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The education treatment effect on the non-farm income of Chinese western rural labors

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Abstract

Purpose – Education plays an important role in improving Chinese rural laborers' non-farm incomes. However, in Chinese western rural area, the level of return to education is very low due to the underdeveloped economy and the condition of the education system. For improving the schooling returns level, Chinese central government is paying great attention to the condition of education in the rural western area. To date, no research has examined what educational style is more favorable for improving western rural laborers' non-farm incomes. To answer this question, the purpose of this paper is to compare the treatment effect of high school education and secondary vocational education on their non-farm incomes. That will provide significant evidence for the government to carry out educational policy.

Design/methodology/approach – Base on the Mincer model, several methods is used to estimate the average return to a year education on western rural labors' non-farm income, including OLS, IV and Heckman tow-steps method, to accounting for the ability endogenous and self-selection bias. And the propensity score matching method is used in estimate the treatment effects of high school education and secondary vocational education.

Findings – The results from Mincer model showed that the schooling returns in Chinese western rural area were estimated to range from 2.7 to 3.9 percent, that were lower than the average levels in Chinese whole rural area that are estimated in the other recent studies. By using propensity score matching to roll out the heterogeneous bias, show that the treatment effect from high school education was higher than that from secondary vocational education, indicating that the secondary vocational education is better.

JEL Classification — I2, J3

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Originality/value – Studies concerning the causal relationship between schooling (high school education and secondary vocational education) and non-farm earnings in the western region of China remain very limited, even empty. This paper will make an update contribution to the literature in the area of education earnings in China.

Keywords Chinese western rural area, High school education, Non-farm income, Secondary vocational education, Treatment effect

Paper type Research paper

1. Introduction

Problems affecting agriculture, rural areas, and the peasantry have seriously troubled Chinese economic development for a long time. How to improve rural laborers' incomes is a key issue affecting China's even and harmonious social development. The non-farm income percentage of total income keeps increasing, from 20 percent in 1990 to 43 percent in 2011, becoming the main source of income growth (National Bureau of Statistics of China, 2013) since the 1980s, when rural laborers started to move to the non-agricultural sector(Chen *et al.*, 2013).

Education plays an important role in improving Chinese rural laborers' non-farm incomes (Rosenzweig and Zhang, 2013). Rural laborers can gain non-farm job skills and opportunities through education. Many researchers have analyzed the returns to schooling in Chinese rural area and found that it was effective in improving non-farm incomes. De Brauw and Rozelle (2008) estimated the return to an additional year of education among Chinese rural area is 6.3 percent; according to the research conducted by the Han and Guo (2007), it was about 7.5 percent; and it was 5.3-6.8 percent in Wang *et al.* (2008) research.

However, in Chinese western rural area, the level of schooling returns is very low due to the underdeveloped economy and the condition of the education system. This will seriously threaten Chinese economic development and widen the gap between eastern and western regional economic. CAO *et al.* (2009) concluded that the schooling return in the northwest area was 1.1-5.5 percent; Li (2003) analyzed the eastern, central, and western rural schooling returns separately and found that the schooling returns of high school education and vocational education in the western area were 7 and 13 percent lower than the levels in the eastern part of the country, respectively. This phenomenon will enlarge the regional gap in Chinese regional economic development and income level. According to data from the State Statistical Bureau, the difference between eastern and western rural income per capita has widened from 1,386 RMB in 2005 to 3,470 RMB in 2011 (taking the price level in 2005 as the base price), an increase of 150 percent.

For the sake of improving the schooling returns level and narrowing the income gap between the eastern and western areas, the Chinese central government is paying great attention to the condition of education in the rural western area, highlighting the importance of secondary vocational education, which is mainly aimed at improving students' vocational skills. This style of education links education with vocation more closely, whereas Chinese high school education targets the college entrance examination. The State Council and Ministry of Education issued "The Education Development Plan from 2004 to 2010 in Western Regions" in 2004, which promised more efficient development of secondary vocational education. The Ministry of Education started to implement the policy providing free secondary vocational education in 2012. This is the second free tuition policy in Chinese education history, preceded only by the nine-year compulsory education program.

To date, no research has examined whether high school education or secondary vocational education is more favorable for improving western rural laborers' non-farm incomes. The reason for this is twofold. First, very few researches specifically compare the schooling returns on high school education with those of secondary vocational education. Additionally, almost all studies have employed qualitative analysis, whereas quantitative analysis using survey data and econometrics methods are nearly nonexistent. Second, the analytic methods for estimating the schooling returns used in most research are based on the hypothesis that all samples are homogeneous. However, human resources are actually quite heterogeneous (Roy, 1951; Willis and Rosen, 1979). For example, the kind of education a person chooses is based on individual skills and interests, and it depends on the student's comparative opportunity to access that education. So, we must consider this heterogeneity. To what degree can high school education and secondary vocational education improve the non-farm incomes of rural laborers in the west of China? Which education style is better? If these basic questions are not answered, there will no basis for the government to carry out educational policy.

The remainder of the paper is organized as follows. In Section 2, we present the model and estimation method. We use the Mincer earnings model to estimate the returns on education and then utilize the propensity-score matching method used to estimate the education treatment effect, taking heterogeneity into account. In Section 3, we provide a brief discussion of the data used in this study. In Section 4, we present the empirical results and their implications. In Section 5, we present our concluding remarks.

2. The model

2.1 Mincer earnings model

Most researchers use the Mincer earnings model to analyze the returns to education (Mincer, 1974). The basic model equation is:

$$\text{In}\, y = \alpha + \beta_1 D + \beta_2 \exp + \beta_3 \exp^2 + \mu$$

where y is the laborer's income, D is years of education, exp is years of experience, and $E(\mu) = 0$. Using the regression method, we can estimate the parameters in Equation (1). Then, β_1 gives the returns to education.

