1,000 people in a year estimated at mid-year | /     | 4094 | 0.086<br>(0.036) | 0.008 | 0.249 |
| Intermediate variable | AE           | The percentage of employed persons in agriculture in the total employment     | /     | 4094 | 0.295<br>(0.244) | 0.007 | 0.925 |
|                       | lnFertilizer | The number of fertilizers consumed per hectare of cultivated land             | Kg/ha | 4094 | 4.022<br>(1.612) | 0     | 7.741 |

Table 1 presents the descriptive statistics results. The average food production is 14.129 tons, with a standard deviation of 2.842 tons, indicating a certain degree of fluctuation in food production levels across countries. The relatively high standard deviation suggests significant differences in food production among countries, which may be influenced by various factors, such as climate conditions, agricultural technology levels, and land resource availability. The mean grain harvested area is 13.225 hectares, with a standard deviation of 2.821 hectares, indicating variation in grain cultivation scale across countries. The average aging rate is 0.075, with a minimum value of 0.002, a maximum value of 0.296, and a

standard deviation of 0.055, indicating significant differences in the extent of population aging among countries. Some countries are facing severe aging issues, with aging rates approaching 30%, while others are just beginning to confront this challenge. These disparities may reflect differences in economic development and social policies across countries.

To check for multicollinearity among the explanatory variables, a Variance Inflation Factor (VIF) test was conducted. The results, shown in Table 2, indicate that the VIF of all explanatory variables is less than 10, with an average VIF of 3.330, suggesting that there is no multicollinearity problem among the variables.

**Table2 VIF test**

| Variable   | VIF   | 1/VIF |
|------------|-------|-------|
| lnGDP      | 6.990 | 0.143 |
| LE         | 3.750 | 0.266 |
| AAV        | 3.640 | 0.275 |
| Urban      | 3.060 | 0.327 |
| AG         | 2.970 | 0.337 |
| Gender     | 1.680 | 0.595 |
| lnRainfall | 1.200 | 0.833 |
| Mean VIF   | 3.330 |       |

## 4.2 Benchmark Regression

**Table3 Benchmark regression**

| Variable name | (1)               | (2)               | (3)               |
|---------------|-------------------|-------------------|-------------------|
| AG            | -6.263*** (0.586) | -5.196*** (0.600) | -5.196*** (1.393) |
| Gender        |                   | -0.958*** (0.133) | -0.958*** (0.363) |

|                               |                   |                  |                   |
|-------------------------------|-------------------|------------------|-------------------|
| LE                            |                   | 0.032*** (0.003) | 0.032*** (0.007)  |
| lnGDP                         |                   | 0.129*** (0.020) | 0.129*** (0.038)  |
| Urban                         |                   | 0.687*** (0.209) | 0.687 (0.766)     |
| AAV                           |                   | 0.553*** (0.177) | 0.553 (0.390)     |
| lnRainfall                    |                   | -0.358 (1.308)   | -0.358 (0.683)    |
| Constant                      | 14.359*** (0.052) | 14.184** (8.794) | 12.585*** (5.239) |
| Year                          | Yes               | Yes              | Yes               |
| Country                       | Yes               | Yes              | Yes               |
| Cluster-RobustStandard Errors | No                | No               | Yes               |
| N                             | 4094              | 4094             | 4094              |

Note: \*p < 0.1, \*\*p < 0.05, \*\*\*p < 0.01. Cluster-robust standard errors in parentheses.

This study adopts a two-way fixed effects model to perform a regression analysis on panel data for 162 countries globally from 1991 to 2020, examining the relationship between population aging and food production. Results are shown in Table 3. Column (1) presents the regression results for the core explanatory variable including the aging rate (*AG*) and food production (*lnGY*). In the absence of control variables, the coefficient for the aging rate is -6.263, which is significantly negative at the 1% level, indicating that population aging has a significant negative impact on food production. In Column (2), after incorporating the control variables, the coefficient for the aging rate becomes -5.196. Although the coefficient has decreased, it remains negative and significant at the 1% level, suggesting that even after controlling for other related factors, the negative impact of population aging on food production persists. Column (3) displays the results after clustering robust standard errors at the country level. Compared to Column (2), while the coefficient for the aging rate remains unchanged, the standard error increases. The increase in the standard error may be due to the robust standard error correcting for heteroscedasticity or other error correlations in the model, making the results more reliable and robust after considering country-level differences. Despite the increase in the standard error, the conclusion remains consistent. That is, population aging has a significant negative effect on food production.

The regression results for the main control variables show that, in terms of labor factors, gender structure is significantly negatively correlated with food production, indicating that the "feminization" of labor has a positive effect on

food production. Life expectancy is significantly positively correlated with food production, suggesting that longer life expectancy may promote food production growth by improving labor health and increasing agricultural labor productivity. Regarding economic factors, GDP per capita, urbanization rate, and labor productivity in agriculture are all significantly positively correlated with food production. This suggests that improvements in economic development have a positive impact on food production. In terms of climate factors, rainfall is negatively correlated with food production, but the coefficient is not statistically significant.

### 4.3 Robustness Tests

#### 4.3.1 Change the Dependent Variable Measure

Total grain production is primarily determined by harvested area and yield per unit area. Thus, harvested area can indirectly reflect grain production capacity (Li et al., 2024). To further verify the impact of population aging on grain production, this study adopts harvested area as an alternative measure of grain production, using cereal harvested area data published by the World Bank. The results in Column (1) of Table 4 indicate that, even when using harvested area as a measure, population aging has a significant negative effect on grain harvested area. This suggests that as aging intensifies, harvested area declines. This may attribute to the insufficient supply of effective agricultural labor, which in turn reduces the scale of grain production. This result confirms the robustness of the negative impact of aging on grain production. Regardless of whether grain output or harvested area is used as the measure, aging exerts a negative shock on grain production.

