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# Aging of Agricultural Labor Force and Technical Efficiency in Tea Production: Evidence from Meitan County, China

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**Abstract:** While the aging of agricultural labor force and its impact on agricultural production have been attracting extensive attention, little is known about the relationship between aging of agricultural labor force and technical efficiency in tea production. Using the stochastic frontier analysis and cross-sectional survey data covering 241 tea-producing farmers in Meitan County in China, this study attempts to investigate the impact of aging of tea-producing farmers on technical efficiency in tea production in the mountainous areas of southwestern China. The results show that the average technical efficiency in tea production is 0.581, implying a great room for improving technical efficiency in tea production in Meitan County. While there might exist an inverted U-shaped relationship between farmers' age and technical efficiency, the aging of tea-producing farmers would exert negative impact on technical efficiency in tea production. In addition, rural–urban migration experience, number of household laborers, distance from home to village committee, and township location are also significantly related with technical efficiency. The findings in this study are proved to be robust. Hence, several policy implications for meeting the challenges from aging of agricultural labor force and improving technical efficiency in tea production in the mountainous areas of southwestern China are also discussed.

**Keywords:** aging; agricultural labor force; technical efficiency; stochastic frontier analysis; tea

## 1. Introduction

The past decades since the reform and opening up have witnessed an intensifying aging of population and agricultural labor force in China [1,2]. According to the official estimate, the percentage of population aged and over 65 years old in China increased from 4.9% in 1982 to 11.4% in 2017 [3]. Note that the aging population contributes greatly to the aging of agricultural labor force. In addition, a large number of young rural labor force have been entering the city, which further aggravates the aging of agricultural labor force in rural areas in China [4]. In 1996, nearly 8.5% of the total agricultural labor force in China were aged over 60 years old, while it dramatically rose to 11.2% in 2006 [5,6]. A previous study predicted that the average age of agricultural labor force in China would further increase to about 55–56 years old in 2020 [7].

In recent years, the consequences of aging of agricultural labor force have been attracting extensive attention, but the conclusions are mixed [1,8,9]. In China, the aging of agricultural labor force and related impacts are the prominent issues of rural and agricultural development [1]. Some studies argued that the aging of agricultural labor force is detrimental to agricultural production [1,10,11].

Yang et al. found that land use efficiency would first increase and then decrease as the age of farmers grows, and there exists a negative impact of aging of agricultural labor force on land use efficiency [12]. Using Chinese Household Income Survey (CHIP) in 2013, Zhang analyzed the impact of aging of agricultural labor force on land conversion, and found that the aging of agricultural labor force leads rural households to rent out but not to rent in the cultivated land, which in turn is not conducive to agricultural development [13]. Yang employed an ordered probit estimation to investigate the impact of aging of agricultural labor force on technology adoption based on rural household survey data collected in the Yangtze River Basin in China, and the results showed that the aging of agricultural labor force is detrimental to adoption of green technologies in agriculture [14]. Similarly, Wei and Xia argued that the aging of agricultural labor force has significantly negative impact on grain output using data from the main grain-producing regions during the period 2001–2015 [15].

However, some studies concluded that there is not a significantly negative impact of the aging of agricultural labor force on agricultural production in China. Hu and Zhong pointed out that there is no significant difference of factor inputs in grain production between the young and elderly farmers, and thus, the aging of agricultural labor force has no negative impact [8]. Using panel data of 186 rural households in Zhejiang Province from 1995 to 2006, Lin and Deng concluded that the aging of agricultural labor force does not exert significant impact on land use efficiency [16]. Li et al. analyzed the impact of aging of agricultural labor force on agricultural production in China, and concluded that while the aging of agricultural labor force intensifies the shortage of local agricultural labor force, it could then promote technological evolution, which may exert a positive impact on agricultural production [17].

Improving technical efficiency is a core issue in agricultural production, and a growing body of literature focuses on the relationship between aging of agricultural labor force and technical efficiency in China. However, the conclusions are also not consistent. Some studies found an inverted U-shaped relationship between age of agricultural labor force and technical efficiency, and reached a conclusion that the aging of agricultural labor force would worsen technical efficiency in agriculture [2,18,19]. These studies mainly focus on the overall agriculture and grain production. Using survey data covering 745 apple-producing households in Shaanxi and Gansu provinces in China, Qiao et al. argued that there exists an inverted U-shaped relationship between age of farmers and technical efficiency in apple production, and the turning point of age is between 50 and 54 years old [9]. By contrast, Zhou et al. had a different finding that there is no significant difference of technical efficiency in rice production between the young and elderly farmers, and the aging of agricultural labor force does not exert a negative impact on technical efficiency in rice production at the current stage [20]. Similarly, Peng and Wen also concluded that the aging of agricultural labor force does not reduce technical efficiency in grain production nationwide [21]. Moreover, Guo and Zuo pointed out that compared with the young agricultural labor force, the elderly show significant advantage in improving technical efficiency in grain production [22].

While a considerable number of studies have investigated the consequences induced by the aging of agricultural labor force, little is known about the impact of aging of agricultural labor force on technical efficiency in tea production, especially in the mountainous areas of southwestern China. To fill the gap, this study aims to investigate the impact of aging of agricultural labor force on technical efficiency in tea production in the mountainous areas of southwestern China. The motivations are twofold. First, the previous studies regarding the relationship between aging of agricultural labor force and technical efficiency mainly focused on the overall agriculture, and grain production [20–22]. In China, grain crops, such as rice and wheat, are mainly grown in plain area, which facilities the large-scale production and adoption of agricultural machinery. The impact of aging of agricultural labor force can be largely offset by scale effect and mechanization. In the context, the impact of aging of agricultural labor force on technical efficiency in grain production may not be significant as argued in much literature [20–22]. However, this study focuses on tea production in the mountainous areas of southwestern China where it is extremely difficult to promote the large-scale production and adoption of agricultural machinery. Given the fact that tea production is labor intensive, the impact of aging of agricultural labor force on technical efficiency in tea production in the mountainous areas of southwestern China would be quite different. Second, China has been making great efforts to promote the comprehensive poverty alleviation, especially in the southwestern mountainous areas. It should be noted that tea production constitutes a main income source of a large number of farmers in the mountainous areas of southwestern China. During the past decades, meanwhile, a large number of agricultural labor force in the mountainous areas of southwestern China have been migrating to the eastern and coastal areas for higher return to labor, which greatly aggravates the aging of agricultural labor force in the southwestern mountainous areas. In such context, this study focuses on the impact of aging of agricultural labor force on technical efficiency in tea production in the mountainous areas of southwestern China, which is expected to provide several policy implications for meeting the challenges from aging of agricultural labor force, and promoting tea production and income growth of farmers in the mountainous areas.