The basic approach of used to estimate the return to education is OLS which is depend on the assumption that the explanatory variables are uncorrelated with the error term, μ. However, this assumption may be false. For instance, individual ability, which could effect to wage is missing from mincer equation. To avoid the ability bias, researchers use the instrumental variables (IV). This approach exploits a variation in schooling difference that is independent of one's ability. Angrist and Krueger (1991) employ the quarter of birth interacted with year of birth as the instruments, Card (1999) employ the geographical distance, Duflo (2000) employ the school expansion program. There are also many studies using IV to estimate the returns to education in China. Li and Urmanbetova (2002) employ the parental education to estimate the return to education of Chinese rural labor. Most estimates from IV approach is lower than that from OLS.

Selection bias is another bias in estimates the return to education. De Brauw and Rozelle (2008) suggest that a labors will not enter a labor market if the wage is lower than his or her reservation wage. Then the OLS estimates will be biased if not correcting for the selection bias. They use the Heckman two-steps method to account for the selection bias. Heckman two-steps method is based on the inverse mill ratio from a probit model to account for selection bias. The mathematical expression of the inverse mill ratio is $\lambda_1 = \phi(\alpha Z_i)/\Phi(\alpha Z_i)$, where ϕ and Φ are the probability density and cumulative distribution of normal distribution, respectively, and Z is the independent variable of the selection model.

In Section 4, we employ OLS, IV and Heckman two-steps methods to estimate the return to education in Chinese western rural area separately, and compare the estimates with other studies.

2.2 Heterogeneous bias and treatment effect

Another possible source of bias in estimates of the returns to education is heterogeneous bias. If an individual choose to accept the education or not based on the unobserved heterogeneity, both the OLS and IV estimates would be inconsistent (Heckman and Li, 2004; Li and Heckman, 2004).

The theory of heterogeneous bias described in the literature as follows: let $D=1$ if an individual receives the "treatment" (e.g. goes to high school or secondary vocational school) and $D=0$ otherwise (e.g. does not go to high school or secondary vocational school). Then define the income for the individual receives the "treatment" ($D=1$) as y_1, and the income for the "treatment" rejector ($D=0$) as y_0.

If the individuals are chosen at random from the whole sample, the income difference between the participants under conditions of receiving and not receiving education can be defined as the average treatment effect (ATE), and the function is as follows:

$$ATE = E(\ln y_1 - \ln y_0 | X = x) \tag{1}$$

If the individual is chosen at random from the treated group, the ATE of which actually is the ATE on the treated group (ATT), the function is as follows:

$$ATT = E(\ln y_1 - \ln y_0 | X = x, \quad D = 1) \tag{2}$$

If the worker is chosen at random from the control group, the ATE of which actually is the ATE on the untreated participants (TUT), the function is as follows:

$$TUT = E(\ln y_1 - \ln y_0 | X = x, \quad D = 0) \tag{3}$$

If the treated group and the control group are assigned randomly as a randomized experiment, then $ATE = ATT = TUT$. We can estimate ATE by using OLS.

However, the treated group and control group are not divided by random, that result in the ATE estimated by OLS is biased from ATT and TUT. When an individual decides whether to choose education, group assignment is not based on random selection but on the principle of maximized effect, so the former hypothesis of randomized experiment is invalid. The persons who decide to receive education do so because they can get higher returns to education. This creates the heterogeneity problem, i.e., ATT cannot be assumed to be the same as ATE. So the estimates from OLS is biased. The mathematical derivation process could refer to Heckman (2001) and Heckman and Li (2004).

2.3 The propensity-score matching method

For estimating the ATT and TUT defined as formulation (2) and (3) without bias, we must solve the counterfactual problem. For example, we have access to the income data for a laborer who received education, i.e., $E(\ln y_1|D=1)$; however, we do not have access to $E(\ln y_0|D=1)$ for that laborer. The income data that could not be obtained was considered missing or counterfactual data. There is the same problem in estimating the TUT.

In this study, the propensity-score matching method (P-S matching) is employed to estimate the treatment effects, both ATT and TUT, to the rural labors' non-farm income from high school education and secondary vocational education. The propensity score matching is introduced by Rosenbaum and Rubin (1984) was primarily an extension of Cochran. The basic idea of propensity score matching is an attempt in a non-experimental context to replicate the setup of a randomized experiment. The individuals are divided into two groups: treated group ($D=1$) and control group($D=0$). By employing logit or probit model, the propensity for each individual to receive the education can be estimated. Each $D=1$ individual can be matched with a $D=0$ individual who has similar propensity scores. Then the income of that $D=0$ individual can be considered the potential income of that $D=1$ individual. Counting the weighted average of $D=0$ individuals as the potential outcome for the $D=1$ group , we can obtain the $E(\ln y_0|D=1)$. Then the ATT can be calculated by Equation (2), and TUT can also be calculated by the same way. There are four matching methods: stratification matching (SM), nearest-neighbor matching (NNM), radius matching (RM), and kernel matching (KM).

SM entails dividing the groups into several strata. ATT is the average for $D=1$ workers minus the average for $D=0$ workers in each stratum. Some researchers have suggested that five strata are enough to remove 95 percent of the bias associated with the covariates (Cochrane and Chambers, 1965). NNM involves matching each $D=1$ individual with a $D=0$ individual whose propensity is most similar to that of the $D=1$ individual. Then, ATT is the weighted average of treatment effects for all $D=1$ participants. RM refers to setting a matching radius for each $D=1$ individual. The weighted average of the $D=0$ individuals within that radius constitutes the $D=1$ sample's potential outcome. KM entails comparing the weighted average of scores for all $D=0$ participants as a group with each $D=1$ participant. The more detail can refer to the research of Rosenbaum and Rubin (1984).

