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Empirical Study on the Effects of Technology Training on the Forest-Related Income of Rural Poverty-Stricken Households—Based on the PSM Method

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Abstract: The implementation of technology training is essential to promote the commercialization of research achievements, and plays a crucial role in poverty alleviation in China. Based on the microcosmic survey data of farmers in four poverty-stricken counties officially assisted by National Forestry and Grassland Administration, the effects of technology training on forest-related income of rural poverty-stricken households is analyzed by using Propensity Score Matching (PSM) method. The study found that after eliminating the deviation from the self-selection and the endogenous issues, the forestry technology training has increased the total forest-related family income and forestry production and operation income by 3.09 times and 2.82 times, respectively. The effect of technology training on income increase is remarkable. Besides, the behavior of poor farmers participating in forestry technology training is significantly affected by the following factors, such as gender, age, family size, managed forestland area, whether they held forest tenure/equity certificate, whether they joined forestry professional cooperatives, and whether they cooperated with forestry enterprises. In order to further improve the effect of technology in poverty alleviation, the following policy recommendations are proposed, including: (1) to encourage poverty-stricken households to actively participate in forestry technology training; (2) to establish a diversified system of forestry technology training; and (3) to ensure the training content is based on the actual needs of the poor.

Keywords: rural poverty-stricken household; technology training; forest-related income; PSM method

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1. Introduction

Science and technology constitute a primary productive force, and transforming scientific and technological achievements into real productive forces through scientific and technological promotion and training is an important way to lift farmers out of poverty and increase their income, and it is also the main means to improve the overall quality of poverty-stricken farmers. The "13th Five-Year Plan" for Poverty Alleviation issued by the State Council stated that science and technology should be implemented for poverty alleviation, promoting the transformation of scientific and technological achievements to poverty-stricken areas, and increasing the promotion and training of agricultural and forestry technologies in poverty alleviation in the agricultural and forestry industries. Poverty elimination through scientific and technological training is one of the important measures designated by the National Forestry and Grassland Administration to help poverty-stricken counties. Through the promotion of forestry technology, technical personnel were organized to conduct technology training at the grassroots level, helping local poor farmers to improve their forestry production and operation technology and capabilities. In the context that China attaches so much importance to poverty alleviation through science and technology and the widespread development of agricultural and forestry-based technology training in poverty-stricken areas, there are questions that are worthy of our in-depth discussion, including: what is the effect of technology training on poverty alleviation and income increase for poor farmers? How much does it contribute to the forest-related income of the poor? How to carry out scientific quantitative assessment? The answers to these questions are also of certain reference significance to China's poverty alleviation efforts and the National Forestry and Grassland Administration's designated assistance work.