In this study, we first develop a theoretical analysis about the impact of aging of agricultural labor force on technical efficiency in tea production, and then empirically investigate the impact of aging of tea-producing farmers on technical efficiency in tea production using a cross-sectional survey data covering a total of 241 tea-producing rural households in Meitan, a main tea-producing county located in Guizhou Province in the mountainous areas of southwestern China. The results in this study support that there exists an inverted U-shaped relationship between age of tea-producing farmers and technical efficiency in tea production, and the turning point of the age is about 43 years old. Given the fact that the sampled farmers averagely aged over 50 years old and more than 83.4% of them are aged and over 43 years old, this study reveals that the aging of agricultural labor force has a negative impact of technical efficiency in tea production. Overall, this study contributes to the literature from two aspects. First, we provide a theoretical analysis about how the aging of agricultural labor force influences technical efficiency in tea production, which forms the solid foundation for the empirical analysis. Second, this study focuses on tea instead of grain crops. As mentioned, the previous studies mainly examine the relationship between aging of agricultural labor force and overall agriculture or grain production, of which the conclusions and the interpretations are limited and not enough to reveal the actual impact of aging of agricultural labor force on agricultural production. Hence, this study enriches the literature by focusing on tea production.

The following parts of this study includes four sections. Section 2 first develops a theoretical analysis about the impact of aging of agricultural labor force on technical efficiency in tea production, and then provides the research hypothesis. In Section 3, a stochastic frontier production function used to calculate technical efficiency and analyze the impact of aging of agricultural labor force on technical efficiency is constructed, and data source is described. The econometric results with robustness tests are presented and discussed in Section 4. In addition, Section 5 concludes with policy implications.

## 2. Theoretical Analysis

The output growth of crops depends mainly on factor inputs, such as fertilizer, pesticide and irrigation, and the adoption of good technologies. In modern agriculture, it has been frequently documented that the adoption of technologies and technical efficiency play crucial roles in promoting agricultural output growth [23–25]. That is, the wholly efficient utilization of the adopted technologies could result in the maximum output given the certain factor inputs. Hence, technical efficiency is often used to measure whether the best available technologies are adopted and efficiently utilized in agricultural production [26]. In general, the best available technologies are adopted and efficiently utilized if technical efficiency equals one. Otherwise, there might be some loss of technical efficiency. Much literature pays attention to the determinants of technical efficiency in agriculture [24,26–28], among which were a growing number of studies focusing on the aging of agricultural labor force [2,9].

The impact of aging of agricultural labor force on technical efficiency in tea production might depend on the experience effect and physical effect. In this study, better experience (a proxy of knowledge and skills about tea production) and physical strength would contribute to the adoption and more efficient utilization of better technologies [9]. Hence, it is reasonably assumed that better experience and physical strength would in turn induce higher technical efficiency in tea production [2,8]. Let $TE$, $E$, $P$, and $C$ denote technical efficiency, experience, physical strength, and other factors influencing technical efficiency, respectively. The technical efficiency function in tea production could be developed as:

$$TE = f(E, P, C) \tag{1}$$

$$\frac{\partial TE}{\partial E} \geq 0 \tag{2}$$

$$\frac{\partial TE}{\partial P} \geq 0 \tag{3}$$

It should be noted that both experience and physical strength could be treated as the functions of farmers' age, denoted by the term $A$ in this study. As farmers become older, the knowledge and skills represented by the experience would be improved, which could contribute to the adoption and efficient utilization of better technologies. However, physical strength would unavoidably decline as farmers' age increases, which is detrimental to the adoption and utilization of better technologies. In the context, the following equations are obtained:

$$\frac{\partial E}{\partial A} \geq 0 \tag{4}$$

$$\frac{\partial P}{\partial A} \leq 0 \tag{5}$$

According to the analysis above, the impact of farmers' age on technical efficiency could be described by the first derivative as follows:

$$\frac{\partial TE}{\partial A} = \frac{\partial TE}{\partial E} \cdot \frac{\partial E}{\partial A} + \frac{\partial TE}{\partial P} \cdot \frac{\partial P}{\partial A} \tag{6}$$

Combined with Equations (2)–(5), the part before the plus sign on the right side of Equation (6) is positive, while the other part after the plus sign is negative. Hence, it is not explicit to identify whether the impact of farmers' age on technical efficiency is positive or negative. When farmers are relatively young, the improvement of experience of tea production would be prominent, while the decline of physical strength due to the increase of farmers' age would be limited. In the context, the impact of farmers' age might be overall positive. However, when farmers become relatively old, the increase in farmers' age would not result in obvious improvement of experience of tea production, but the continuous decline of physical strength would greatly hinder the adoption and utilization of technologies, which is harmful to technical efficiency. Hence, we assume that the positive experience effect would be more important than the negative physical effect when farmers are relatively young, while the negative physical effect would gradually play a more important role when farmers are relatively old. In sum, a potential inference is that technical efficiency in tea production would first increase and then decrease as farmers' age grows.