There are various balancing test for checking the overall quality of the estimation and which matching method is appreciate to the sample data. Rosenbaum and Rubin (1984) presented that if the data matched on the propensity score, defined as:

$$p(X) = \text{prob}(D=1|X)$$

leads to the following two conditions:

$$D \perp Y(0), \quad Y(1)\big|p(X)$$

and:

$$D \perp X\big|p(X)$$

The idea behind balancing test is to check whether the propensity score is an adequate balancing score, that is, to check to see if at each value of the propensity score, X has the same distribution for the treatment and control groups. It is reasonable to expect that observations with the same propensity score should have the same distribution of observable covariates. Only if passing balancing test leads to more unbiased treatment effect estimates.

The balancing tests we employ are: first, the test for standardized differences that allows comparisons in the differences in X before and after matching. Rosenbaum and Rubin (1984) suggest that the difference is lower than 20 should be considered as passing this test. Second, testing for the equality of each covariate mean between groups using *t*-tests; third, testing for the joint equality of covariate means between groups using the hotelling test or *F*-test.

A seminal selection model is introduced by Heckman (1979) that also can be used to estimate the ATT and TUT allowing for the heterogeneity. Heckman and Li (2004) estimates Chinese return to college education base on this method. The same as propensity score matching, the propensity score plays a critical role in capturing the assignment mechanism. However, a key difference is they use the propensity score in a different way (Lee, 2013). In particular, they focus on exclusion restrictions and do not focus on creating balance in the observed covariates.

In China, rural laborers have three options after completing the nine-year compulsory education: work, high school education, or secondary vocational education. Only one of these options is possible for each laborer. Thus we divided the rural labor samples into three groups: the nine-year compulsory education group (NCEG) included the laborers who, when their nine-year compulsory education was complete, went immediately to work; the high school education group (HSEG) included the laborers who received high school education; and the secondary vocational education group (SVEG) included laborers who received a vocational education. Then, we set the HSEG as the treatment group for high school education, SVEG as the treatment group for secondary vocational education, and NCEG as the control group for both types of education. Then we can count for both the two degree educations' treatment effects, and compare which one was better for improving western rural laborers' incomes.

3. The data

The data we used to analyze this issue were from a survey of rural laborers in the west of China conducted by Beijing Forestry University in 2012. This project surveyed Gansu and Shaanxi, two important western provinces of China, choosing four counties in each province randomly. Then, we selected three townships in each county, three villages within each township, and ten peasant households within each village in accordance with the principle of stratified random sampling. Then we interviewed all the members of the family. If a family member was out that could not be captured, then we would interview another family member who knows his/her condition well. If the other family members do not know the outer's situation well, we would interview him/ her by mobile phone. In all, we surveyed 726 peasant households. Within this sample, 1,454 of the laborers aged 17-60 had taken part in non-farm work for at least three months and had a non-farm income in 2012.

Table I illustrates the summary statistics for the individual characteristics. There are 946 laborers in the NCEG group, 274 in the SEG group, and 234 in the SVEG group. Overall, these laborers' degree of education was low; the NCEG group constituted 82 percent of all participants. The average years of education for all of the laborers was 7.73, about grade 2 of junior school. The average monthly income of the entire sample was about 1,755 RMB. It was highest in the SVEG group and lowest in the NCEG

Variables	Whole	NCEG	HSEG	SVEG	Min.	Max.
Average monthly income (RMB)	1,755.61 (1,374.07)	1,725.41 (1,325.37)	1,778.39 (1,570.49)	2,037.71 (1,579.71)	33	12,500
Average age	33.32 (10.56)	33.53 (10.47)	36.06 (11.31)	26.88 (7.60)	17	60
Education (years)	7.73 (3.70)	6.60 (3.04)	12.58 (1.19)	12.40 (0.50)	0	15
Male (1 = male, 0 = female)	0.66 (0.48)	0.68 (0.47)	0.70 (0.46)	0.66 (0.47)	0	1
Additional skills training received (1 = yes, 0 = no)	0.18 (0.39)	0.19 (0.39)	0.21 (0.41)	0.10 (0.30)	0	1
Married (1 = yes, 0 = no)	0.77 (0.46)	0.79 (0.41)	0.77 (0.42)	0.57 (0.50)	0	1
Self-employed (1 = yes, 0 = no)	0.04 (0.21)	0.04 (0.19)	0.11 (0.32)	0.02 (0.15)	0	1
Non-agricultural work experience (years)	10.16 (7.98)	10.27 (7.99)	10.97 (8.71)	6.95 (5.47)	1	40
Length of time per year engaged in non-farm work (months)	8.84 (3.29)	8.45 (3.35)	10.51 (2.33)	10.74 (2.22)	1	12
Health (1 = good, 0 = poor)	0.76 (0.42)	0.75 (0.43)	0.78 (0.42)	0.83 (0.42)	0	1
Sample numbers	1,454	946	274	234	–	–

Note: The numbers listed in the brackets are standard deviation

Table I.
Summary statistics for the individual characteristics

group. The average age of the entire sample was 33.32 years. The SVEG group was clearly the youngest, indicating that younger laborers regarded secondary vocational education favorably. Due to their younger age, the average level of non-agricultural work experience among those in the SVEG group was the lowest among the three groups.

The average working time of the HSEG and the SVEG groups was two months longer than that of the NCEG laborers. A higher degree of education can guarantee the laborers more stable employment and more income. The additional skill training is a progress that the labors learn vocational skills. But it is different from the secondary vocational education. The labors accept additional skills training after graduated from school. The training mainly held by company or government, and do not offer any diploma when labors complete it. Besides, the additional skill training sustain for a shorter time than the secondary vocational education, always last for days or months. The laborers who chose additional training accounted for 18 percent of the entire sample. Overall, 21 and 19 percent of laborers received skill training in the HSEG and the NCEG groups, respectively. This proportion was only 10 percent in the SVEG, in some degree because the secondary vocational education mainly teaches the students work skills, and the SVEG laborers' demands for skills training is lower. About 4 percent of laborers were self-employed.