**Table 4 Robustness test**

| Variable name | Change variable      |                       | Tail reduction 2.5%   |                       | Tail reduction 5%     |                      | Tail reduction 7.5%   |                      |
|---------------|----------------------|-----------------------|-----------------------|-----------------------|-----------------------|----------------------|-----------------------|----------------------|
|               | (1)<br>lnGA          | (2)<br>EDR            | (3)<br>lnGY           | (4)<br>lnGA           | (5)<br>lnGY           | (6)<br>lnGA          | (7)<br>lnGY           | (8)<br>lnGA          |
| AG            | -5.281***<br>(0.482) |                       | -6.401*<br>** (0.586) | -6.114**<br>* (0.437) | -7.155*<br>** (0.590) | -6.110***<br>(0.416) | -7.192**<br>* (0.578) | -6.237***<br>(0.427) |
| EDR           |                      | -2.438***<br>(0.344)  |                       |                       |                       |                      |                       |                      |
| Gender        | -1.567***<br>(0.107) | -0.917<br>*** (0.133) | -0.904*<br>** (0.117) | -1.417**<br>* (0.087) | -0.461<br>*** (0.111) | -0.355***<br>(0.078) | -0.161<br>(0.104)     | -0.271***<br>(0.076) |
| LE            | 0.026***<br>(0.002)  | 0.034***<br>(0.003)   | 0.032**<br>* (0.003)  | 0.023***<br>(0.002)   | 0.033**<br>* (0.002)  | 0.022***<br>(0.002)  | 0.034***<br>(0.002)   | 0.022***<br>(0.002)  |
| lnGDP         | 0.014<br>(0.016)     | 0.119***<br>(0.020)   | 0.130**<br>* (0.018)  | 0.021<br>(0.013)      | 0.138**<br>* (0.017)  | 0.029**<br>(0.012)   | 0.147***<br>(0.016)   | 0.031***<br>(0.012)  |
| Urban         | 0.670***<br>(0.168)  | 0.686***<br>(0.210)   | 0.292<br>(0.185)      | 0.262*<br>(0.138)     | 0.153<br>(0.175)      | 0.049<br>(0.124)     | 0.202<br>(0.163)      | 0.173<br>(0.121)     |
| AAV           | 0.046<br>(0.142)     | 0.503***<br>(0.177)   | 0.600**<br>* (0.156)  | 0.187<br>(0.116)      | 0.560**<br>* (0.148)  | 0.199*<br>(0.104)    | 0.494***<br>(0.138)   | 0.161<br>(0.102)     |
| lnRainfall    | -0.061<br>(1.049)    | -0.375<br>(1.312)     | -0.233<br>(1.152)     | -0.046<br>(0.858)     | 0.203<br>(1.092)      | 0.109<br>(0.771)     | 0.352<br>(1.020)      | 0.128<br>(0.754)     |
| Constant      | 13.459*<br>(7.054)   | 14.151<br>(8.822)     | 13.493*<br>(7.745)    | 13.604**<br>(5.771)   | 10.183<br>(7.343)     | 11.547**<br>(5.183)  | 8.804<br>(6.862)      | 11.321**<br>(5.067)  |
| Year          | Yes                  | Yes                   | Yes                   | Yes                   | Yes                   | Yes                  | Yes                   | Yes                  |
| Country       | Yes                  | Yes                   | Yes                   | Yes                   | Yes                   | Yes                  | Yes                   | Yes                  |
| N             | 4094                 | 4094                  | 4094                  | 4094                  | 4094                  | 4094                 | 4094                  | 4094                 |

Note: \*p < 0.1, \*\*p < 0.05, \*\*\*p < 0.01. Cluster-robust standard errors in parentheses.

### 4.3.2 Change the Independent Variable Measure

To further test the robustness of the model, this study replaces the core explanatory variable with the elderly dependency ratio, which is the proportion of the population aged 65 and above to the population aged 15-64. This indicator is also commonly used to measure the degree of aging in a country (Chen et al., 2018; Yu et al., 2024). According to the regression results in Column (2) of Table 4, the negative effect of the elderly dependency ratio on food production remains significant and robust. This indicates that regardless of whether the aging degree is measured by the proportion of the elderly in the total population or by the elderly dependency ratio, an increase in aging significantly negatively impacts food production. This further validates the robustness of the model.

### 4.3.3 Shrinkage Treatment

Due to the potential interference of outliers on the regression results, this study applies Winsorization to the aging rate at the 2.5%, 5%, and 7.5% tails. The processed data is then used for regression analysis. The empirical results in Columns (3) to (8) of Table 4 show that after trimming, the conclusion that population aging has a negative impact on food production remains robust.

### 4.4 Endogenous Problems

To ensure the reliability of the above empirical analysis results, this study considers the potential endogeneity issue in the baseline regression model that could lead to biased results. Endogeneity issues mainly arise from two aspects: omitted variable bias and reverse causality. Since food production is unlikely to influence population aging, reverse causality is not a concern in this study. However, there could still be omitted variables. If omitted variables are correlated with

the error term in the model, endogeneity bias may occur. The instrumental variable (IV) method is an effective way to solve this problem. Therefore, the study selects the crude death rate, as reported by the World Bank, as the instrument for population aging. The crude death rate refers to the estimated number of deaths per 1,000 people in a year, which, apart from accidental deaths, roughly reflects the mortality rate of the elderly population and indirectly indicates the degree of aging, thus satisfying the relevance condition. Furthermore, the crude death rate does not directly affect a country's food production, fulfilling the exogeneity requirement for an instrument variable. Table 5 reports the two-stage regression results using the instrument variable. The

identification test for the instrument variable shows that the Kleibergen-Paap rk LM statistic rejects the null hypothesis of "the instrument variable being unidentified" at the 1% level. The weak instrument test shows that the Cragg-Donald Wald F statistic exceeds the critical value under Stock and Yogo (2005) for a 10% distortion tolerance, indicating no issue with weak instruments. The estimated results indicate that, after addressing the endogeneity issue, the conclusion that population aging negatively affects food production remains valid. This is consistent with the baseline regression results, further confirming the robustness and reliability of the findings.

**Table 5 Instrumental variable test**

| Variable               | AG                  | lnGY                 |
|------------------------|---------------------|----------------------|
|                        | The first stage (1) | The second stage (2) |
| AG                     |                     | -9.063*** (2.099)    |
| Death                  | 0.855*** (0.069)    |                      |
| Control                | Yes                 | Yes                  |
| Year                   | Yes                 | Yes                  |
| Country                | Yes                 | Yes                  |
| N                      | 4090                | 4090                 |
| F                      | 154.640             | 12.210               |
| Cragg-Donald Wald F    | 4232.650            | 4232.647             |
| Kleibergen-Paap Wald F | 154.640             | 154.643              |

Note: \*p < 0.1, \*\*p < 0.05, \*\*\*p < 0.01. Cluster-robust standard errors in parentheses.