In the existing research, a large number of domestic and foreign scholars have discussed the content of agricultural science and technology training. For instance, there are some studies on the effects of participating in agricultural science and technology training for farmers. Zebo Ma believe that technical education is more useful for farmers than the implementation of a broad strategy of universal education and various professional education strategies [1]. Mukesh Singh et al. [2] intensively studied the impact of training, and organized various trainings work in KVK Rajgarh according to needs. They concluded that these trainings are helpful to increase the level of knowledge of the farmer's regarding agriculture technology. The suggestions for effective trainings in relation to increasing agriculture production are also presented in the paper. Bayissa D D pointed out that agricultural science and technology training for farmers will have a great impact on the transformation of traditional agriculture, and the enhancement of farmers' knowledge level and operation ability can promote the improvement of agricultural production efficiency [3]. Yao Pan et al. [4] evaluated the causal impacts of a large-scale agricultural extension program for smallholder women farmers on technology adoption and food security in Uganda and found that eligible farmers used better basic cultivation methods and achieved improved food security. Their results highlight the role of information and training in boosting agricultural productivity among poor farmers and, indirectly, improving food security. Xu He and Takeshi Sakurai [5] assessed a technology training project in Northern Ghana. Their results are as follows: First, the training project successfully improved the adoption rates of the technologies, such as modem varieties, etc. Second, the adoption rates became higher in villages where longer time had passed since the training. Third, inter-village diffusion of technology took longer time than the intra-village one. Yuhong Zhou pointed out that the agricultural science and technology training that "varies from person to person and adapts to local conditions" can make it easier for farmers to accept and master the use of agricultural science and technology, play a positive role in improving the quality and yield of products, and further meet the high requirements for agricultural products in the process of market changes [6]. The Outlooks On Pest Management Group studied how education and training in science and technology can be used to improve agriculture and alleviate poverty in Africa [7]. There are many studies on how agricultural science and technology training can promote the growth of farmers' income. Fonta et al. believe that by integrating science and technology into the production process, Malawian farmers can effectively improve agricultural production efficiency and obtain a higher income [8]. Schreinemachers P et al. [9] quantified the effect of training in off-season tomato production on the income and pesticide use of smallholder vegetable farmers in southwestern Bangladesh. The results showed that training increased net household income by about 48% for the average smallholder vegetable farmer, and farm households who discontinued using the technology in the second year also experienced significant income gains from the training. Huaning Chen [10] analyzed the current situation, demand, and performance of Chinese farmers' science and technology training, and found that the participation rate of Chinese farmers' science and technology training is low, but the desire to participate is strong. The most needed training for farmers is production technology training. Science and technology training improves the output of farmers' grain and other crops, and increases farmers' household income. Hui Qiao et al. [11] used the two-stage estimation and maximum likelihood estimation in the treatment effect model to empirically study the impact of agricultural technology training on Farmers' agricultural income. The results showed that participation in training has a significant positive effect on the increase of agricultural net income. Dan Pan's research results based on micro-farmer household survey data in seven provinces in China showed that the average logarithm of the average income of households participating in agricultural technology training is only 0.151 higher than that of non-training households, and the effect of agricultural technology training on rural residents' income is limited [12]. Regarding the research on agricultural science and technology training models, Zhengzhou Zhao et al. conducted a relatively comprehensive study on Chinese farmer training from the perspective of theoretical analysis, and concluded that the existing training models include: field conduction type, typical demonstration type, project promotion type, talent cultivation and media communication-based farmer training model, etc. [13]. There are some studies on the factors affecting farmers' participation in agricultural science and technology training. According to the attribution theory, Giannoccaro G et al. believe that the external factors that affect farmers' participation in agricultural science and technology training mainly include training methods, training content, training time, training teachers, and government policies on farmers' science and technology training [14]. Zemo K H et al. analyzed that the factors that affect farmers' demand for participation in science and technology training include age, education level, income level, level of part-time employment, agricultural production scale, government support, and the degree of regional industrialization [15]. Domestic scholars have found that the main factors affecting farmers' acceptance of science and technology training are gender, age, education level, economic conditions, social capital, awareness of technology and training, training experience, and government services, etc. [16–20]. In the study of non-agricultural vocational skills training, Fonta et al. [8] believe that compared with the macro education model, technical education, and vocational skills training are more helpful to the rural population. It also further explains that more attention should be paid to increasing education and vocational training programs for farmers′ non-agricultural employment. Sampson Tawiah et al. [21] investigated and reported on the strategies for introducing Information and Communication Technology Training in the teaching and learning of rural women through the lens of the human capital theory. The study concluded that the introduction of ICT in the curriculum of rural women can ensure their socio-economic transformation. Wanchun Luo, Xiaonan Li and others [22,23] analyzed the status of Chinese farmers participating in agricultural technology training and non-agricultural vocational skills training. The research results all show that compared with agricultural technology training, non-agricultural vocational skills training has an impact on farmers' income, and the effect is greater. With regard to forest-related scientific and technological training, experts and scholars have mainly studied the needs and contributing factors of forestry production technology by forest farmers, application of forestry technology by forest farmers, and the effect of technical training on income growth of oil tea farmers [20,24,25]. In summary, we found that a large number of scholars have conducted research on farmers' participation in agricultural science and technology training. There are relatively few literatures on the analysis of the effect of technology training on farmers' forestry income, and there is almost no research on the impact of poor farmers' forestry income.

To this end, the survey data of poor farmers in four poverty-stricken counties financially supported by the National Forestry and Grassland Administration is used in this paper. Considering the self-selection bias and endogenous problems of poverty-stricken farmers participating in technology training, this paper applies Propensity Score Matching method (PSM model) to scientifically evaluate the effect of technology training on the total forest-related family income and forestry production and operation income of poverty-stricken households.