The non-farm work characteristics are showed in Table II. Many laborers preferred to work in other provinces. Approximately 38 percent of laborers moved to the economically developed eastern area to work; this was the highest proportion among areas. The second most popular area to which laborers migrated for work was other

Variables	Whole	NCEG	HSEG	SVEG	Min.	Max.
Work area (1 = yes, 0 = no)						
Work in own county	0.26	0.22	0.50	0.32	0	1
	(0.41)	(0.39)	(0.49)	(0.44)		
Work in other counties in home province	0.06	0.06	0.10	0.14	0	1
	(0.24)	(0.22)	(0.30)	(0.33)		
Work in eastern provinces	0.38	0.39	0.26	0.38	0	1
	(0.49)	(0.49)	(0.44)	(0.50)		
Work in central provinces	0.04	0.05	0.00	0.00	0	1
	(0.20)	(0.22)	(0.00)	(0.00)		
Work in other western provinces	0.26	0.28	0.14	0.16	0	1
	(0.44)	(0.45)	(0.35)	(0.33)		
Vocational roles(1 = yes, 0 = no)						
Manager	0.08	0.07	0.12	0.09	0	1
	(0.26)	(0.25)	(0.32)	(0.26)		
Skilled worker	0.23	0.23	0.15	0.29	0	1
	(0.42)	(0.42)	(0.36)	(0.46)		
Unskilled worker	0.44	0.52	0.13	0.07	0	1
	(0.50)	(0.50)	(0.34)	(0.26)		
Technician	0.04	0.02	0.15	0.12	0	1
	(0.18)	(0.11)	(0.36)	(0.33)		
Servicer	0.15	0.13	0.20	0.33	0	1
	(0.35)	(0.34)	(0.36)	(0.45)		
Village cadre	0.05	0.02	0.25	0.10	0	1
	(0.22)	(0.15)	(0.44)	(0.30)		

Note: The numbers listed in the brackets are standard deviation

Table II. Summary statistics for the non-farm work characteristics

western provinces such as Xinjiang, Sichuan, Ningxia, etc.; the proportion of those migrating to these areas for work was 26 percent. That proportion is similar to the study of Li *et al.* (2013). However, few laborers moved to the central area, perhaps because it did not have an obvious advantage in terms of economic development compared with eastern and western areas. The other laborers moved within their own provinces, mainly within their own counties. The differences in the likelihood of moving among the three groups were significant. The HSEG laborers preferred to stay in the same area, and about half of them had jobs in their own counties. The NCEG laborers tended to move farther away, with 72 percent moving to other provinces. The HSEG workers had the advantage of working near to their hometowns. However, the NCEG workers lacked education, and it was hard to find jobs nearby, so they had to move farther away.

We divided the vocational role into six groups: manager, skilled worker, unskilled worker, technician, servicer, village cadre. Where the manager refers to the labors mainly supervise and manage the other labors to work in an organization. Skilled worker and unskilled worker specific indicate the workers in the factory, construction site and mine field. The skilled workers' job ask for professional skill. But the unskilled workers' job are physical work with little professional skill. The technicians are proficient in some dominants and must obtain the official certification, such as teachers, doctors. The servicer mainly indicated the workers in service factory, such as waiter, cashier, barber. The village cadres are elected by the villagers, responsible for the clerical work of the village. Regarding laborers' occupations, secondary industries were the main source of jobs. About 67 percent of laborers were engaged in the manufacturing and construction industries. The service industry absorbed 13 percent of the entire sample of laborers. The proportions of managers and technicians were 8 and 4 percent, respectively. The other 5 percent of laborers worked as village cadres. The proportion of managers and technicians was higher in the HSEG group than in the two other groups. The SVEG laborers mainly worked in service industries and as skilled workers, and NCEG laborers mainly worked as unskilled laborers such as construction workers and miners.

The most important family background variables are the education years of father and mother, that will be employed as the instrument in the IV regression in this paper. The overall mean education years of father and mother are 4.80 and 2.54 separately. That is significantly lower than the labors' mean level, indicates that the younger generation receive higher education than the former generation. The mean education years of the parents of SVEG is higher than the other two groups, while that is lowest of NCEG (Table III).

Table IV describing the education distribution of different cohorts. First, the group with higher average monthly income, the more average education years it has. Second, the male labors' average education years is higher than the female labors'. The male labors are always preferred to accept the education in rural family than the female labors in Chinese western rural area. Third, the younger labor group has higher average education years. As a result of the education spread policy, more younger labors have chance to accept a higher education level.

4. Results

4.1 Non-farm income return to education

The results for the returns to education are presented in Table V. The estimates of the returns to education using OLS from the Mincer earnings model was 3.5 percent, meaning that the income of a laborer with one more additional year of education would increase by 3.5 percent. The gender, non-agricultural work experience, health, skill-training, cultivated land area, self-employment, and work region also had effects on non-farm income. However, the estimates by OLS always had an upward bias because of the individual's unobserved endogenous factors such as native ability (Wooldridge,

Variables	Whole	NCEG	HSEG	SVEG	Min.	Max.
Education years of father (years)	4.80	4.37	5.77	8.14	0	15
	(4.16)	(4.02)	(4.24)	(3.90)		
Education years of mother (years)	2.54	2.20	3.23	5.36	0	12
	(3.37)	(3.18)	(3.57)	(3.72)		
Number of family members	5.55	5.64	4.97	5.36	1	14
	(1.80)	(1.81)	(1.58)	(1.79)		
Family poverty (thousand RMB)	90.26	85.45	110.41	115.26	8.50	345.75
	(71.81)	(71.16)	(72.64)	(69.22)		
Cultivated land area (ha)	0.51	0.51	0.50	0.50	0	1.6
	(0.30)	(0.30)	(0.27)	(0.35)		
Number of parcels of cultivated land	3.91	4.08	3.39	2.83	0	20
	(3.06)	(3.14)	(2.11)	(3.07)		