In fact, the effects of experience of tea production and physical strength should not be treated as linear. Indeed, the knowledge and skills of tea production would probably increase at a diminishing rate as farmers' age increases. By contrast, physical strength of farmers would then decrease at an increasing rate. As a result, we could obtain the second derivatives of the experience and physical strength on farmers' age as:

$$\frac{\partial^2 E}{\partial A^2} \leq 0 \tag{7}$$

$$\frac{\partial^2 P}{\partial A^2} \leq 0 \tag{8}$$

Hence, the second derivative of technical efficiency in tea production on farmers' age could be derived as follows:

$$\frac{\partial^2 TE}{\partial A^2} = \frac{\partial TE}{\partial E} \cdot \frac{\partial^2 E}{\partial A^2} + \frac{\partial TE}{\partial P} \cdot \frac{\partial^2 P}{\partial A^2} \leq 0 \tag{9}$$

As show in Equation (9), it is apparent that the sign of the second derivative is negative, which once again confirms the inference analyzed above. Hence, the hypothesis of interest to be validated in this study is that although there might exist an inverted U-shaped relationship between farmers' age and technical efficiency in tea production, the impact of aging of farmers on technical efficiency would be negative.

## 3. Methods and Data

### *3.1. Stochastic Frontier Analysis and Econometric Model*

This study aims at investigating the impact of aging agricultural labor force on technical efficiency in tea production in the mountainous areas of southwestern China, for which the estimation of technical efficiency is crucial. In this section, we begin with introducing the method of technical efficiency estimation, and then develop the model examining the impact of aging of agricultural labor force on technical efficiency.

In general, there are two basic approaches estimating technical efficiency: (a) Non-parametric method, such as the data envelopment analysis (DEA), and (b) parametric method, such as the stochastic frontier analysis (SFA) [29,30]. In the previous literature with regard to efficiency analysis, both methods are widely adopted. In short, DEA could calculate technical efficiency in a linear-programming manner, while SFA could calculate technical efficiency based on the estimation of a stochastic frontier production function [22]. In terms of technical efficiency estimate in agriculture, SFA is more often used because it could better control the impact of random factors, such as weather and natural disasters, on crop yield [2].

In this study, we adopt the SFA method to estimate technical efficiency in tea production. In terms of production function, there are often two forms. The first one is Cobb–Douglas form, and the other one is the translog form. It has been well documented that Cobb–Douglas production function is a reduced form of the translog production function [2,31]. When the coefficients of quadratic and interaction terms are zero, the translog production function would become the Cobb–Douglas form. In this study, tea yield is subject to four kinds of inputs, and seasons of tea-leaves picking. In the context, a translog stochastic frontier production function is first constructed as:

$$lny_i = \alpha_0 + \sum_{j=1}^{5} \alpha_j lnx_{ji} + 0.5 \sum_{j=1}^{5} \sum_{k=1}^{5} \alpha_{jk} lnx_{ji} lnx_{ki} + \sum_{l=1}^{2} \beta_{li} S_{li} + v_i - u_i \tag{10}$$

where the subscript $i$ denotes the $i$-th tea-producing household. The dependent variable $y_i$ denotes tea yield; the independent variable $x_{ji}$ (and $x_{ji}$) denotes a vector of inputs in tea production, including manual labor, pesticide, fertilizer, and other cost; and $S_{li}$ denotes two kinds of variables. The first kind includes the seasons of tea-leaves picking, including (a) any two seasons of spring, summer and fall, and (b) all of spring, summer and fall, with (c) only one season of spring, summer and fall as the benchmark; and the second kind includes the township dummy variable. In addition, both $\alpha$ and $\beta$ are the coefficients to be estimated; $v_i$ is the zero-mean random disturbance term, and assumed to be independent and identically distributed, and $u_i$ is a non-negative technical inefficiency term, and in this study assumed to be half-normal distributed. Both $v_i$ and $u_i$ are distributed independently of each other, and of the independent variables. It should be noted that $\alpha_{jk} = \alpha_{kj}$ ($j \neq k$). Note that Equation (10) can be reduced into the Cobb–Douglas form when $\alpha_{jk} = 0$, as follows:

$$lny_i = \alpha_0 + \sum_{j=1}^{5} \alpha_j lnx_{ji} + \sum_{l=1}^{2} \beta_{li} S_{li} + v_i - u_i \quad (11)$$

While there would not be significant difference of technical efficiency estimation between the translog and Cobb–Douglas forms [32], this study also conducts a log-likelihood ratio test to determine which form is better [33]. As for the log-likelihood ratio test, the null hypothesis is that all the coefficients of the quadratic and interaction terms ($\alpha_{jk}$) equal zero, and thus, the Cobb–Douglas production function might be better for its apparent sense of economics. Hence, the statistics of the log-likelihood ratio test could be described as:

$$LR = 2(lnTR - lnCD) \quad (12)$$

where $LR$ denotes the statistics of the log-likelihood ratio, and $lnTR$ and $lnCD$ denote the maximum log-likelihood values of the translog and Cobb–Douglas production function, respectively.

Once the stochastic frontier production function is correctly estimated, we are able to estimate the value of technical efficiency for each tea-producing household. Since technical efficiency refers to the ratio of actual tea yield ($y_i$) to the maximum possible yield ($y_i^*$), technical efficiency could be derived as shown in Equation (13):

$$TE_i = \frac{y_i}{y_i^*} = exp(-u_i) \quad (13)$$

Hence, we could further develop an econometric model to estimate the relationship of age of agricultural labor force and other factors with technical efficiency. A two-step approach was previously utilized, in which Equation (13) predicts the value of technical efficiency, and then a separate regression model is estimated for determinants of technical efficiency as the second step. However, the two-step approach could lead to inconsistency of the estimated parameters, which could be addressed using the one-step approach [2]. Using the one-step approach, the production function and technical inefficiency model could be estimated simultaneously. Note that the technical inefficiency model is shown as:

$$u_i = \gamma_0 + \sum_{m=1}^{M} \gamma_m lnz_{mi} + \omega_i \quad (14)$$

As for Equation (14), the selection of independent variables is based on the theoretical analysis developed above and previous studies [2,22,33,34]. In total, there are five groups of independent variables. The first group includes the linear and quadratic terms of age of tea-producing farmers who are also the household heads. According to the theoretical analysis constructed above, it is probably that there may exist a non-linear relationship between age of agricultural labor force and technical efficiency in tea production. The second group of independent variables describe the other individual characteristics of household head, including gender, degree of education, and whether the farmer has rural–urban migration experience. The third group of independent variables describe the household characteristics, among which are the number of agricultural laborers, total area of tea orchards, age of tea trees, and dummy variables of tea-leaves picking seasons as mentioned earlier. The fourth group of independent variables include the distance from household home to village committee, and access to internet, both of which are used to control for the effect of access to agricultural extension services. In the context of rural China, agricultural extension activities are often conducted at the village committee. Hence, it becomes reasonable to assume that the distance from tea-producing household home to village committee may influence farmers' acquisition of agricultural extension information and participation in agricultural extension activities. The final group of independent variable include the township dummy variable.