2. Materials and Methods

2.1. Econometric Model

In order to evaluate the effect of technology training on the total forest-related family income and forestry production and operation income, the traditional linear regression model, namely OLS model, is generally used to estimate unknown parameters through the principle of least squares. The model equation is set as follows:

$$Y_i = \alpha + \beta_1 X_i + \beta_2 D_i + u_i, \tag{1}$$

where Y_i indicates the total forest-related income or forestry production and operation income of the i^{th} poverty-stricken household; X_i is the observable individual and family characteristic variables and resource endowments that affect the forest-related income of the i^{th} poverty-stricken farmer; D_i indicates whether the poor farmer i has participated in forestry related technological training; D_i = 1 means he/she has participated, D_i = 0 means he/she has not participated; β_2 is the effect of participating forestry related technological training on the forest-related income of poverty-stricken household, and u_i is a random error term. However, it is worth noting that whether to participate in forest-related technological training is the decision made by the farmer themselves. Due to the heterogeneity among the samples, they will decide whether to participate in the training based on their actual conditions. For example, poor farmers who rely on forests for their main income and have high personal quality may be more inclined to participate in the training. If the OLS model is directly used to estimate the effect of technology training on the forest-related income of poverty-stricken households, there will be a selection bias. In addition, if some of the missing variables in the random error term are related to participating forestry related technological training, endogenous problems will occur, so there will be a certain degree of deviation in estimating the effect of training on income.

To this end, the propensity score matching method (PSM model) is applied in this paper to solve the problem of self-selection bias and endogenous problems by constructing a "counterfactual framework", so as to estimate the true effect of technology training on the forest-related income of poverty-stricken households. This method was first proposed by Rosenbaum and Rubin [26]. The basic idea of using this method in this study is as follows: the "propensity score" is used to represent the conditional probability of the sample of farmers choosing to participate in forestry technology training by giving a measurable covariate. The sample farmers with similar or identical propensity scores are matched, that is, the sample farmers with similar characteristics in the trained group are found in the untrained group, and their forest-related family income is analyzed and compared, which will be considered as the effect of technology training on forest-related family income of the poor. The dummy variable D_i is usually called "processing variable", X_i is called "covariate", and Y_i is the "result variable" for forestry related technological training. Among them, it is assumed that, Y_{1i} is the total forest-related family income or forestry production and operation income after sample farmer i participated in the training; Y_{0i} is the total forest-related family income or forestry production and operation income of sample farmer i before he/she participated in the training. As Y_{0i} cannot be observed in practice, therefore, Y_{0i} is obtained by matching the propensity scores. Thus, the average treatment effect model of technology training on total forest-related family income or forestry production and operation income is as below:

$$\text{ATT} = \frac{1}{N_1} \sum i : D_i = 1(Y_{1i} - Y_{0i}), \tag{2}$$

where ATT is the average treatment effect of sample farmers participating in forestry technology training, N_1 indicates the number of sample farmers participating in the training, and $\sum i : D_i = 1$ means that only the sample farmers participating in forestry technology training are aggregated [27–29].

The econometric software Stata 12.0 is used in this paper, and the propensity score is estimated by applying the Logit model. The radius matching method and the kernel matching method are used to perform propensity score matching, so as to estimate the average treatment effect of participating forestry technology training.

2.2. Data Source

The data used in this paper is from a survey conducted for 24 poor villages under the 4 designated poverty-stricken counties (namely Dushan County and Libo County in Guizhou Province, and Longsheng County and Luocheng County in Guangxi Province.) at the end of 2017. It is financially supported by the National Forestry and Grassland Administration. On-site quantitative investigation was conducted by visiting the villages and households. On-site quantitative investigation refers to investigating the quantified content involved in the basic characteristics of poor rural households (such as age, years of education, area of arable and forest land, etc.) and various income of family. In addition, qualitative in-depth interviews were carried out. The average household interview time was about 40 min. Taking into account the sampling theory and incidence of poverty, 3 townships (towns) were selected in each county, and 2 poor villages were sampled in each township (town). In each village, about 20 households (including 18 registered poverty-stricken households and 2 un-registered households). In total, 499 sample households were obtained. Since the main target of this study is poverty-stricken farmers, 444 registered households were selected (originally a total of 447, but 3 invalid samples were removed) for empirical analysis. The main contents of the survey include the forestry-related poverty alleviation status at the county, township (town), village, and household levels. The micro-observation at the household level mainly involves the basic information of the interviewees, household information, organizational level, and family income—especially forest-related family income. Survey contents related to forestry technology training include the training subject, target audience, content, location, and method.