#### 4.5 Heterogeneity Analysis

To further explore the heterogeneity in the impact of population aging on food production, this study conducts subgroup regression analysis from four dimensions: aging level, urbanization level, income level, and geographical location. The results are presented in Tables 6 and 7. Firstly, in terms of aging level, following the standards set by the United Nations (UN. ESCAP, 2022), the sample is divided into four stages: aging rate below 7% means that the country has not yet entered an aging society; an aging rate between 7% and 14% indicates a mild aging stage; an aging rate between 14% and 21% represents a moderate aging stage; and when the aging rate exceeds 21%, the country is considered to be in a severe aging stage. Next, for the urbanization level, this study refers to the different stages of urbanization development (Fang et al., 2008) and

categorizes urbanization into four levels: countries with an urbanization rate below 30% are in the low-growth stage; countries with an urbanization rate between 30% and 60% are in the growth stage; countries with an urbanization rate between 60% and 80% are in the maturity stage; and countries with an urbanization rate between 80% and 100% are in the final stage. As for income level, this study adopts the World Bank's latest income classification standard (World Bank, 2024), where countries with a Gross National Income (GNI) per capita  $\leq 1,145$  USD are categorized as low-income; countries with  $1,145$  USD < GNI per capita  $\leq 14,005$  USD are in the middle-income group; and countries with a GNI per capita  $> 14,005$  USD are classified as in high-income group. Due to the significant missing values in the GNI per capita data, and given the high correlation between GNI per capita and GDP per capita in reflecting national economic levels,

this study uses GDP per capita as a substitute variable for subgroup analysis. Finally, based on geographical differences, this study divides the sample into five regions: Asia, Oceania, Europe, Americas and Africa.

The subgroup regression results, as shown in Table 6, indicate that in the analysis of aging levels, in the severe aging group, the regression coefficient for population aging is positive but not statistically significant. In the other three groups including non-aging, mild aging and moderate aging stages, the regression coefficients for population aging are negative and statistically significant at the 1% level, suggesting that in countries with lower or moderate levels of aging, aging has a significant negative impact on food production.

In the subgroup regression analysis based on urbanization levels, the results in Table 6 show that in the low urbanization growth stage, the regression coefficient for population aging is negative but not statistically significant, indicating that in countries with low urbanization, the negative impact of population aging on food production is not evident. However, in the other three groups including growth stage, maturity stage and final stage, the regression coefficients for population aging are negative and statistically significant at the 1% level, suggesting that in countries with higher levels of urbanization, population aging has a significant negative impact on food production.

In the subgroup regression analysis based on income levels, the results shown in Table 7 indicate that in the middle-income group, the regression coefficient for population aging is negative but not statistically significant. In the low-income group, the regression coefficient for population aging is positive and statistically significant at the 1% level, suggesting a significant positive correlation between population aging and food production. In contrast, in the high-income group, population aging is significantly negatively correlated with food production.

The regional subgroup regression results indicate significant differences in the impact of population aging on food production across different regions. These differences may stem from variations in socioeconomic structures, agricultural production methods, and policy systems across regions. In Oceania, although the regression coefficient for population aging is negative, it is not statistically significant, indicating that the negative impact of aging on food production is relatively weak. In contrast, in Asia, the Americas, and Africa, the regression coefficients for population aging are negative and statistically significant at the 1% level. However, in European countries, the regression coefficient for population aging is positive and statistically significant at the 1% level, indicating that aging has a positive effect on food production in this region.

**Table6 Ageing and Urbanization Heterogeneity analysis**

| Variable name | Ageing               |                     |                     |                    | Urbanization       |                      |                      |                      |
|---------------|----------------------|---------------------|---------------------|--------------------|--------------------|----------------------|----------------------|----------------------|
|               | AG<7%<br>(1)         | 7%≤AG<14%<br>(2)    | 14%≤AG<21%<br>(3)   | 21%≤AG<br>(4)      | Urban<30%<br>(5)   | 30%≤Urban<60%<br>(6) | 60%≤Urban<80%<br>(7) | 80%≤Urban<br>(8)     |
| AG            | -5.229***<br>(1.616) | -8.140**<br>(0.955) | -5.392**<br>(0.662) | 12.497<br>(8.873)  | -2.332<br>(2.910)  | -8.776***<br>(0.966) | -6.064***<br>(0.740) | -5.332***<br>(0.600) |
| Constant      | 12.828<br>(9.422)    | 15.024<br>(9.344)   | 14.232<br>(8.819)   | 13.423<br>(16.107) | 14.036<br>(16.675) | -4.667<br>(19.023)   | 11.200<br>(9.044)    | 14.376<br>(8.805)    |
| Control       | Yes                  | Yes                 | Yes                 | Yes                | Yes                | Yes                  | Yes                  | Yes                  |
| Year          | Yes                  | Yes                 | Yes                 | Yes                | Yes                | Yes                  | Yes                  | Yes                  |
| Country       | Yes                  | Yes                 | Yes                 | Yes                | Yes                | Yes                  | Yes                  | Yes                  |
| N             | 2609                 | 3328                | 4044                | 50                 | 694                | 2271                 | 3444                 | 4094                 |

Note: \*p < 0.1, \*\*p < 0.05, \*\*\*p < 0.01. Cluster-robust standard errors in parentheses.

**Table7 Income Group and Continent Heterogeneity analysis**

| Variable name | Income Group         |                      |                      | Continent            |                       |                      |                       |                        |
|---------------|----------------------|----------------------|----------------------|----------------------|-----------------------|----------------------|-----------------------|------------------------|
|               | Low (9)              | Middle (10)          | High (11)            | Asia (12)            | Oceania (13)          | Europe (14)          | America (15)          | Africa (16)            |
| AG            | 9.074*<br>** (2.757) | -0.879<br>(1.262)    | -5.749***<br>(1.152) | -5.938***<br>(1.169) | -10.138<br>(7.847)    | 1.956**<br>*(0.691)  | -6.307*<br>** (2.193) | -10.853*<br>** (2.849) |
| Constant      | 5.405 (15.217)       | 24.129*<br>*(10.163) | 18.324**<br>*(1.497) | 13.510**<br>*(0.570) | 39.718*<br>** (4.637) | 6.506**<br>* (0.871) | 25.415*<br>* (11.279) | -0.326<br>(23.287)     |
| Control       | Yes                  | Yes                  | Yes                  | Yes                  | Yes                   | Yes                  | Yes                   | Yes                    |
| Year          | Yes                  | Yes                  | Yes                  | Yes                  | Yes                   | Yes                  | Yes                   | Yes                    |
| Country       | Yes                  | Yes                  | Yes                  | Yes                  | Yes                   | Yes                  | Yes                   | Yes                    |
| N             | 1174                 | 1983                 | 937                  | 1112                 | 120                   | 905                  | 800                   | 1157                   |

Note: \*p < 0.1, \*\*p < 0.05, \*\*\*p < 0.01. Cluster-robust standard errors in parentheses.