Note: The numbers listed in the brackets are standard deviation

Table III.
Summary statistics for the family background variables

	Average education years	The number of individuals in different education groups NCEG	HSEG	SVEG	Total
Average monthly income (RMB)					
< 1,000	7.01	272	67	36	375
1,000~2,000	7.73	351	91	84	526
2,000~3,000	8.13	203	76	48	327
3,000~4,000	8.42	59	21	42	122
> 4,000	8.26	61	19	24	104
Gender					
Male	7.96	632	191	158	981
Female	7.25	304	83	86	473
Age					
17~30	8.96	387	138	180	705
30~40	6.85	244	72	30	346
40~50	6.51	223	52	18	293
50~60	5.87	92	12	6	110
Length of time per year engaged in non-farm work (months)					
1~3 months	6.08	187	50	50	287
4~6 months	7.54	273	60	50	383
7~9 months	7.93	224	70	57	351
10~12 months	8.83	262	94	77	433
Additional skills training received					
Received	7.78	177	58	24	259
Not received	7.72	769	216	210	1,195
Self-employed					
Yes	9.39	34	29	5	68
No	7.65	912	245	229	1,386

Table IV. The education distribution of different cohorts

2003). Thus, we used the IV method to estimate the returns to education to control for bias related to unobserved abilities; the result was a return of 2.8 percent. Additionally, to account for the self-selection bias introduced by individuals choosing non-farm job, we used the Heckman two-steps method to estimate the returns on education is 3.3 percent. From the results of this model, it is clear that education affected laborers' participation in non-farm employment, even though the returns on education were reduced somewhat compared with the earnings model.

The returns on education in the western rural area were about 2.8-3.5 percent according to the three methods. These results show lower returns than the average value found in other studies of Chinese rural workers in recent years. For example, Liu (2008) use OLS to estimate the mincer return to education in rural China is 6.03 percent; the result estimated by De Brauw and Rozelle (2008) is 6.5 percent by employing Heckman two-steps method to correct for selection bias. That likely due to the undeveloped regional economy and the lower educational levels in the western rural area.

Finally, we replaced the years of education with educational degree dummy variables in the earnings model. The results suggest the return to high school education is 31.3 percent and the return to secondary vocational education is 43.2 percent. A Wald-test is used to test the significance of the difference in the estimated returns. The Wald-test value is 12.72, indicates the difference is statistically significant at the $p < 0.05$ level according to a Wald-test. This is mainly because the secondary vocational education links education with the vocation more closely than the high

Table V.
The results for returns to education estimated by various methods

Variables	OLS	IV	Heckman two-steps method: Earning model	Heckman two-steps method: Selection model	Educational dummy variables regression
Years of education	0.035***	0.028**	0.033***	0.083***	
	(0.015)	(0.015)	(0.016)	(0.009)	
High school education					0.313**
					(0.155)
Secondary vocational education					0.432***
					(0.162)
Gender	0.327***	0.314	0.267***	0.382***	0.355***
	(0.064)	(0.419)	(0.115)	(0.067)	(0.067)
Non-agricultural work experience	0.033***	0.037***	0.039***		0.042***
	(0.011)	(0.014)	(0.011)		(0.019)
Squared non-agricultural work experience	−0.007**	−0.007***	−0.008***		−0.001***
	(0.004)	(0.003)	(0.003)		(0.000)
Married	−0.043	0.235	0.128	−0.015*	−0.030
	(0.036)	(0.280)	(0.093)	(0.008)	(0.033)
Health	0.259***	0.268***	0.167***	0.477***	0.235
	(0.023)	(0.061)	(0.015)	(0.133)	(0.210)
Age				−0.015***	
				(0.003)	
Skill trained	0.192***	0.296	0.231**	0.727***	0.183**
	(0.061)	(0.211)	(0.113)	(0.085)	(0.096)
Area of cultivated land	−0.015*	0.013	−0.014**	−0.010	−0.015*
	(0.008)	(0.026)	(0.007)	(0.013)	(0.008)
Number of family members	0.033	0.141	0.021	0.034**	0.030
	(0.021)	(0.103)	(0.018)	(0.014)	(0.021)
Family poverty				0.004	
				(0.014)	
Self-employed	0.332**	0.247	0.315*		0.256
	(0.171)	(0.316)	(0.171)		(0.170)

(continued)

Table V.

Variables	OLS	IV	Heckman two-steps method Earning model	Selection model	Educational dummy variables regression
Work in other counties in home province	0.292*	0.337	0.282*		0.396***
	(0.158)	(0.274)	(0.157)		(0.144)
Work in Eastern area provinces	0.482***	0.676	0.489***		0.571***
	(0.153)	(0.613)	(0.146)		(0.185)
Work in Central area provinces	0.378***	0.613**	0.392***		0.365***
	(0.093)	(0.299)	(0.095)		(0.081)
Work in other Western area provinces	0.313***	0.574	0.317***		0.216**
	(0.108)	(0.628)	(0.117)		(0.076)
Vocational characteristic	controlled	controlled	controlled		controlled
County dummy variable	controlled	controlled	controlled	controlled	controlled
Inverse mill ratio			−0.064***		
			(0.020)		
Constant term	6.132***	2.819	6.713***	−0.219	5.192***
	(0.387)	(6.773)	(0.323)	(0.141)	(0.398)
R^2	0.260	0.247	0.261	0.066	0.247
Prob > F	0.000				0.000
Prob > χ^2		0.004	0.000	0.000	

Notes: We used the 2SLS method to estimate in the IV regression, where the instrumental variables were years of education of the individual's father and mother; the "controlled" in vocational characteristics and county dummy variable estimates mean that we have employed the set of dummy variables in mincer model. But the variables are too many and not so important in this research, so we omit these estimates in this table. *,**,***Significant at 10, 5 and 1 percent, respectively school education which targets the college entrance examination. Base on this result, it is a good way for the government to improve the return to education by supporting the secondary vocational education more forcefully in the western area.