2.3. Descriptive Statistics of Main Variables

According to the traditional income linear regression model and related literature, it can be known that the forest-related income of poverty-stricken households is affected by the individual and household characteristics and resource endowment of the farmers. Therefore, descriptive statistical analysis is performed for the main variables between the trained group and the untrained group before matching propensity scores, and the results are shown in Table 1. As can be seen from Table 1, there are significant differences between the two groups. The total forest-related family income and forestry production and operation income of poor farmers who have participated in forestry technology training are significantly higher (4.13 times and 3.93 times, respectively) than those who have not participated in the training at a statistical level of 1%. In addition, variables such as gender, age, education level, family size, managed forestland area, whether they held a forest tenure certificate/equity certificate, whether they joined a forestry professional cooperative, and whether they cooperated with forestry enterprises are significant differences at statistical levels of 1% or 5%. The poor in the trained group are mostly male and younger, with an average age of 3.50 years younger than the untrained group. The poor in the trained group have a higher education level and a larger size of family, meaning more labor forces. The average managed forestland area by poverty-stricken farmers in the trained group is 12.55 mu (0.837 hectare) more than that of the untrained group The farmers in the trained group are more organized, and the number of farmers who have forest tenure certificates/equity certificates, joined forestry professional cooperatives, and cooperated with forestry enterprises is higher.

Table 1. The descriptive statistical results of main variables.

Variable Name	Variable Description	All Samples (444)	Training Group (191)	Untrained Group (253)	Difference	*t* Value
Dependent variable						
Total forest-related family income (thfi)	Unit: CNY	4752.446	8780.639	1711.400	7069.239	9.457 ***
Household forestry production and operation income (hfpi)	Unit: CNY	2065.861	3783.222	767.536	3015.686	4.764 ***
Independent variable						
Gender (g)	1 = male; 0 = female	0.795	0.869	0.739	0.130	3.395 ***
Age (a)	Unit: years old	49.890	47.895	51.395	−3.500	−3.346 ***
Education level (edu)	1 = illiterate or semi-literate; 2 = primary school; 3 = elementary school; 4 = high school; 5 = college and above.	2.333	2.414	2.273	0.141	2.380 **
Health status (h)	1 = healthy; 2 = Long-term chronic disease; 3 = major illness; 4 = disable	1.356	1.346	1.364	−0.018	−0.227
Employment status (l)	1 = working within the county; 2 = working within the province but outside the county; 3 = working outside of the province; 4 = Other	3.061	2.979	3.123	−0.143	−1.135
Family size (fs)	Unit: person	3.809	4.000	3.664	0.336	2.469 **
Managed forestland area (fa)	Unit: mu	28.950	36.098	23.553	12.545	3.006 ***
Whether held forest tenure certificate/equity certificate (frc)	1 = Yes; 0 = No	0.273	0.346	0.217	0.128	3.027 ***
Whether joined the forestry cooperatives (fpco)	1 = Yes; 0 = No	0.099	0.141	0.067	0.074	2.604 ***
Whether cooperated with forestry enterprises (cfc)	1 = Yes; 0 = No	0.025	0.042	0.012	0.030	2.020 **

Note: (1) *, **, *** represent significance at the statistical levels of 10%, 5%, and 1%, respectively; (2) When testing the differences of forestry production and operation income between two groups, there are missing values in the regression variables, therefore, only 439 households samples are used, the same below.

The comparison results between the trained group and the untrained group indicate that forestry technology training has promoted the increase in total forest-related family income and forestry production and operation income of poverty-stricken households. However, there are significant differences between the observable independent variables of the two groups. This simple comparison and analysis of the contribution of the training to forest-related family income is not scientific, nor can it truly reflect the causal relationship between the two.