#### 4.6 Mechanism Analysis of the Impact of Population Aging on Food Production

Based on the theoretical analysis in the previous sections, population aging may influence food production through changes in the proportion of agricultural employment and the input of

production factors such as fertilizers. To further explore the mechanisms through which population aging affects food production, this study uses the three-step regression coefficient method for testing mediation effects, following the approach of Baron and Kenny (1986). The specific models are as follows:

$$AE_{it} = \beta_0 + \beta_1 AG_{it} + \beta_j Controls_{it} + \mu_k + \vartheta_t + \varepsilon_{it} \quad (2)$$

$$\ln GY_{it} = \gamma_0 + \gamma_1 AG_{it} + \gamma_2 AE_{it} + \theta_j Controls_{it} + \mu_k + \vartheta_t + \varepsilon_{it} \quad (3)$$

$$\ln Fertilizer_{it} = \delta_0 + \delta_1 AG_{it} + \delta_j Controls_{it} + \mu_k + \vartheta_t + \varepsilon_{it} \quad (4)$$

$$\ln GY_{it} = \theta_0 + \theta_1 AG_{it} + \theta_2 \ln Fertilizer_{it} + \theta_j Controls_{it} + \mu_k + \vartheta_t + \varepsilon_{it} \quad (5)$$

In equations (2)–(5), *AE* represents the proportion of agricultural employment. *Fertilizer* represents fertilizer input, and other variables remain consistent with model (1).

The specific procedure for this method is as follows: ① Test the effect of population aging on food production, focusing on the regression coefficient  $\alpha_1$  in model (1). ② Test the regression coefficients  $\beta_1$  in model (2),  $\gamma_2$  in model (3),  $\delta_1$  in model (4), and  $\theta_2$  in model (5). The empirical analysis above has already confirmed that  $\alpha_1$  is significantly negative (as shown in Table 3), so this section primarily focuses on the coefficients  $\beta_1$ ,  $\gamma_2$ ,  $\delta_1$  and  $\theta_2$ . If  $\beta_1$ ,  $\gamma_2$  and  $\delta_1$ ,  $\theta_2$  are all significant, the mediation effect is considered significant. If at least one of  $\beta_1$  or  $\gamma_2$  ( $\delta_1$  or  $\theta_2$ ) is not significant, the Sobel test is used to determine the significance of the mediation effect.

The regression results of models (2)–(5) are presented in Table 8. Specifically, Column 2 of Table 8 shows the results of model (2), where the regression coefficient indicates a significant positive relationship between aging rate and the proportion of agricultural employment. This suggests that as the aging rate increases, the proportion of agricultural workers in total employment rises. This result may reflect an adjustment in the labor structure in aging societies. Due to physical and skill limitations, the elderly are less likely to integrate into the urban labor market, and agriculture becomes their primary option for livelihood, leading to an increase in the agricultural employment share. In Column 3 of Table 8, the results show that the proportion of agricultural employment is significantly negatively correlated with food production, indicating that an increase in agricultural labor may not enhance production

efficiency. Instead, factors such as a decline in labor quality or outdated technical skills may lead to a reduction in food output. Therefore, it can be inferred that the proportion of agricultural employment plays a partial mediating role in the effect of aging on food production, as aging indirectly suppresses food production by increasing the share of agricultural workers.

Regarding the impact of fertilizer input, Column 5 of Table 8 reports the regression results of model (4), showing a significant negative correlation between aging rate and fertilizer input. As aging intensifies, the proportion of elderly labor in agriculture increases. They often reduce the cultivation area or decrease farming intensity to accommodate their physical and technical

limitations. This reduction in farming scale directly leads to a decreased demand for agricultural inputs such as fertilizers and pesticides, resulting in lower fertilizer use. Meanwhile, the results in Column 6 of Table 8 show that fertilizer input is positively correlated with food production, indicating that fertilizer, as a critical agricultural input, can effectively increase food output. Therefore, it can be inferred that fertilizer input also plays a partial mediating role in the impact of aging on food production. Overall, these results suggest that population aging not only affects the composition of agricultural labor but also suppresses food production by reducing the input of agricultural production factors.

**Table 8 Mediating effect test of aging rate on farmland abandonment**

|                    | AE                   |                     |                      | lnFertilizer         |                      |                      |
|--------------------|----------------------|---------------------|----------------------|----------------------|----------------------|----------------------|
|                    | lnGY<br>(1)          | AE<br>(2)           | lnGY<br>(3)          | lnGY<br>(4)          | lnFertilizer<br>(5)  | lnGY<br>(6)          |
| AG                 | -5.196***<br>(0.600) | 0.438***<br>(0.058) | -4.771***<br>(0.602) | -5.196***<br>(0.600) | -3.730***<br>(0.797) | -4.750***<br>(0.594) |
| AE                 |                      |                     | -0.972***<br>(0.165) |                      |                      | 0.120***<br>(0.012)  |
| Control            | Yes                  | Yes                 | Yes                  | Yes                  | Yes                  | Yes                  |
| Year               | Yes                  | Yes                 | Yes                  | Yes                  | Yes                  | Yes                  |
| Region             | Yes                  | Yes                 | Yes                  | Yes                  | Yes                  | Yes                  |
| N                  | 4094                 | 4094                | 4094                 | 4094                 | 4094                 | 4094                 |
| Adj-R <sup>2</sup> | 0.986                | 0.982               | 0.986                | 0.986                | 0.923                | 0.986                |

Note: \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ . Cluster-robust standard errors in parentheses.

## 5 Discussion

Differences in economic development levels, agricultural technology adoption, and labor structures across countries and regions contribute to the complexity of the impact of population aging on food production globally. Unlike previous studies that have focused on the micro-level, this paper conducts an empirical analysis using macro-level global data to confirm the negative impact of aging on food production. This finding aligns with the conclusions of most scholars who have studied individual countries or regions (Rigg *et al.*, 2020; Liu *et al.*, 2021; Liu *et al.*, 2023). Therefore, from an overall perspective, population aging significantly negatively impacts food production. Although Lee *et al.* (2024), using sample data from China, concluded optimistically that the development of artificial intelligence has

not led to a significant negative impact of population aging on food security, this situation may not be applicable globally.