However, this is a simple estimation that does not account for heterogeneity. We will discuss the education treatment effect using the P-S matching method.

4.2 Treatment effect result

First, we used the logit model to separately estimate the propensity of the samples to choose high school education and secondary vocational education. Various variables were controlled in the logit model such as gender, age, father's and mother's years of education, family's cultivated land area, number of family members, county dummy variables, etc. Table VI shows the marginal effect for each explanatory variable.

A few samples were lost after propensity-score matching because no matching participant could be found. For high school education, the range of propensity for SEG was [0.03, 0.96] and that for NCEG was [0, 0.92]. There were 253 individuals left in the SEG group and 926 in the NCEG group after matching. For secondary vocational education, the range of propensity for SVEG was [0.04, 0.97] and that for NCEG was [0, 0.93]. There were 218 workers left in the SVEG group and 922 left in the NCEG group after matching. The propensity-distribution conditions are showed in Figures 1 and 2.

The results for the education treatment effects are presented in Tables VII and VIII. Generally, secondary vocational education had a greater effect on non-farm incomes than did high school education. The ATT range for high school education was 27.9-31.2 percent, and that for secondary vocational education was 31-32.8 percent based on

Variables	High school education	Secondary vocational education
Gender	0.071**	0.057*
	(0.036)	(0.032)
Age	−0.043**	−0.086***
	(0.019)	(0.030)
Age^2	0.008	0.022***
	(0.011)	(0.009)
Father's years of education	0.113*	0.158***
	(0.066)	(0.050)
Father's years of education – squared	0.035	0.041
	(0.022)	(0.021)
Mother's years of education	0.070	0.086
	(0.057)	(0.066)
Mother's years of education – squared	0.017	0.037
	(0.019)	(0.033)
Cultivated land area	0.184***	0.172*
	(0.065)	(0.089)
Number of family members	−0.013	−0.030
	(0.037)	(0.045)
County dummy variables	controlled	controlled
Constant term	−5.714***	−2.290
	(1.335)	(1.600)
R^2	0.214	0.219
Prob > χ^2	0.000	0.000

Notes: *,**,***Significant at 10, 5 and 1 percent, respectively

Table VI.
The results marginal effect from logit model for both of the two educations

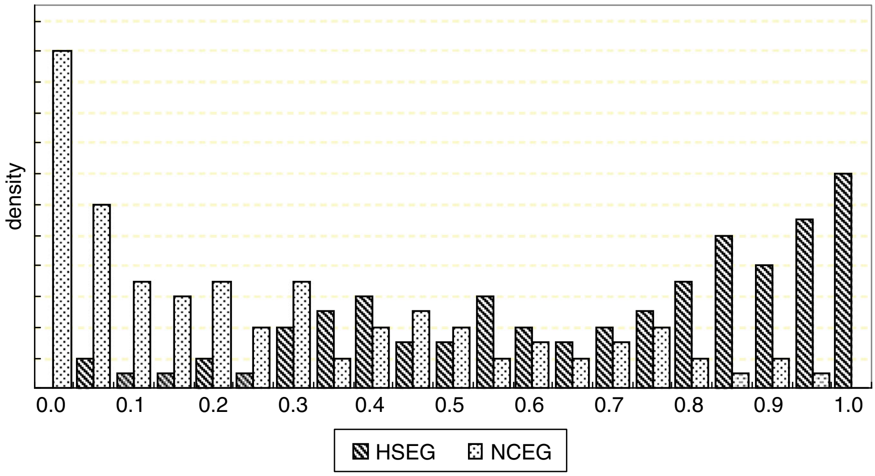

Figure 1.
The propensity-distribution conditions for HSE

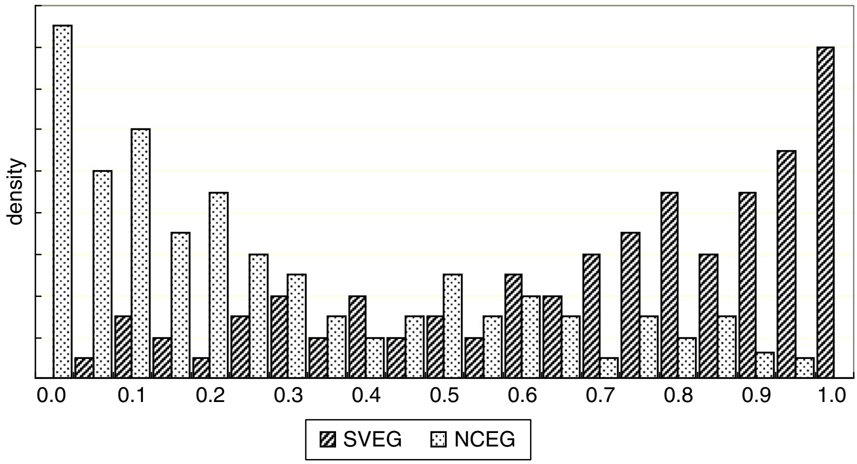

Figure 2.
The propensity-distribution conditions for SVE

Table VII.
The treatment effect of high school education estimated by P-S matching

Matching methods	HSEG/NCEG	ATT	95% CI		HSEG/NCEG	TUT	95% CI	
SM	156/474	0.279*** (0.102)	0.08	0.48	164/504	0.283*** (0.102)	0.08	0.48
NNM	274/566	0.303 (0.193)	−0.08	0.68	244/926	0.313*** (0.125)	0.07	0.558
RM	149/276	0.306** (0.159)	−0.00	0.62	149/276	0.312 (0.168)	−0.02	0.64
KM	253/926	0.312 (0.204)[b]	−0.09	0.71	253/926	0.319** (0.161)[b]	0.00	0.63

Notes: The radius in RM is 0.05. The "b" superscripted on the standard deviation were calculated by the bootstrap method. *,**,***Significant at 10, 5 and 1 percent, respectively various matching methods. Table IX indicates the ATTs from high school education and secondary vocational education estimated by SM have passed the balancing test, illustrate that are more reliable. By comparing the ATTs of two educations estimated by SM, we can conclude that for the workers who received a higher degree education, secondary vocational education was better for improving their non-farm incomes. The ATT to the high school education is 27.9 percent that is 4.9 percentage lower than the ATT to the secondary vocational education. When accounting for the heterogeneity, the result is significantly lower than the estimates by regression, that is consistent with Heckman and Li (2004) who estimated by another semiparametric method.