3. Results

3.1. Estimation of Propensity Score by Using Logit Model

The Logit model is applied in this paper to estimate propensity scores, and the results are shown in Table 2. The estimation results by using the Logit model indicate the probability that poverty-stricken farmers choose to participate in forestry technology training under the influence of individual and family characteristics covariates and resource endowments. It can be found that gender, age, family size, managed forestland area, whether they held forest tenure certificate/equity certificate, whether they joined forestry professional cooperatives and whether they cooperated with forestry enterprises, etc. have a statistically significant impact on the poor farmers' choice of participation in forestry technology training.

Table 2. Propensity score estimation results by using Logit model.

Whether They Participated in Forestry Technology Training (Ftt)	Coefficient	Standard Error	*z* Value	*p* > |z|	95% Confidence Interval	
Gender (g)	0.978 ***	0.276	3.54	0.000	0.437	1.519
Age (a)	−0.030 ***	0.010	−2.86	0.004	−0.050	−0.009
Education level (edu)	0.176	0.173	1.02	0.308	−0.162	0.514
Health status (h)	0.024	0.132	0.18	0.854	−0.234	0.283
Employment status (l)	−0.053	0.083	−0.64	0.525	−0.216	0.110
Family size (fs)	0.215 ***	0.074	2.89	0.004	0.069	0.361
Managed forestland area (fa)	0.005 *	0.003	1.74	0.082	−0.001	0.011
Whether they held forest tenure/equity certificate (frc)	0.478 *	0.248	1.93	0.054	−0.009	0.965
Whether they joined the forestry cooperatives (fpco)	0.963 ***	0.349	2.76	0.006	0.279	1.646
Whether they cooperated with forestry enterprises (cfc)	1.326 *	0.749	1.77	0.077	−0.143	2.795
Constant term	−1.118	0.782	−1.43	0.153	−2.650	0.414

Note: (1) *, **, *** represent significant at the statistical levels of 10%, 5%, and 1%, respectively; (2) Number of observations = 444, LR chi2(10) = 57.60, Prob > chi2 = 0.0000, Pseudo R2 = 0.0949, Log likelihood = −274.61256; (3) Due to the sample size used for estimating the total forest-related income and forestry production and operation income of the poverty-stricken households by the Logit model being different, the estimated results will also be different, but it will not affect the analysis. Therefore, this study takes the example of the propensity scores estimation results of the total forest-related family income by using the Logit model, to analyze the impact of covariates on the poverty-stricken farmers' choice of participating in forestry technology training.

Among them, gender has a positive impact on the poor farmers' decision on participation of the training at the statistical level of 1%. This may be due to the difference in the division of labor between male and female members of households. According to our investigation, we understood that men are usually working outside, and women are responsible for housework, such as taking care of the elderly and children, etc. Thus, the level of women in information acquisition and awareness of technology training is far below that of men. Therefore, the probability of choosing to participate in the training is low. Age has a negative correlation with poverty-stricken farmers' participation in forestry technology training and is significant at the statistical level of 1%. The younger people gain new knowledge and technologies faster, and their ability to accept new knowledge and technology is stronger. Relatively speaking, it is harder for the older farmers to accept new technologies as they have their own practices in agricultural and forestry management. Family size, managed forestland area, and holding forest tenure/equity certificates have a significant positive impact on poor farmers' choice of participating in the training. The possible reason is that there are more laborers in the bigger sized families, households who hold forest tenure/equity certificates are legally guaranteed in the management of forest land, and the transfer of forest land promotes forest management on a large scale, etc. These poverty-stricken farmers have a relatively greater demand for new forest management technology and new varieties and a stronger desire for forestry technology training, so it is more likely for them to choose to participate in forest-related training. Whether they join forestry professional cooperatives and cooperate with forestry enterprises has a positive correlation with the poor farmers' choice of participation of the training at the statistical levels of 1% and 10%, respectively. The poor who join forestry professional cooperatives and cooperate with forestry enterprises have a higher probability of choosing to participate in the training, mainly because they have more access to relevant training. Except for the technical training opportunities jointly provided by forestry department at county level and scientific research units, professional cooperatives and enterprises will also organize activities to promote planting, management, pest control and other related knowledge to raise the awareness of technology training, so they are more enthusiastic about participating in forestry technology training.