Existing research suggests that as the degree of aging increases, it will continue to adversely affect food production (Liu *et al.*, 2021). However, in the age group analysis, the results of this study show that in heavily aged countries, the impact of population aging on food production is not significant. In contrast, in the other three groups including pre-aging, mild aging, and moderate aging stages, population aging has a significant negative impact on food production. A possible reason for this is that heavily aged countries, having entered the aging stage earlier, have accumulated experience in addressing aging issues. Typical heavily aged countries such as Japan, Greece, and Italy have implemented measures such as technological research and

development or agricultural structural adjustments to alleviate labor shortages in food production, thus maintaining or even improving food production levels in the context of aging. Japan has invested heavily in agricultural automation and intelligence, introducing robotic harvesting and precision farming techniques, which has reduced reliance on human labor for production (Yoshida et al., 2022). Greece has established training systems to improve the ability of elderly farmers to master modern agricultural technologies, such as greenhouse cultivation and integrated water and fertilizer management, to increase labor productivity and promote food production (Kavga et al., 2021). In addition, countries like Italy have encouraged migrant labor participation in agriculture, particularly during seasonal production peaks, filling labor gaps and effectively alleviating the pressure on food production (Palumbo & Corrado, 2020).

Regarding the heterogeneous impact of urbanization levels, existing studies have shown that the impact of population aging on food production varies significantly across different urbanization levels (Lee et al., 2021; Hou et al., 2022). This finding provides theoretical support for the conclusions of this study: in regions with low-speed urbanization, the impact of population aging on food production is not significant. However, in regions with growing, mature, and late-stage urbanization, population aging has a significant negative effect on food production. The possible reason is that highly urbanized regions provide more non-agricultural employment opportunities, reducing the dependence of farmers on land (Li et al., 2016). As population aging intensifies, farmers in highly urbanized areas are more likely to exit agriculture, thereby significantly negatively affecting food production. In contrast, in regions with low urbanization, due to limited non-agricultural employment opportunities, farmers remain more dependent on land, and thus the negative impact of population aging on food production is not significant (Gutiérrez et al., 2016; Wang et al., 2020).

Regarding the impact of income levels, existing studies typically explore the heterogeneous effects of income differences from a micro perspective (Zhou et al., 2020). However, the global perspective analysis in this study shows that in

middle-income groups, the impact of population aging on food production is not significant. In low-income countries, population aging has a significant positive correlation with food production and in high-income countries, population aging is significantly negatively correlated with food production. A possible reason for this is that in low-income countries, agriculture is often the primary livelihood and economic backbone. Elderly people, lacking other non-agricultural employment opportunities, continue to rely on agriculture to maintain their livelihood (Gutiérrez et al., 2016). Therefore, aging does not lead to a significant reduction in agricultural labor. Instead, it may encourage families to maintain or increase food production to sustain their livelihoods and ensure food security, leading to a significant positive impact of population aging on food production (Carolan, 2018). In high-income countries, agricultural mechanization and technological advancement are more common, and farmers are more likely to choose non-agricultural employment or rely on other economic sources, reducing their dependence on agriculture (Li et al., 2016). As aging intensifies, elderly laborers are more likely to exit agricultural production, resulting in a decrease in agricultural labor and negatively impacting food production (Jansuwan & Zander, 2021). In middle-income countries, agriculture and non-agricultural industries are typically in a transitional phase, with the non-agricultural economy gradually developing, although agriculture still holds significance in certain regions. In these countries, despite some elderly labor exiting agriculture, the impact of population aging on food production is not significant, as other family members, technological investments, or the increase in agricultural mechanization offset the effects.

Existing studies typically classify regions based on East, Central, and West regions or based on major and non-major food-producing areas (Li et al., 2024; Lee et al., 2024), with limited analysis conducted at the continental level globally. This paper conducts a group analysis by continent, and the heterogeneous results indicate that in Oceania, the impact of population aging on food production is not significant, In Asia, the Americas, and Africa, population aging is significantly negatively correlated with food production. Whereas in European countries, population aging

has a positive impact on food production. According to reports by the FAO and the World Bank on agricultural mechanization, mechanization plays an increasingly important role in food production, but the level of mechanization varies across regions (FAO, 2016; FAO, 2024; World Bank, 2024). Oceania countries have achieved high levels of agricultural mechanization, which reduces reliance on labor and alleviates the labor shortages caused by aging. For example, Australia is a leader in agricultural mechanization, using modern equipment and technologies that make agricultural production more efficient. In this context, the impact of aging on agricultural labor is relatively not obvious (FAO, 2016). In contrast, many countries in Asia and Africa still rely on labor-intensive agricultural methods, which makes the impact of population aging on labor supply more pronounced, thus negatively affecting food production. According to World Bank data, mechanization levels in Africa and South Asia are relatively low, and many areas still rely on traditional farming methods (World Bank, 2024). This dependence makes the impact of aging on labor supply more significant, negatively affecting food production. In the Americas, while some regions, such as the United States and Canada, have relatively high levels of mechanization, small and medium-sized farms still rely on family labor, meaning that the production capacity of family farms may be negatively affected by aging. In Europe, the situation is different, as population aging has significantly promoted food production, which is closely related to the high level of mechanization and advanced technology in European agriculture (FAO, 2016; World Bank, 2024). By reducing reliance on labor, agricultural mechanization has somewhat mitigated the negative impact of aging on food production. Moreover, the advancement of agricultural technology not only improves production efficiency but also provides new growth momentum for food production, thus continuing to promote food production in Europe despite the aging population (World Bank, 2024).