### 3.2. Data

Data used in this study is collected using a face-to-face rural–household questionnaire survey conducted in Meitan County, Guizhou Province in 2017. Guizhou is one of the origin regions of tea trees, and also important tea-production base in China [35]. In 2016, the area of tea orchards in Guizhou reached 439.8 thousand ha, accounting for nearly 15.2% of the total tea-producing area in China, and the total output of tea was up to 141.3 thousand tonnes [35]. Meitan is a county located in Guizhou, and it is also the main tea-producing county in China. In 2016, the area of tea orchards in Meitan was about 40 thousand ha, and the correspondingly total output of tea was about 50 thousand tonnes [36].

A multi-stage random sampling method was employed to select the sample. In sum, all townships in Meitan were sorted by their per capita gross domestic product. A systematic sampling method was used to select four townships. These four townships include Mashan, Xihe, Xima, and Xinglong. Note that the former three townships are near and located in North Meitan County, while Xinglong is located in the central Meitan County. Following the similar approach, three villages were selected within each township. In each selected village, we randomly selected 20 tea-producing rural households to construct the sample. In the context, a total of 241 sampled rural households were obtained.

A face-to-face questionnaire survey was conducted for each sampled household. To ensure the data accuracy and completeness, only the member in charge of tea production in each sampled rural household, also the actual household head, was identified as the respondent of the questionnaire survey. The designed questionnaire covered a wide range of information for each sampled rural household. Specifically, data in this study mainly consist of three parts. The first part includes the basic characteristics of the rural household as a whole. The second part mainly involves the information of the household head, such as age, gender, degree of education, and whether the farmer has rural–urban migration experience. The third part collected information of the inputs and output in tea production in 2017.

Table 1 summarizes the descriptive statistics of the main variables used in the econometric models.

**Table 1.** Summary of descriptive statistics of the main variables.

| Variable | Mean | Standard Deviation |
|---|---|---|
| (1) Stochastic frontier production function | | |
| Yield (kg/ha) | 2388.347 | 3189.603 |
| Manual labor (1000 h/ha) | 11.040 | 7.916 |
| Pesticide (kg/ha) | 833.2729 | 2062.539 |
| Fertilizer (kg/ha) | 865.4721 | 848.8439 |
| Other cost (yuan/ha) | 550.4281 | 1305.508 |
| (2) Technical inefficiency model | | |
| Age (years) | 52.730 | 10.714 |
| Male (1 = yes, 0 = no) | 0.614 | 0.488 |
| Degree of education (years) | 7.025 | 3.507 |
| Migration experience (1 = yes, 0 = no) | 0.336 | 0.47 |
| Number of agricultural laborers (persons) | 2.050 | 0.952 |
| Total area of tea orchards (ha) | 0.349 | 0.496 |
| Age of tea trees (years) | 8.992 | 3.632 |
| Single season (1 = picking tea leaves in only one season, 0 = otherwise) | 0.149 | 0.357 |
| Double seasons (1 = picking tea leaves in two seasons, 0 = otherwise) | 0.237 | 0.426 |
| Triple seasons (1 = picking tea leaves in three seasons, 0 = otherwise) | 0.614 | 0.488 |
| Distance from home to village committee (km) | 1.232 | 1.398 |
| Access to the Internet (1 = yes, 0 = no) | 0.149 | 0.357 |
| Mashan (1 = yes, 0 = no) | 0.249 | 0.433 |
| Xihe (1 = yes, 0 = no) | 0.249 | 0.433 |
| Xima (1 = yes, 0 = no) | 0.253 | 0.436 |
| Xinglong (1 = yes, 0 = no) | 0.249 | 0.433 |

Note: Data came from the authors' survey.

## 4. Results and Discussion

### *4.1. Main Results*

Prior to the one-step estimation of stochastic frontier production function and technical inefficiency model, we separately estimate Cobb–Douglas and the translog production functions (Table A1). According to the log-likelihood ratio test, the value of $\chi^2$ equals 2.930 and is not statistically significant, which illustrates that the test refuses to reject the null hypothesis that all the coefficients of the interaction terms ($\alpha_{jk}$) equal zero. It demonstrates that Cobb–Douglas production function performs better. Hence, the analysis below is based on the estimated results of Cobb–Douglas production function. Table 2 summarizes the results of one-step estimation of stochastic frontier production function and technical inefficiency model.