3.2. Analysis of the Impact of Technology Training on Forest-Related Income of Poverty-Stricken Rural Households

This paper chooses the radius matching method and the kernel matching method for propensity score matching, and estimates the impact of forestry technology training on total forest-related income and forestry production and operation income of poor farmers. The estimated results are shown in Table 3. The results show that, in terms of total forest-related family income, the average treatment effects (ATT) estimated by the two matching methods are 6625.248 and 665.8481, respectively (the trained group is 3.06 times and 3.12 times higher than the untrained group under the two matching methods). That is, participating in forestry technology training has increased the total forest-related family income of poor farmers by 3.06 times and 3.12 times, with an average increase of 3.09 times, and both have a significant impact at the statistical level of 1%. In terms of forestry production and operating income, the average treatment effects (ATT) estimated by using the two matching methods are 2760.045 and 2817.717 (the trained group is 2.71 times and 2.93 times higher than the untrained group under the two matching methods), that is, participating in the training has increased the forestry production and operation income of poverty-stricken household by 2.71 times and 2.93 times, with an average increase of 2.82 times, and both have a significant impact at the statistical level of 1%. In addition, the estimation results obtained by using two different matching methods, whether the ATT estimates or the significance, are very similar, which explains the robustness of the matching results to a certain extent.

Table 3. Average treatment effects of participants of forestry technology training by using different matching method.

Variable Name	Matching Method	Trained Group	Untrained Group	ATT	Standard Error	*t* Value
Total forest-related family income (thfi)	Radius matching (R = 0.04)	8792.291	2167.043	6625.248 (3.06)	819.683	8.08 ***
	Kernel matching	8792.292	2133.811	6658.481 (3.12)	810.563	8.21 ***
Forestry production and operation household income(hfpi)	Radius matching (R = 0.04)	3779.920	1019.875	2760.045 (2.71)	747.653	3.69 ***
	Kernel matching	3779.920	962.203	2817.717 (2.93)	743.954	3.79 ***

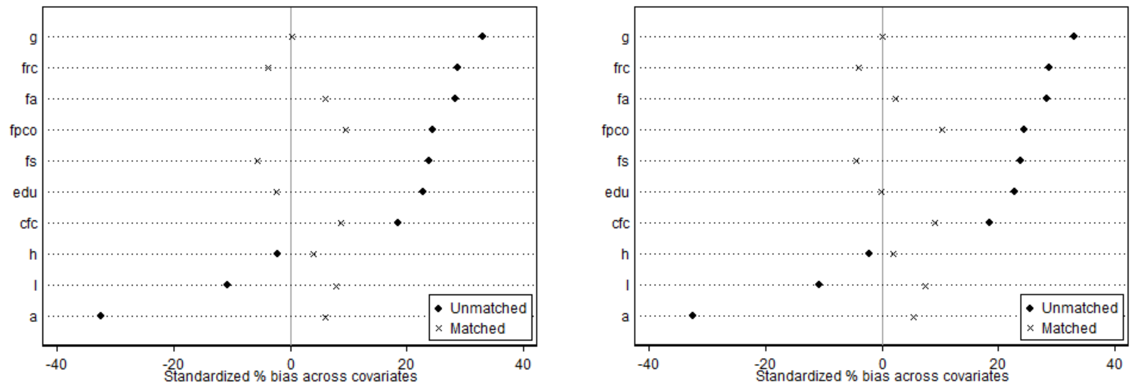
Note: (1) *, **, *** indicate that it is significant at the statistical levels of 10%, 5%, and 1%, respectively; (2) the standard error and the *T* test value are obtained by the Bootstrap method, and the number of repeated sampling is 500 times; (3) The value in brackets of the ATT item indicates how many times the trained group is higher than the untrained group after matching.