Finally, this study incorporates the share of agricultural employment and fertilizer input into the analytical framework, expanding the research on the mechanisms through which population aging affects food production. The results indicate that both the share of agricultural employment and fertilizer input play partial mediating roles in the

impact of population aging on food production. A possible explanation is that as the degree of aging increases, the rural elderly population, due to physical and skill limitations, struggles to integrate into urban labor markets, making agricultural work their primary livelihood option (Wang *et al.*, 2020). Although the aging of agricultural workers intensifies, the labor efficiency of this group is limited, making it difficult to meet the demands of large-scale food production (Harper, 2014; Choi & Shin, 2015). Therefore, despite an increase in agricultural labor, the actual contribution to food production is limited due to the predominance of low-efficiency elderly workers, leading to a situation where "the share of agricultural labor increases but output declines." Moreover, elderly laborers, due to physical and health limitations, typically reduce the cultivated area or decrease farming intensity to accommodate their declining production capacity (Shao *et al.*, 2015; Jansuwan & Zander, 2021). As the cultivated area shrinks, the demand for agricultural inputs such as fertilizers and pesticides decreases, leading to an overall decline in agricultural inputs, which adversely affects food production (Ren *et al.*, 2023). It is noteworthy that the mediating effect results in this study show that population aging has increased the share of agricultural employment, which differs from the conclusions of some scholars. Bloom (2015) and Liu (2023), for example, argue that aging leads to labor shortages, reducing the proportion of agricultural labor and jeopardizing food security. Despite differences in conclusions regarding the share of agricultural labor, both indicate that aging negatively affects food production. The possible reason is that although the elderly population increases the number of agricultural laborers, their low labor efficiency reduces the actual effective labor supply, leading to a decline in productivity and ultimately negatively affecting food production.

## 6 Conclusions and Policy Implications

This study uses a panel data covering 162 countries from 1991 to 2020 to empirically analyze the impact of population aging on food production from a globalization perspective. It is concluded that population aging is significantly negatively correlated with food production, meaning that an increase in the aging population will have an adverse effect on food production. At

the same time, this impact of population aging on food production shows significant heterogeneity across different levels of aging, urbanization, income, and geographical locations. In terms of aging levels, in countries with severe aging, the impact of population aging on food production is not significant. However, in countries with no aging, mild aging, and moderate aging, population aging is significantly negatively correlated with food production. Regarding urbanization, in the stages of urbanization development, maturity, and advanced phases, population aging has a significant negative impact on food production. Whereas in the early stages of urbanization, the effect of aging on food production is not significant. In terms of income levels, in low-income countries, population aging is significantly positively correlated with food production. In high-income countries, aging is significantly negatively correlated with food production. While in middle-income countries, the impact of aging on food production is not significant. Geographically, the negative impact of aging on food production is primarily observed in Asia, the Americas, and Africa. In Europe, population aging is significantly positively correlated with food production. While in Oceania, the impact of aging on food production is not significant. Besides, it is interesting to find that the share of agricultural employment and fertilizer input also play a partial mediating role in the impact of aging on food production. Aging not only affects the composition of agricultural labor, but also further suppresses food production by reducing the input of agricultural production factors. To address this adverse effect, the crucial point lies in improving the productivity of elderly agricultural laborers, which can be achieved by focusing on healthy aging, lifelong learning and skill enhancement. Besides, since mechanization and new technologies not only compensate for the inefficiencies in labor caused by aging but can also increase productivity to some extent. Therefore, it is significant to increase investment in agricultural mechanization and the development of new technologies. The limitations of this study are as follows: Firstly, due to data limitations at the country level, this study did not fully examine the specific effects of elderly labor productivity or technical proficiency on food production. Aging brings not only changes in labor quantity but, more importantly, differences

in labor quality, which has not been deeply explored in this study. Secondly, when assessing the impact of aging on food production, due to the lack of global-level data on agricultural patents and other indicators of agricultural technological progress, this study did not fully consider the role of technological progress in food production. Future research should further refine the impact of elderly labor productivity and technical proficiency on food production, particularly regarding labor quality. In addition, efforts should be made to continue exploring ways to collect and integrate information on agricultural technology, further analyzing the role of technological progress in promoting food production at different stages of aging.

#### **Funding:**

This research is supported by National Natural Science Foundation of China (No.72303218 ; No.42271284) and the Ministry of Education Philosophy and Social Sciences Fund (No. 21YJC630074).

#### **Acknowledgement**

This research is supported by National Natural Science Foundation of China (No.72303218 ; No.42271284) and the Ministry of Education Philosophy and Social Sciences Fund (No. 21YJC630074).

#### **References**

1. Alexandratos, N., & Bruinsma, J. (2012). World agriculture towards 2030/2050: the 2012 revision.
2. Augspurger, C. K. (2013). Reconstructing patterns of temperature, phenology, and frost damage over 124 years: spring damage risk is increasing. *Ecology*, 94(1), 41-50.
3. Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology*, 51(6), 1173.
4. Burholt, V., & Dobbs, C. (2012). Research on rural ageing: Where have we got to and where are we going in Europe? *Journal of rural studies*, 28(4), 432-446.
5. Bloom, D. E., Chatterji, S., Kowal, P., Lloyd-Sherlock, P., McKee, M., Rechel, B., ... & Smith, J. P. (2015). Macroeconomic