**Table 2.** Estimates of stochastic frontier production function and technical inefficiency model.

| Variable | Coefficient | Standard Error |
|---|---|---|
| (1) Stochastic frontier production function | | |
| Ln(Manual labor) | 0.299 *** | 0.064 |
| Ln(Pesticide) | 0.022 * | 0.012 |
| Ln(Fertilizer) | 0.096 *** | 0.023 |
| Ln(Other cost) | 0.016 | 0.012 |
| Double seasons | 0.083 | 0.227 |
| Triple seasons | 0.348 * | 0.201 |
| Mashan | 1.283 *** | 0.192 |
| Xihe | 1.500 *** | 0.206 |
| Xima | 0.255 | 0.198 |
| Constant | 3.539 *** | 0.595 |
| (2) Technical inefficiency model | | |
| Ln(Age) | −24.705 ** | 12.317 |
| Ln(Age) × Ln(Age) | 3.288 ** | 1.614 |
| Male | −0.344 | 0.359 |
| Ln(Degree of education) | −0.121 | 0.126 |
| Migration experience | −0.571 * | 0.294 |
| Number of household laborers | 0.053 | 0.140 |
| Ln(Total area of tea orchards) | −0.198 | 0.227 |
| Ln(Age of tea trees) | −0.095 | 0.349 |
| Double seasons | −0.917 | 0.606 |
| Triple seasons | −0.755 | 0.487 |
| Ln(Distance from home to village committee) | 0.178 * | 0.104 |
| Access to the Internet | 0.330 | 0.396 |
| Mashan | 1.510 * | 0.907 |
| Xihe | 2.249 ** | 0.902 |
| Xima | 1.664 * | 0.880 |
| Constant | 45.390 * | 23.578 |
| Sigma_$v$ | 0.497 *** | 0.060 |
| Turning point of age | 42.813 | |
| Number of observations | 241 | |

Note: *, **, and *** denote the statistical significance at 10%, 5%, and 1% levels, respectively. Data came from the authors' survey.

In terms of Cobb–Douglas stochastic frontier production function, we found that manual labor, pesticide, and fertilizer show significant effect on tea yield (Table 2). According to the regression results, the estimated coefficient of manual labor is 0.299, and statistically significant. It implies that each 1% increase in manual labor input would significantly result in a 0.299% increase in tea yield, with other factors held constant. Similarly, the use of pesticide, and fertilizer could also promote the increase of tea yield. With other factors held constant, each 1% increase in pesticide and fertilizer use would induce a 0.022% and 0.096% increase in tea yield, respectively. These findings demonstrate that pesticide and fertilizer use could contribute to increasing tea yield. China is the largest user of pesticide and fertilizer [37–39], and farmers are often accused of overusing pesticide and fertilizer in agricultural production [38–42]. Note that these previous studies regarding pesticide and fertilizer overuse mainly focused on grain crops, cotton, fruit, and vegetables [38–42]. Hence, the results in this study provide evidence that pesticide and fertilizer in tea production may not be overused in the context of higher price of tea. In addition, the estimated results shown in Table 2 also show that the yield of tea production would be significantly higher when tea-producing farmers pick tea-leaves in all of spring, summer, and fall.

Based on the estimated results of stochastic frontier production function shown in Table 2, we calculate technical efficiency for each household. The calculation results of technical efficiency are summarized in Table 3. It shows that technical efficiency in the whole Meitan County ranges from 0.052 to 0.884, with the mean value being at 0.581. It is obvious that there exists a great room for the improvement of technical efficiency in tea production in Meitan. We also found that technical efficiency differs greatly across townships. The average technical efficiency in Xinglong reaches 0.740, which is also the highest among these four townships, followed by Mashan (0.582), and Xima (0.531). By contrast, the average technical efficiency in Xihe is merely 0.472 and the lowest.

**Table 3.** Summary of the estimated technical efficiency.

| Region | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|
| Meitan | 0.581 | 0.208 | 0.052 | 0.884 |
| Mashan | 0.582 | 0.178 | 0.052 | 0.884 |
| Xihe | 0.472 | 0.221 | 0.091 | 0.855 |
| Xima | 0.531 | 0.208 | 0.093 | 0.833 |
| Xinglong | 0.740 | 0.108 | 0.315 | 0.869 |

Note: Data came from the authors' survey.

A bar graph was drawn, as shown in Figure 1, to intuitively describe the relationship between age of tea-producing farmers and technical efficiency in tea production. It is obvious that technical efficiency of the sampled farmers aged between 35 and 45 years old reaches 0.663, ranking the highest among the five age groups. By contrast, technical efficiency of the sampled farmers aged below 35 years old is merely 0.518. It demonstrates that technical efficiency in tea production would increase as the age of tea-producing farmers grow when their age remains below 45 years old. However, such a trend no longer exists when the age of farmers becomes over 45 years old. As shown in Figure 1, technical efficiency exhibits a continuous decline as the age of tea-producing farmers grows when their age is over 45 years old. As for tea-producing farmers aged over 65 years old, technical efficiency is only 0.495. In the context, it could provide initial evidence that the aging of tea-producing farmers is likely to be negatively associated with technical efficiency in tea production. To further describe the marginal effect of age on technical efficiency, we draw a scatter of technical efficiency against farmers' age (Figure A1). It clearly shows that the marginal effect is around zero when farmers' age is between 35 and 45 years old. Additionally, the marginal effect is positive when farmers' age is below 35 years old, and negative when farmers' age is above 45 years old (Figure A1).

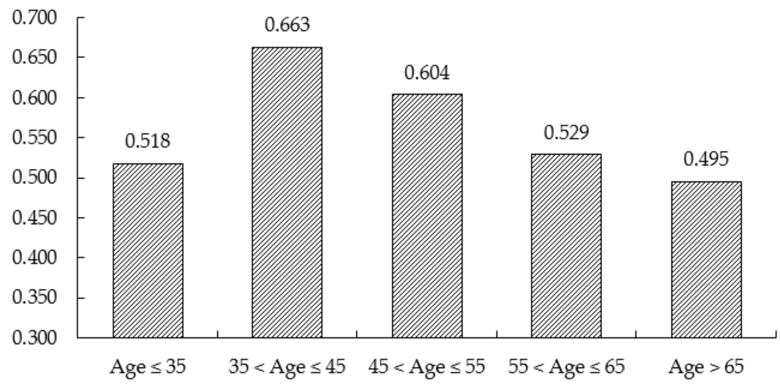


**Figure 1.** Average technical efficiency by age group.

The estimated results of relationship between age of tea-producing farmers and technical efficiency in tea production are also presented in Table 2. It should be noted that the dependent variable in technical inefficiency model is the inefficiency term. In the context, a negative coefficient of the independent variable illustrates a positive impact on technical efficiency, and vice versa.