From the above estimation results, we can find that compared with the previous descriptive statistical results, the total forest-related income of poor households and the forestry production and operation income of the trained group are 4.13 and 3.93 times higher than the untrained group, respectively. After matching the propensity scores, the income effect has been reduced by 1.04 and 1.11 times, respectively, which shows that if the sample self-selection and endogenous problems are not considered, it will lead to overestimation of the effect of forestry technology training on the forest-related income of poverty-stricken household. The main reason for this result is that the forest-related family income of the poor is often affected by a variety of socioeconomic development factors, and there is heterogeneity among the poor households. Even if those farmers with strong qualities and capabilities do not participate in the training, their income will still be higher than that of ordinary farmers. Therefore, the forestry technology training will play a smaller role when it estimates the income effect independently from other factors that affect the forest-related income of poverty-stricken household. However, from the perspective of the matching income effect, the income increase of the poor participating in the training is also significant. According to our research, about 30% of the investigated farmers are poverty-stricken due to lack of production technology, which shows the importance of technology to poverty alleviation and to increase the income of poor farmers.

3.3. Balance Test of Matching Results

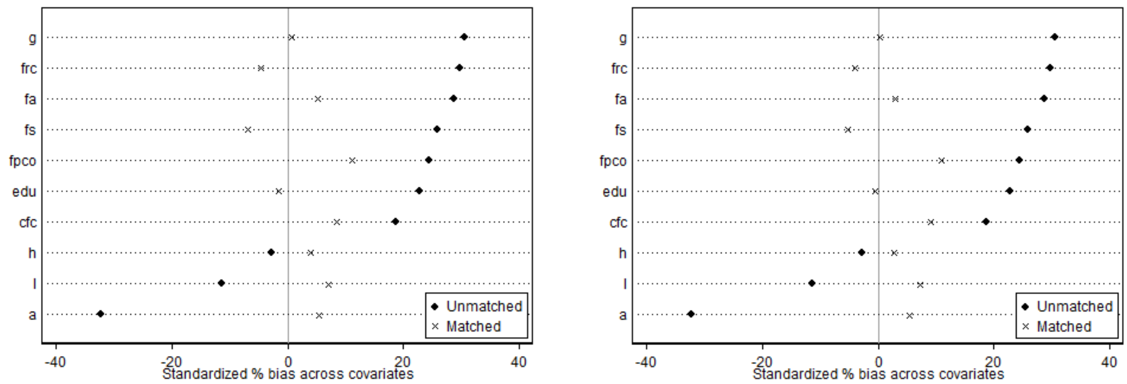
This paper used the Stata command pstest to examine if the match results obtained through different matching methods can better balance the data. Figures 1 and 2 shows the standardized deviation of each variable of the total forest-related family income and forestry production and operation income of poverty-stricken households by using different matching methods, respectively. As shown in the figures, regardless of total forest-related family income or forestry production and operation income, the standardized deviation of most variables (% bias) are significantly reduced after matching by using both matching methods and are reduced to less than 10%. In addition, most results of the *t*-test do not refuse the null hypothesis of no systematic difference for the treatment and control groups. Usually, it is required that the standardization gap of variables does not exceed

10% (Qiang Chen, 2014), thus, after PSM process, the deviations due to the heterogeneity of the observed variables for the trained and untrained group have been substantially eliminated, and the matching results balanced the data well.



(**a**) (**b**)

Figure 1. Standardized deviations of variables before and after matching the forest-related family income. (**a**) Radius matching method; (**b**) Kernel matching method.



(**a**) (**b**)

Figure 2. Standardized deviations of variables before and after matching the forestry production and operation income. (**a**) Radius matching method; (**b**) Kernel matching method.

4. Conclusions and Reflection

4.1. Conclusions

Based on micro-survey data from 444 registered households in 4 poverty-stricken counties assisted by the National Forestry and Grassland Administration, this paper used the PSM model to analyze the effect of participating in forestry technology training on the total forest-related family income and forestry production and operation income of poverty-stricken households. The main conclusions are summarized as follows:

Firstly, forestry technology training has a significant positive effect on promoting poverty alleviation and increasing income for poor farmers. Participation in the technology training has increased the total forest-related family income and forestry production and operation income of poverty-stricken households by about 3 times. The income growth effect is obvious, and both are statistically significant. In addition, forestry technology training has a self-selection of samples and endogenous problems. If these problems are not considered in estimating the income effect, there will be a certain bias.