- implications of population ageing and selected policy responses. *The Lancet*, 385(9968), 649-657.
6. Choi, K. H., & Shin, S. (2015). Population aging, economic growth, and the social transmission of human capital: An analysis with an overlapping generations model. *Economic modelling*, 50, 138-147.
  7. Conway, S. F., McDonagh, J., Farrell, M., & Kinsella, A. (2016). Cease agricultural activity forever? Underestimating the importance of symbolic capital. *Journal of Rural Studies*, 44, 164-176.
  8. Carvalho, F. P. (2017). Pesticides, environment, and food safety. *Food and energy security*, 6(2), 48-60.
  9. Carolan, M. (2018). Lands changing hands: Experiences of succession and farm (knowledge) acquisition among first-generation, multigenerational, and aspiring farmers. *Land Use Policy*, 79, 179-189.
  10. Chen, Q.L., Xu, D., Zhou, Y. (2018). Labor substitution effect of artificial intelligence in the context of population aging: An analysis based on transnational panel data and Chinese provincial panel data. *Chinese Journal of Population Science* (06),30-42+126-127. (in Chinese)
  11. Chen, W., Wang, G., Cai, W., Che, X., Zhou, W., Zhang, C., & Zeng, J. (2023). Spatiotemporal mismatch of global grain production and farmland and its influencing factors. *Resources, Conservation and Recycling*, 194, 107008.
  12. Cohen, S. A., & Greaney, M. L. (2023). Aging in rural communities. *Current epidemiology reports*, 10(1), 1-16.
  13. Fang, C. L., Liu, X. L & Lin, X. Q.(2008). Revision and regularity analysis of urbanization development stages in China. *Arid geography* (4), 512-523. (in Chinese)
  14. FAO. (2016). Agricultural mechanization. <https://www.fao.org/interactive/agricultural-mechanization/en/>
  15. FAO, IFAD, UNICEF, WFP, WHO. (2020). *The State of Food Security and Nutrition in the World 2020: Transforming Food Systems for Affordable Healthy Diets*.
  16. FAO, IFAD, UNICEF, WFP and WHO. (2021). *The State of Food Security and Nutrition in the World 2021. Transforming food systems for food security, improved nutrition and affordable healthy diets for all*. FAO, Rome.
  17. FAO; IFAD; UNICEF; WFP; WHO. (2023). *The State of Food Security and Nutrition in the World 2023. Urbanization, Agrifood Systems Transformation and Healthy Diets across the Rural–Urban Continuum*; FAO: Rome, Italy.
  18. Fu, J., Jian, Y., Wang, X., Li, L., Ciais, P., Zscheischler, J., ... & Zhou, F. (2023). Extreme rainfall reduces one-twelfth of China's rice yield over the last two decades. *Nature Food*, 4(5), 416-426.
  19. FAO. (2024). Why mechanization is important. <https://www.fao.org/sustainable-agricultural-mechanization/overview/why-mechanization-is-important/en/>
  20. Guo, G., Wen, Q., & Zhu, J. (2015). The impact of aging agricultural labor population on farmland output: from the perspective of farmer preferences. *Mathematical problems in Engineering*, 2015(1), 730618.
  21. Gutiérrez Rodríguez, L., Hogarth, N. J., Zhou, W., Xie, C., Zhang, K., & Putzel, L. (2016). China's conversion of cropland to forest program: a systematic review of the environmental and socioeconomic effects. *Environmental Evidence*, 5, 1-22.
  22. Ge, D., Long, H., Zhang, Y., Ma, L., & Li, T. (2018). Farmland transition and its influences on grain production in China. *Land Use Policy*, 70, 94-105.
  23. Guo, Z., & Zhang, X. (2023). Carbon reduction effect of agricultural green production technology: A new evidence from China. *Science of the Total Environment*, 874, 162483.
  24. Harper, S. (2014). Economic and social implications of aging societies. *Science*, 346(6209), 587-591.
  25. Hou, M., Deng, Y., & Yao, S. (2022). Coordinated relationship between urbanization and grain production in China: Degree measurement, spatial differentiation and its factors detection. *Journal of Cleaner Production*, 331, 129957.
  26. Hu, Y., & Liu, Y. (2024). Impact of fertilizer and pesticide reductions on land use in China based on crop-land integrated model. *Land Use Policy*, 141, 107155.
  27. Ingram, J., & Kirwan, J. (2011). Matching new entrants and retiring farmers through farm

- joint ventures: Insights from the Fresh Start Initiative in Cornwall, UK. *Land Use Policy*, 28(4), 917-927.
28. Ji, H., Xiao, L., Xia, Y., Song, H., Liu, B., Tang, L., ... & Liu, L. (2017). Effects of jointing and booting low temperature stresses on grain yield and yield components in wheat. *Agricultural and Forest Meteorology*, 243, 33-42.
29. Jansuwan, P., & Zander, K. K. (2021). What to do with the farmland? Coping with ageing in rural Thailand. *Journal of Rural Studies*, 81, 37-46.
30. Kavga, A., Thomopoulos, V., Barouchas, P., Stefanakis, N., & Liopa-Tsakalidi, A. (2021). Research on innovative training on smart greenhouse technologies for economic and environmental sustainability. *Sustainability*, 13(19), 10536.
31. Lutz, W., Sanderson, W., & Scherbov, S. (2008). The coming acceleration of global population ageing. *Nature*, 451(7179), 716-719.
32. Liu, L., Xu, X., Liu, J., Chen, X., & Ning, J. (2015). Impact of farmland changes on production potential in China during 1990–2010. *Journal of Geographical Sciences*, 25, 19-34.
33. Li, Y., Westlund, H., Zheng, X., & Liu, Y. (2016). Bottom-up initiatives and revival in the face of rural decline: Case studies from China and Sweden. *Journal of Rural Studies*, 47, 506-513.
34. Li, F., Meijun, Z., & Hu, M. (2019). Climate change in different geographical units and its impact on land production potential: A case study of Shaanxi Province, China. *Environmental Science and Pollution Research*, 26(22), 22273-22283.
35. Liu, J. C., Xu, Z. G., Zheng, Q. F., & Hua, L. (2019). Is the feminization of labor harmful to agricultural production? The decision-making and production control perspective. *Journal of Integrative Agriculture*, 18(6), 1392-1401.
36. Lee, J., Oh, Y. G., Yoo, S. H., & Suh, K. (2021). Vulnerability assessment of rural aging community for abandoned farmlands in South Korea. *Land Use Policy*, 108, 105544.
37. Lin, W., & Huang, J. (2021). Impacts of agricultural incentive policies on land rental prices: New evidence from China. *Food Policy*, 104, 102125.
38. Liu, Y., & Zhou, Y. (2021). Reflections on China's food security and land use policy under rapid urbanization. *Land use policy*, 109, 105699.
39. Liu, X., Xu, Y., Engel, B. A., Sun, S., Zhao, X., Wu, P., & Wang, Y. (2021). The impact of urbanization and aging on food security in developing countries: The view from Northwest China. *Journal of Cleaner Production*, 292, 126067.
40. Liu, M., Zheng, W., & Zhong, T. (2022). Impact of migrant and returning farmer professionalization on food production diversity. *Journal of Rural Studies*, 94, 23-36.
41. Liu, J., Fang, Y., Wang, G., Liu, B., & Wang, R. (2023). The aging of farmers and its challenges for labor-intensive agriculture in China: A perspective on farmland transfer plans for farmers' retirement. *Journal of Rural Studies*, 100, 103013.
42. Lee, C. C., & Yuan, Z. (2024). Impact of energy poverty on public health: A non-linear study from an international perspective. *World Development*, 174, 106444.
43. Lee, C. C., Yan, J., & Wang, F. (2024). Impact of population aging on food security in the context of artificial intelligence: Evidence from China. *Technological Forecasting and Social Change*, 199, 123062.
44. Li, R., Chen, J., & Xu, D. (2024). The Impact of Agricultural Socialized Service on Grain Production: Evidence from Rural China. *Agriculture*, 14(5), 785.
45. Meng, M., Yu, L., & Yu, X. (2024). Machinery structure, machinery subsidies, and agricultural productivity: Evidence from China. *Agricultural Economics*, 55(2), 223-246.
46. Niu, S., Yu, L., Li, J., Qu, L., Wang, Z., Li, G., ... & Lu, D. (2024). Effect of high temperature on maize yield and grain components: A meta-analysis. *Science of The Total Environment*, 175898.
47. Pingali, P. L. (2007). Agricultural growth and economic development: a view through the globalization lens. *Agricultural Economics*, 37, 1-12.
48. Peng, X. (2011). China's demographic history and future challenges. *science*, 333(6042), 581-587.