Next, we estimated the TUT in the same way and found that the secondary vocational education was also better for improving non-farm incomes than was high school education. The TUT range for high school education was 28.3-31.9 percent, and that for secondary vocational education was 32.5-33.4 percent based on various matching methods. The balancing test indicated that the estimates by KM is more quality (Table IX). If the non-treated individuals (i.e. those who did not receive education) were to participate in high school education, their non-farm incomes would increase by 31.9 percent. However, if they participated in secondary vocational education, their non-farm incomes would increase by 33.4 percent.

Note that the value for TUT was generally higher than that for ATT according to results of various matching methods. This suggests that the educational resources in the western rural area are not arranged efficiently, as these results indicate that if the NCEG individuals engaged in more education, the treatment effect would be even greater for them than that for the SVEG and HSEG groups. This phenomenon indicates

Matching methods	SVEG/NCEG	ATT	95% CI		SVEG/NCEG	TUT	95% CI	
SM	192/522	0.328*** (0.106)	0.54	0.12	185/576	0.325* (0.182)	−0.03	0.68
NNM	206/644	0.322** (0.161)	0.01	0.64	217/922	0.326 (0.237)	−0.14	0.79
RM	173/422	0.320** (0.161)	0.00	0.64	178/420	0.330* (0.188)	−0.04	0.70
KM	218/922	0.310*** (0.136)[b]	0.04	0.58	218/922	0.334*** (0.151)[b]	0.04	0.63

Note: The radius in RM is 0.05. The "b" superscripted on the standard deviation were calculated by the bootstrap method. *,**,***Significant at 10, 5 and 1 percent, respectively

Table VIII.
The treatment effect of secondary vocational education estimated by P-S matching

	Matching by SM	Matching by NNM	Matching by RM	Matching by KM
ATT from high school education	*Pass*	Fail	Fail	Fail
ATT from secondary vocational education	*Pass*	*Pass*	Fail	Fail
TUT from high school education	Fail	Fail	Fail	*Pass*
TUT from secondary vocational education	Fail	Fail	Fail	*Pass*

Notes: The detail of balancing test results are listed in Tables AI-AIX, the italic digits mean it is fail to pass the test

Table IX.
Summary of the balancing test result

that the secondary education should be popularzied more forcefully. A rural individual's choice regarding whether to pursue a higher degree of education is typically a family decision rather than a personal decision. For example, the householders usually prefer to let the son to go to school and the daughter drop out due to the traditional view that values males more highly, this can be illustrated by the logit model result presented in Table VI. Furthermore, there are many impoverished families in the western rural area, and it would be hard for them to afford the cost of education, even if the opportunity were available. Although most rural residents know that more education could increase their non-farm incomes, many exogenous variables affect laborers' decisions.

5. Summary and conclusion

This paper provides a direct view of the effect of education on non-farm incomes in China's western rural area. We used the parametric method to estimate the returns on education and the P-S matching method to compare the treatment effects of high school education and secondary vocational education while accounting for heterogeneity. The main conclusions of this paper are as follows. First, the returns on education in the western rural area range between 2.7 and 3.9 percent using various estimation methods in the Mincer earnings model. This result is lower than that found in most research on rural China, suggesting that education has less impact on human resources in western rural area. Second, next, we estimated the treatment effect of education after accounting for heterogeneity. The ATT of high school education ranged between 27.9 and 31.2 percent, and that for secondary vocational education ranged between 31 and 32.2 percent. For the education-treated individuals, secondary vocational education was better for increasing their non-farm incomes. The TUT results for high school education and secondary vocational education, estimated by the same methods as ATT, also indicated that secondary vocational education would be more effective in increasing non-farm incomes for untreated individuals. Third, after completing the results of ATT and TUT analyses, we conclude that the high school education and secondary vocational education should be popularized more forcefully in the western rural area. This is mainly because of limited educational opportunity resulting from various exogenous variables.

Policy-related suggestions derived from this research are as follows. First, enhance investments in education in the western rural area. The government should pay attention to urban-rural integration in education and give political support to education in the western rural area, sending more excellent teachers there, designing a good rural school distribution, and relaxing the restrictions on moving from rural to urban places. Second, the secondary vocational education should be forcefully sustained, including improving its position in the Chinese education system and promoting cooperation between schools and business so that more western rural laborers are able to become technical workers. Third, improve the continuing education and skill-training system, providing laborers who have less education with more opportunities to improve their work skills.

Although the results estimated by propensity score matching indicate the treatment effect of secondary vocational education is higher than that of high school education, the confidence intervals for the treatment effects overlap, which means the differences are not statistically Significant. This is the main shortage of this paper, and we will try to solve this problem in the future research.