The econometric results show that while an inverted U-shaped relationship between age of tea-producing farmers and technical efficiency is observed, the aging of agricultural labor force might actually exert negative impact on technical efficiency in tea production. As shown in Table 2, the estimated coefficients of linear and quadratic terms of age of agricultural labor force are significantly negative and positive, respectively. It demonstrates that technical efficiency would first increase and then decrease as the age of tea-producing farmers grows. Using the relevant estimated coefficients, the turning point of the age of tea-producing farmers could be calculated. The calculation results show that the value of turning point of age of tea-producing farmers equals exp[24.705/(3.288 × 2)], or 42.813 years old (Table 2). Hence, it means that technical efficiency in tea production would become the highest when farmers are about 43 years old. Given the fact that the average age of tea-producing farmers in this study is 52.730 years old (Table 1) and more than 83.4% of them are aged and over 43 years old, technical efficiency of the sampled tea-producing farmers would monotonically decline as their age further grows. In other words, the actual impact of aging of tea-producing farmers on technical efficiency in tea production is apparently negative. The results here provide empirical evidence for the theoretical analysis in Section 2, but are inconsistent with some previous studies [20,21]. It should be noted that the previous studies mainly focused on crop production in which agricultural machinery could be easily and commonly utilized. The negative impact of aging of agricultural labor force on crop production could be partly or even wholly mitigated by the utilization of agricultural machinery. For example, some previous studies argued that in the context of intensifying aging of agricultural labor force, the elderly farmers would utilize more agricultural machinery in rice production, which in turn reduces the loss of technical efficiency [20]. By contrast, tea is a labor-intensive cash crop. In addition to a huge demand for manual labor, it is difficult to utilize agricultural machinery in tea production, especially in the mountainous areas in southwestern China. In fact, the mountainous topography in Meitan County is detrimental to the widely utilization of agricultural machinery in tea production. As the age of tea-producing farmers grows, the manual labor input in tea production would be not sufficient, in which the under-utilization of agricultural machinery plays a crucial role. The intensifying aging of tea-producing farmers, in the context, would unavoidably negatively influence technical efficiency in tea production.

In terms of the other factors, the results show that rural–urban migration experience, distance from home to village committee, and township dummy variable are also significantly associated with technical efficiency in tea production. As shown in Table 2, a positive relationship between rural–urban migration experience and technical efficiency is observed in Meitan County. As analyzed in several previous studies, rural–urban migrants would provide financial and human capital to promote agricultural production [43–45]. We also found that the distance from home to village committee is negatively associated with technical efficiency. Given the fact that most of agricultural extension activities are organized in village committee, the distance from home to village committee in this study could be used as a proxy of the availability of access to new agricultural technologies. As mentioned earlier in this study, agricultural extension activities in China are often conducted at the village committee. Note that Meitan County is located in the mountainous areas in China, the distance from household home to village committee greatly differ across households in the same village. It may become quite difficult for the tea-producing households whose home is far from village committee to acquire agricultural extension information and participate in agricultural extension activities, and thus, their technical efficiency in tea production would be relatively lower. Hence, the result here also illustrates that better access to new agricultural technologies would contribute to the improvement of technical efficiency in tea production. In addition, technical efficiency of tea-producing farmers from the townships located in North Meitan, such as Mashan, Xihe, and Xima, is significantly lower than that in central Meitan (referring to Xinglong).

### 4.2. Robustness Tests

To examine the robustness of econometric estimation results analyzed above, we adopt two measures. First, we replace the linear and quadratic terms of age of agricultural labor force with five dummy variables that describe different age groups. In sum, the sampled farmers are categories into five groups as mentioned in Figure 1: (1) Aged and below 35 years old, (2) between 35 and 45 years old, (3) between 45 and 55 years old, (4) between 55 and 65 years old, and (5) over 65 years old. According to the analysis above, the farmers aged between 35 and 45 years old constitute the control group. In the context, the stochastic frontier production function and technical inefficiency model are re-estimated, and the results are shown in Table 4.

**Table 4.** Estimates of the robustness test.

| Variable | Coefficient | Standard Error |
|---|---|---|
| (1) Stochastic frontier production function | | |
| Ln(Manual labor) | 0.296 *** | 0.063 |
| Ln(Pesticide) | 0.024 ** | 0.012 |
| Ln(Fertilizer) | 0.095 *** | 0.023 |
| Ln(Other cost) | 0.015 | 0.011 |
| Double seasons | 0.065 | 0.228 |
| Triple seasons | 0.327 | 0.200 |
| Mashan | 1.272 *** | 0.190 |
| Xihe | 1.504 *** | 0.204 |
| Xima | 0.249 | 0.194 |
| Constant | 3.582 *** | 0.585 |
| (2) Technical inefficiency model | | |
| Dummy (Age ≤ 35) | 1.464 ** | 0.715 |
| Dummy (45 < Age ≤ 55) | 0.548 | 0.432 |
| Dummy (55 < Age ≤ 65) | 1.016 ** | 0.479 |
| Dummy (Age > 65) | 1.057 * | 0.541 |
| Male | −0.345 | 0.362 |
| Ln(Degree of education) | −0.135 | 0.129 |
| Migration experience | −0.543 * | 0.298 |
| Number of household laborers | 0.021 | 0.145 |
| Ln(Total area of tea orchards) | −0.178 | 0.231 |
| Ln(Age of tea trees) | −0.143 | 0.360 |
| Double seasons | −0.935 | 0.621 |
| Triple seasons | −0.800 | 0.490 |
| Ln(Distance from home to village committee) | 0.156 | 0.105 |
| Access to the Internet | 0.198 | 0.404 |
| Mashan | 1.347 | 0.894 |
| Xihe | 2.175 ** | 0.884 |
| Xima | 1.550 * | 0.852 |
| Constant | −1.108 | 1.487 |
| Sigma_$v$ | 0.495 *** | 0.058 |
| Number of observations | 241 | |

Note: *, **, and *** denote the statistical significance at 10%, 5%, and 1% levels, respectively. Data came from the authors' survey.