49. Prosekov, A. Y., & Ivanova, S. A. (2018). Food security: The challenge of the present. *Geoforum*, 91, 73-77.
50. Puma, M. J. (2019). Resilience of the global food system. *Nature Sustainability*, 2(4), 260-261.
51. PALUMBO, L., & CORRADO, A. (2020). COVID-19, agri-food systems, and migrant labour: the situation in Germany, Italy, The Netherlands, Spain, and Sweden. Open Society Foundations.
52. Qiu, T., Shi, X., He, Q., & Luo, B. (2021). The paradox of developing agricultural mechanization services in China: Supporting or kicking out smallholder farmers? *China Economic Review*, 69, 101680.
53. Ray, D. K., Mueller, N. D., West, P. C., & Foley, J. A. (2013). Yield trends are insufficient to double global crop production by 2050. *PLoS one*, 8(6), e66428.
54. Rigg, J., Phongsiri, M., Promphakping, B., Salamanca, A., & Sripun, M. (2020). Who will tend the farm? Interrogating the ageing Asian farmer. *The Journal of Peasant Studies*, 47(2), 306-325.
55. Ren, C., Zhou, X., Wang, C., Guo, Y., Diao, Y., Shen, S., ... & Gu, B. (2023). Ageing threatens sustainability of smallholder farming in China. *Nature*, 616(7955), 96-103.
56. Stock, J. H., & Yogo, M. (2002). Testing for weak instruments in linear IV regression.
57. Shao, J. A., Zhang, S., & Li, X. (2015). Farmland marginalization in the mountainous areas: Characteristics, influencing factors and policy implications. *Journal of Geographical Sciences*, 25, 701-722.
58. Song, J., & Chen, X. (2019). Eco-efficiency of grain production in China based on water footprints: A stochastic frontier approach. *Journal of Cleaner Production*, 236, 117685.
59. UN. ESCAP. (2022). Asia-Pacific report on population ageing 2022: Trends, policies, and good practices regarding older persons and population ageing. United Nations.
60. United Nations. (2022). World Population Prospects: The 2022 Revision. New York. United Nations.
61. Wang, J., Zhang, Z., & Liu, Y. (2018). Spatial shifts in grain production increases in China and implications for food security. *Land use policy*, 74, 204-213.
62. Walls, H., Baker, P., Chirwa, E., & Hawkins, B. (2019). Food security, food safety & healthy nutrition: are they compatible? *Global Food Security*, 21, 69-71.
63. Wang, Y., Li, X., He, H., Xin, L., & Tan, M. (2020). How reliable are cultivated land assets as social security for Chinese farmers? *Land Use Policy*, 90, 104318.
64. Wang, Q., & Wang, L. (2021). The nonlinear effects of population aging, industrial structure, and urbanization on carbon emissions: A panel threshold regression analysis of 137 countries. *Journal of Cleaner Production*, 287, 125381.
65. Wang, X., Cui, C., Xu, M., Cheng, B., & Zhuang, M. (2024). Key technologies improvements promote the economic-environmental sustainability in wheat production of China. *Journal of Cleaner Production*, 443, 141230.
66. World Bank. (2024). Agriculture overview. <https://www.worldbank.org/en/topic/agriculture/overview>.
67. World Bank. (2024). World Bank country and lending groups. World Bank Data Help Desk. <https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups>.
68. Xie, K., Ding, M., Zhang, J., & Chen, L. (2021). Trends towards coordination between grain production and economic development in China. *Agriculture*, 11(10), 975.
69. Yi, F., Sun, D., & Zhou, Y. (2015). Grain subsidy, liquidity constraints and food security—Impact of the grain subsidy program on the grain-sown areas in China. *Food Policy*, 50, 114-124.
70. Yamashita, R., & Hoshino, S. (2018). Development of an agent-based model for estimation of agricultural land preservation in rural Japan. *Agricultural systems*, 164, 264-276.
71. Yu, B., Wei, Y. M., Gomi, K., & Matsuoka, Y. (2018). Future scenarios for energy consumption and carbon emissions due to demographic transitions in Chinese households. *Nature Energy*, 3(2), 109-118.
72. Yoshida, T., Onishi, Y., Kawahara, T., & Fukao, T. (2022). Automated harvesting by a dual-arm fruit harvesting robot. *ROBOMECH journal*, 9(1), 19.

73. Yang Q, Jia J F, Liu J & Xu Q. (2023). How do subsidies for agricultural machinery purchase affect comprehensive grain production capacity? -- Based on the social service of agricultural machinery. *Management world* (12), 106-123. (in Chinese)
74. Yu, Z., Chen, J., & Yu, R. (2024). Dose the increasing burden of social endowment affect sustainable development of economy? *Plos one*, 19(1), e0296512.
75. Zhao, X., Zheng, Y., Huang, X., Kwan, M. P., & Zhao, Y. (2017). The effect of urbanization and farmland transfer on the spatial patterns of non-grain farmland in China. *Sustainability*, 9(8), 1438.
76. Zhang, Y.X. & Xia, J.C. (2020). How can Increasing Healthy life expectancy Promote economic growth? -- Empirical research based on transnational macro data. *Management* (10) in the world, and 53 + 41-214-215. (in Chinese)
77. Zhou, C., Zhang, R., Ning, X., & Zheng, Z. (2020). Spatial-temporal characteristics in grain production and its influencing factors in the Huang-Huai-Hai Plain from 1995 to 2018. *International Journal of Environmental Research and Public Health*, 17(24), 9193.
78. Zheng, D., An, Z., Yan, C., & Wu, R. (2022). Spatial-temporal characteristics and influencing factors of food production efficiency based on WEF nexus in China. *Journal of Cleaner Production*, 330, 129921.
79. Zhang, Y., Li, X., Shi, T., Li, H., & Zhai, L. (2023a). Understanding cropland abandonment from economics within a representative village and its empirical analysis in Chinese mountainous areas. *Land Use Policy*, 133, 106876.
80. Zhang, L., Che, L., & Wang, Z. (2023b). Where are the critical points of water transfer impact on grain production from the middle route of the south-to-north water diversion project? *Journal of Cleaner Production*, 1404 65.