Secondly, poverty-stricken farmers' choice to participate in forestry technology training will be affected by factors such as their gender, age, family size, managed forestland area, whether they held forest tenure certificate/equity certificate, whether they joined a forestry professional cooperative, and whether they cooperated with forestry enterprises.

4.2. Discussion

In the existing research, scholars have proved that technology training plays an important role in promoting farmers' industrial production and increasing the household income through the research on the related content of technology and skills training. Schreinemachers P, Dan Pan, Xiaomin Jiang and other scholars [9,12,25] also used the PSM method adopted in this paper to analyze the net effect of agricultural and forestry technology training on farmers' income. Compared with the results obtained by using the traditional regression method and descriptive statistical analysis method, the effect of technology in their training studies is reduced, which is consistent with the research results of this paper. The main reason is that after adopting the PSM method, the problems of sample self-selection and endogeneity are controlled, so the effect of technology training is reduced. However, the income of farmers participating in the training is still significantly higher than that of farmers not participating in the training, and the results are reliable after the applicability test in this paper. On the other hand, the above existing research results have been published in well-known core journals abroad, which to a certain extent shows the universality and relative scientific aspect of the application of the PSM method.

In addition, most scholars have concluded that the increased rate of farmers' household income caused by technology training is no more than one time in the existing studies [9,25,30,31]. After the analysis, this paper concludes that participation in the technology training has increased the total forest-related family income and forestry production and operation income of poverty-stricken households by about three times. This is mainly because the research objects of this paper are poor farmers who have insufficient resource endowments, poor development capabilities, and a small family income base. Therefore, after farmers receive technology training, the marginal benefits of technology training will be relatively large. This also proves that technology training plays an important role in increasing the income of poor rural households, and the promotion of technology to poor farmers and the transformation of scientific and technological achievements is an effective way to promote poverty alleviation and increased income of the poor. However, there are still some problems in China's agricultural and forestry technology training, such as low participation of farmers, scattered training resources, small training scale, and inconsistent technical training content organized by government departments with the characteristics of local farmers. Therefore, the technical training measures and policies still need to be further optimized and improved.

4.3. Policy Recommendations

Based on the above research conclusions and discussions, the policy recommendations are summarized as follows:

Firstly, poverty-stricken farmers should be encouraged to actively participate in forestry technology training. Only about 40% of the poor farmers in the surveyed area have participated in forestry technology training. It is essential to involve them first if it is planned to lift them out of poverty and enhance their income through technology training. Demonstration can be set up by selecting some farmers who increased their income by applying new forestry technologies or new varieties to drive more poor farmers to increase their income. In addition, since most young and middle-aged men work outside, and the majority in the village are women and elderly people, it is necessary to encourage women and elderly people who have the ability to work to participate actively.

Secondly, a diversified forestry technology training system should be established. At this stage, the main bodies that have organized training and promotion activities related to forestry technology in poverty-stricken areas are local forestry technology promotion stations and government based training institutions such as science and technology associations. The channel for poverty-stricken farmers to participate in forestry related technological training is limited. Therefore, it is necessary to vigorously introduce a variety of technology training and promote organizations, to provide farmers with diversified and market-oriented forestry technologies. For example, at present, farmers' professional cooperatives, as important carriers of poverty alleviation, have played an important role in improving the organization level of the poor and optimizing the allocation of poverty alleviation resources [32,33]. Cooperatives can be used to achieve scientific and technological assistance. In addition, local leading enterprises can also be used to provide poor farmers with more practical forestry production and management technologies by cooperating with them or forming benefits linkage mechanisms.

Finally, the content of technology training should be based on the actual needs of poverty-stricken farmers. From our research, we found that forestry related technological training has a significant effect on the forest-related family income of the poor. However, in order to further extend the role of forestry scientific and technological in poverty alleviation, the training content needs to be based on the local reality and targets the needs of poor farmers. In addition, since most of the farmers receiving training have a lower education level, the theoretical knowledge explained in the training process should be as easy to understand as possible, focusing on practical teaching, so as to improve the efficiency of training and further increase the income of the poor.

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