Second, it should be noted that there may exist technical heterogeneity in tea production for different farmers. As a result, the production frontier of farmers may accordingly differ, which would cause a biased estimation of technical efficiency. In this study, our sampled farmers are located in three townships in North Meitan County, including Mashan, Xihe, and Xima, and one township in the central Meitan County, namely Xinglong. Note that Mashan, Xihe, and Xima townships are closely neighboring to each other. Hence, it is reasonable to assume that the production frontier in Mashan, Xihe, and Xima are highly similar, but it differs from that in Xinglong. To account for technological heterogeneity, we separately estimate the stochastic frontier production function for North Meitan, and central Meitan, and the results are presented in Table 5.

**Table 5.** Estimates of the robustness test by area.

| Variable | North Meitan | | Central Meitan | |
|---|---|---|---|---|
| | Coefficient | Standard Error | Coefficient | Standard Error |
| (1) Stochastic frontier production function | | | | |
| Ln(Manual labor) | 0.351 *** | 0.106 | 0.289 *** | 0.077 |
| Ln(Pesticide) | 0.054 *** | 0.016 | −0.022 | 0.018 |
| Ln(Fertilizer) | 0.125 *** | 0.033 | 0.131 *** | 0.029 |
| Ln(Other cost) | 0.013 | 0.016 | −0.008 | 0.018 |
| Double seasons | −0.432 | 0.454 | 0.014 | 0.314 |
| Triple seasons | 0.547 | 0.355 | 0.083 | 0.278 |
| Constant | 3.618 *** | 0.943 | 3.917 *** | 0.775 |
| (2) Technical inefficiency model | | | | |
| Ln(Age) | −39.519 ** | 17.852 | −99.718 ** | 48.858 |
| Ln(Age) × Ln(Age) | 5.236 ** | 2.348 | 13.371 ** | 6.482 |
| Male | −0.575 | 0.603 | −1.743 | 1.174 |
| Ln(Degree of education) | −0.045 | 0.223 | −0.486 | 0.547 |
| Migration experience | −0.622 | 0.471 | −1.494 | 1.271 |
| Number of household laborers | −0.607 | 0.383 | 0.203 | 0.508 |
| Ln(Total area of tea orchards) | 0.117 | 0.312 | 0.743 | 0.599 |
| Ln(Age of tea trees) | −0.443 | 0.615 | −1.020 | 1.011 |
| Double seasons | −7.250 | 19.753 | 0.250 | 1.663 |
| Triple seasons | −0.564 | 0.865 | 0.357 | 1.598 |
| Ln(Distance from home to village committee) | 0.457 * | 0.206 | 1.610 ** | 0.757 |
| Access to the Internet | 0.724 | 0.673 | −1.371 | 1.835 |
| Constant | 77.356 ** | 34.307 | 187.268 ** | 92.092 |
| Sigma_$v$ | 0.732 *** | 0.065 | 0.360 *** | 0.050 |
| Turning point of age | 43.544 | | 41.633 | |
| Number of observations | 181 | | 60 | |

Note: *, **, and *** denote the statistical significance at 10%, 5%, and 1% levels, respectively. Data came from the authors' survey.

The robustness test in this study shows that both the magnitude and significance of nearly all the estimated coefficients are highly similar to that in Table 2. In terms of the stochastic frontier production function, for example, most of the coefficient of manual labor, pesticide use, and fertilizer use are statistically significant and positive, and exhibit similar production elasticity as shown in Table 2. In technical inefficiency model, we also found a positive relationship between rural–urban migration experience and technical efficiency, and a negative relationship between distance from home to village committee and technical efficiency. In addition, technical efficiency in North Meitan is significantly lower than that in central Meitan.

Overall, the negative impact of aging of tea-producing farmers on technical efficiency in tea production remains. As shown in Table 4, compared with those aged between 35 and 45 years old, the other tea-producing farmers perform significantly lower level of technical efficiency in tea production, since all the estimated coefficients of age dummy variables are statistically significant and positive. This is consistent with the illustration shown in Figures 1 and A1. Moreover, these results imply that compared with those aged below 45 years old, farmers aged over 45 years old are proved to be less technically efficient. Note that technical efficiency would continuously decrease as farmers' age grows when they are aged and over 45 years old. The estimation results of stochastic frontier production function by area also tell a similar story. After accounting for the potential technological heterogeneity in different areas, the results presented in Table 5 also reveal that there is an inverted U-shaped relationship between farmers' age and technical efficiency in tea production. Within our expectations, the estimated turning point of farmers' age ranges from 41–44 years old. In other words, given the fact that most of the sampled farmers are aged and over 43 years old, it illustrates that the aging of agricultural labor force would exert a negative impact on technical efficiency in tea production. In the context, all these results provide highly robust evidence that the aging of agricultural labor force would impose an evidently negative impact on technical efficiency in tea production in the mountainous areas of southwestern China. It also demonstrates that our findings in this study is highly robust.

## 5. Conclusions and Policy Implications

Since the reform and opening up, China has seen an intensifying aging of population and agricultural labor force. During the past decades, the aging of agricultural labor force and its impact on agricultural production have been attracting extensive attention. However, the conclusions of the previous studies are mixed. In addition, little is known about the relationship between aging of agricultural labor force and technical efficiency in tea production especially in the mountainous areas of southwestern China. It is notable that tea is a typically labor-intensive cash crop greatly different from grain crops. This study first constructs a theoretical analysis that illustrates how the aging of agricultural labor force influences technical efficiency in tea production. Using the stochastic frontier analysis and cross-sectional survey data covering 241 tea-producing farmers in Meitan County in China, the econometric results of this study show that there might exist an inverted U-shaped relationship between farmers' age and the technical efficiency index. In the actual context of the sampled tea-producing farmers in China, our finding provides robust evidence that the aging of tea-producing farmers exerts significantly negative impact on technical efficiency in tea production in China. Moreover, the total area of tea orchards, distance from home to village committee, and township location are also significantly associated with the technical efficiency in tea production.