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Appendix

Variables	Standardized difference before matching	Standardized difference after SM	Standardized difference after NNM	Standardized difference after RM	Standardized difference after KM
Gender	102.32	5.10	−3.25	6.73	8.92
Age	−159.73	9.24	*31.83*	5.13	6.37
Father’s years of education	128.92	5.14	*21.20*	12.54	*23.63*
Mother’s years of education	124.14	13.67	6.54	7.87	*31.37*
Cultivated land area	171.27	6.53	*25.82*	12.29	*26.32*
number of family members	−177.16	1.57	3.23	3.46	6.15

Table AI. The test for standardized difference of ATT from high school education

Variables	Standardized difference before matching	Standardized difference after SM	Standardized difference after NNM	Standardized difference after RM	Standardized difference after KM
Gender	109.64	6.34	3.32	8.47	13.72
Age	−173.61	8.73	17.31	11.35	*27.28*
Father’s years of education	165.33	6.59	6.43	11.82	11.53
Mother’s years of education	139.94	6.76	18.37	6.53	6.67
Cultivated land area	137.81	17.68	13.82	12.27	*28.56*
Number of family members	−165.83	5.54	9.54	13.41	16.75

Table AII. The test for standardized difference of ATT from secondary vocational education

Table AIII. The test for standardized difference of TUT from high school education

Variables	Standardized difference before matching	Standardized difference after SM	Standardized difference after NNM	Standardized difference after RM	Standardized difference after KM
Gender	−113.46	6.53	17.54	*26.73*	7.47
Age	−73.49	11.42	16.82	5.13	6.37
Father's years of education	89.56	13.47	7.47	12.54	13.43
Mother's years of education	141.82	9.59	19.56	*27.87*	7.82
Cultivated land area	159.41	12.34	7.43	12.29	16.38
Number of family members	68.73	8.41	6.84	*33.46*	8.19

Table AIV. The test for standardized difference of TUT from secondary vocational education

Variables	Standardized difference before matching	Standardized difference after SM	Standardized difference after NNM	Standardized difference after RM	Standardized difference after KM
Gender	79.32	5.84	7.38	13.62	5.85
Age	178.43	*22.61*	2.54	*31.47*	8.32
Father's years of education	169.58	9.93	16.73	9.53	12.71
Mother's years of education	91.27	15.32	5.49	18.32	6.58
Cultivated land area	177.41	7.14	12.17	6.74	5.54
Number of family members	185.28	6.88	8.59	*24.46*	7.32

Table AV. The *t*-test for ATT from high school education

Variables	*p*-value of *t*-test before matching	Standardized difference after SM	Standardized difference after NNM	Standardized difference after RM	Standardized difference after KM
Gender	0.00	0.67	0.53	0.62	0.35
Age	0.01	0.84	*0.02*	0.53	0.42
Age^2	0.00	0.65	*0.01*	0.82	0.24
Father's years of education	0.05	0.45	0.52	0.31	0.64
Father's years of education – squared	0.00	0.43	0.32	0.59	0.38
Mother's years of education	0.00	0.63	*0.04*	0.24	0.43
Mother's years of education – squared	0.00	0.19	0.17	0.71	0.77
Cultivated land area	0.00	0.34	0.46	*0.00*	*0.05*
Number of family members	0.03	0.83	0.81	*0.02*	0.26

Table AVI.
The *t*-test for ATT from secondary vocational education

Variables	*p*-value of *t*-test before matching	Standardized difference after SM	Standardized difference after NNM	Standardized difference after RM	Standardized difference after KM
Gender	0.01	0.52	0.34	0.75	0.35
Age	0.05	0.69	*0.58*	0.45	0.28
Age^2	0.01	0.49	0.53	*0.02*	0.41
Father's years of education	0.00	0.49	*0.43*	0.67	0.74
Father's years of education – squared	0.00	0.35	0.19	0.31	0.55
Mother's years of education	0.00	0.47	0.87	0.81	0.53
Mother's years of education – squared	0.00	0.72	0.64	0.56	0.74
Cultivated land area	0.00	0.57	0.26	0.19	0.13
Number of family members	0.03	0.83	*0.70*	*0.04*	0.40

Table AVII.
The t-test for TUT from high school education

Variables	Mean for $D=1$	Mean for $D=0$ (weighted by SM)	Mean for $D=0$ (weighted by NNM)	Mean for $D=0$ (weighted by RM)	Mean for $D=0$ (weighted by KM)
Gender	0.00	*0.04*	0.47	0.47	0.45
Age	0.00	0.92	0.52	*0.05*	0.72
Age^2	0.00	0.43	0.73	*0.03*	0.53
Father's years of education	0.06	*0.07*	0.84	0.42	0.17
Father's years of education – squared	0.00	*0.08*	0.66	0.71	0.49
Mother's years of education	0.00	0.52	0.19	0.28	0.46
Mother's years of education – squared	0.00	0.48	0.46	0.76	0.66
Cultivated land area	0.00	0.58	0.63	0.53	0.25
Number of family members	0.00	0.65	0.46	0.49	0.58

Table AVIII.
The t-test for TUT from secondary vocational education

Variables	Mean for $D=1$	Mean for $D=0$ (weighted by SM)	Mean for $D=0$ (weighted by NNM)	Mean for $D=0$ (weighted by RM)	Mean for $D=0$ (weighted by KM)
Gender	0.01	0.52	0.53	0.64	0.28
Age	0.00	*0.03*	0.84	0.87	0.46
Age^2	0.00	*0.00*	0.36	0.38	0.45
Father's years of education	0.07	0.46	*0.08*	0.91	0.83
Father's years of education – squared	0.00	0.27	*0.07*	0.39	0.62
Mother's years of education	0.00	*0.09*	*0.05*	0.85	0.28
Mother's years of education – squared	0.01	0.31	*0.01*	0.37	0.57
Cultivated land area	0.00	0.73	0.84	0.61	0.38
Number of family members	0.03	0.67	0.79	0.37	0.74

Table AIX.
The hotelling-test after matching

Hotelling p-value	Matching by SM	Matching by NNM	Matching by RM	Matching by KM
ATT from high school education	0.93	0.39	0.04	0.87
ATT from secondary vocational education	0.74	0.58	0.51	0.34
TUT from high school education	0.65	*0.05*	0.37	0.53
TUT from secondary vocational education	*0.07*	0.67	0.85	0.68

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