In the context of meeting the challenges from aging of agricultural labor force and mitigating the negative impact of aging of agricultural labor force on technical efficiency in tea production in China, the findings in this study have several important policy implications. First, more efforts should be made to attract and encourage rural–urban migrants to engage in tea production. As well documented in previous studies, return migrants have been playing an increasing role in agricultural production, and often perform better than those non-migrants [46,47]. In the context of the aging of tea-producing farmers, return migrants could become crucial alternatives to those non-migrants for tea production, which might be conducive to improving technical efficiency in tea production. Second, technology extension should be enhanced, and shifted from only introducing new technologies to both introducing new technologies and improving the utilization efficiency of technologies. The negative relationship between the distance from home to village committee and technical efficiency illustrates that better access to agricultural technology extension could improve technical efficiency in tea production. Hence, a strengthened public agricultural extension system as well as socialized agricultural service system is expected to play a crucial role in promoting the increase in technical efficiency. Third, the government is also expected to regulate land conversion to avoid irrational expansion of tea orchards. This study shows that there might be a negative impact of total area of tea orchards on technical efficiency, which means that irrational expansion of tea orchards is detrimental to technical efficiency. In the context, the government should take feasible measures to avoid irrational expansion of tea orchards.

Overall, there exist several methodological drawbacks in this study. First, the rural household survey was not conducted in Guizhou, which to some extent may limit the generalization of the conclusions in this study. Second, some interesting variables are omitted due to the data unavailability. For example, the share of elderly household laborers, a suitable alternative that describes the aging of agricultural labor force, was not taken into account in this study because the survey did not contain the related question. Another variable, land quality, is an important factor influencing tea yield that was also not included since the cost to test land quality is too high.

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## Appendix A

**Table A1.** Estimation results of the Cobb–Douglas and translog production functions.

| Variable | Cobb–Douglas Production Function | Translog Production Function |
|---|---|---|
| Ln(Manual labor) | 0.317 *** (0.071) | −0.581 (1.005) |
| Ln(Pesticide) | 0.028 ** (0.013) | 0.134 (0.172) |
| Ln(Fertilizer) | 0.093 *** (0.025) | −0.042 (0.269) |
| Ln(Other cost) | 0.014 (0.012) | 0.083 (0.162) |
| Ln(Manual labor) × Ln(Manual labor) | | 0.047 (0.060) |
| Ln(Pesticide) × Ln(Pesticide) | | 0.000 (0.005) |
| Ln(Fertilizer) × Ln(Fertilizer) | | −0.005 (0.008) |
| Ln(Other cost) × Ln(Other cost) | | −0.004 (0.006) |
| Ln(Manual labor) × Ln(Pesticide) | | −0.014 (0.019) |
| Ln(Manual labor) × Ln(Fertilizer) | | 0.019 (0.033) |
| Ln(Manual labor) × Ln(Other cost) | | −0.003 (0.018) |
| Ln(Pesticide) × Ln(Fertilizer) | | 0.004 (0.006) |
| Ln(Pesticide) × Ln(Other cost) | | −0.001 (0.003) |
| Ln(Fertilizer) × Ln(Other costr) | | −0.004 (0.006) |
| Double seasons | 0.403 ** (0.166) | 0.384 ** (0.174) |
| Triple seasons | 0.631 *** (0.148) | 0.618 *** (0.151) |
| Mashan | 1.019 *** (0.150) | 1.017 *** (0.163) |
| Xihe | 0.996 *** (0.156) | 0.986 *** (0.166) |
| Xima | −0.082 (0.158) | −0.082 (0.177) |
| Constant | 3.427 *** (0.630) | 7.639 * (4.274) |
| Sigma_$v$ | 0.535 *** (0.098) | 0.565 *** (0.125) |
| Sigma_$u$ | 0.901 *** (0.184) | 0.832 *** (0.256) |
| Log-likelihood ratio test ($\chi^2$) | 2.930 (0.983) | |
| Number of observations | 241 | 241 |

Note: Figures in the parenthesis are standard errors for the independent variables, and $p$ value for log-likelihood ratio test. *, **, and *** denote the statistical significance at 10%, 5%, and 1% levels, respectively. Data came from the authors' survey.

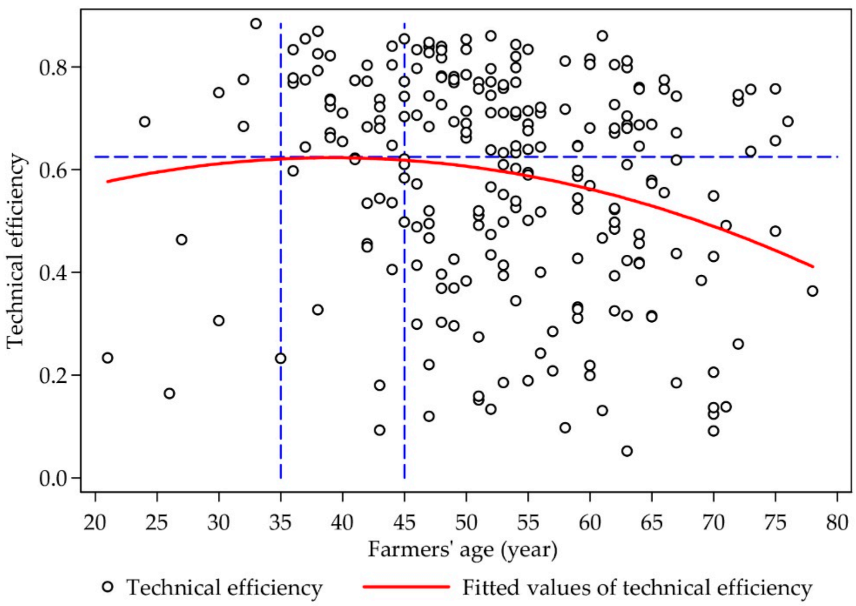


**Figure A1.** Scatter of estimated technical efficiency against farmers' age.

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