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Education, Labor Mobility and Relative Rural Poverty

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Abstract: Relative poverty has become more important since China eliminated absolute poverty. Based on the sample data of rural households in CFPS 2018, this paper studies the impact of education and labor mobility on the relative poverty of rural households. First, A-F is used to construct a multi-dimensional relative poverty index to measure the relative poverty status of rural households. The income dimension uses the relative poverty index of income instead of the absolute poverty line, and then establishes the Logit binary choice model for econometric analysis and robustness test. The results show that: (1) Education, labor mobility and their interactions have significantly reduced the probability of rural households falling into multidimensional relative poverty; (2) Regional heterogeneity exists in the impact effects, education and labor mobility in inland areas The poverty reduction effect for the relative poverty of rural households is better than that of coastal areas. These results are of great significance for exploring the relative poverty in my country's rural areas and their causes.

Keywords: education; labor mobility; relative poverty

JEL Classification: D10; I32; J24; J61

1. Introduction

China has eliminated absolute poverty in 2020 and built a well-off society in an all-round way. However, the elimination of absolute poverty does not mean the elimination of poverty, but a shift from absolute poverty to relative poverty. Common prosperity is the essential requirement of socialism, and how to alleviate the problem of relative poverty has the urgency of the times.

The concept of relative poverty can be traced back to Shorrocks and Townsend (1980). Sen (1999) rejected Townsend's relative interpretation, and proposed a poverty theory of feasible capability, which also expanded the connotation of poverty from one-dimensional to multi-dimensional. Education is an important factor in the causes of relative poverty. One main approach is the accumulation of human capital advocated by Becker (1994). Another way that education affects poverty is intergenerational transmission. Zou and Zheng (2014) explained the problem of persistent poverty in low-income families from the perspective of the risks of education investment and decision-making. For poor rural families, the income sent home by migrant workers has become the main source of family income (Duyang & Pu Zhishui, 2003). Fan and Jiang (2016) used CFPS data and found that the empirical analysis found that rural labor mobility not only improved the household income of farmers, but also reduced the possibility of poverty.

Education and labor mobility are of great significance to poverty alleviation. However, most existing studies focus on absolute poverty, and there are research gaps on relative poverty. This paper will study the impact of education and labor mobility on relative poverty. In addition, it will explore the impact of the interaction between education and labor on relative poverty.

2. Methodology

2.1. Data Source

The data in this article comes from the China Family Panel Studies (CFPS) of 2018, and the sample covers 25 provinces (municipalities and autonomous regions) across the country, which is nationally representative. The research object of this article is rural households, so only the sample of urban households is deleted. According to the completeness of other variable data and the matching degree between the individual and the family sample, this paper screened the data and finally got 4905 family samples.

2.2. Measurement of Relative Poverty

In the multidimensional poverty measurement method, the A-F double critical value method is used. In the income dimension, in order to reflect the difference between relative poverty and absolute poverty, this paper uses relative income poverty indicators to replace the absolute poverty income standard line. According to the Multidimensional Poverty Index (MPI) evaluation system proposed by the United Nations Development Program (UNDP) in 2010 and existing research results, considering the availability of data, this article selects four indicators of income, education, health and living standards to construct Multidimensional poverty index.

First, identify a single dimension of poverty. Set different poverty deprivation thresholds in different dimensions to determine whether it is in a state of poverty deprivation in this dimension. For example, for a certain family, if its status in this dimension is lower than the critical value, it means that the family is in a state of poverty deprivation in that dimension, and the value is assigned to 1 and vice versa to 0. The specific formula is expressed as follows:

$$g_{ij} = \begin{cases} 1, & if\ X_{ij} < Z_j \\ 0, & if\ X_{ij} \geq Z_j \end{cases} \tag{1}$$

Z_j represents the deprivation cut-off in the jth dimension, and X_{ij} represents the deprivation state of the ith family in the jth dimension. When X_{ij} is less than the critical value Z_j, the ith household is in a state of poverty deprivation on dimension j.

Secondly, the deprivation scores on various dimensions are weighted and averaged to judge the multidimensional poverty status. First, set the weight of each dimension to w_j and add up to 1. The formula is as follows:

$$c_i(k) = \sum_{j=1}^{n} w_j\, g_{ij} \tag{2}$$

The n represents the total number of households, w_j is the weight on the jth dimension, and k is the multidimensional deprivation cut-off value. Households are poor when the total number of deprivation dimensions $c_i(k)$ is greater than or equal to the cut-off value k, while households below the cut-off value are considered non-poor. The total number of poor people is calculated and expressed as q. Therefore, the poverty state is affected by both $Z_j$and c_i, which is the double critical value.

This paper uses 50% of the country's per capita disposable income to measure relative poverty in the income dimension. If the per capita household income is less than 50% of the disposable income of the national residents, it is in a state of relative poverty, otherwise it is a non-poor family. The specific indicator system is shown in Table 1.

Table 1. Multidimensional poverty indicators

Dimension	Metric	Deprivation Cutoff	Weight
economy	Per capita household net income	Less than 50% (14,114) of the national per capita disposable income in 2018, it is assigned to 1	0.2
education	Years of education	Adults (16 years old) have education for less than 9 years, assigned 1	0.2
health	The proportion of medical expenditure	In the previous year, household medical expenditure accounted for more than 40% of the total expenditure of 1	0.2
surroundings	drinking water	Well water and other non-clean water source assignment value 1	0.1
	Energy use	Non-clean energy source such as firewood is assigned a value of 1	0.1
social development	Family culture and education expenditure	The proportion of cultural and educational expenditure in net income was less than 10% of 1	0.2

2.3. Main Variables

Core variables: The variable explained in this paper is the multi-dimensional relative poverty state (rmpi), and the total score of deprivation is obtained by the A-F calculation method above. Set the multi-dimensional poverty critical value k to 1/3. If the total deprivation score is higher than k, it is in a multi-dimensional relative poverty state, otherwise it is a non-poverty state. The relative poverty status is assigned a value of 1, and the non-poverty status is assigned a value of 0. The core explanatory variables are the average number of years of education in the family (edu) and labor mobility (outinc). Labor mobility is expressed by the amount sent home by family migrants in the CFPS 2018 questionnaire. The samples of households without migrant workers and those who did not send money home are all assigned a value of 0.

Control variables. This paper selects four control variables: region (area), social subsidy (soc), transfer income (trans), and the number of people eating at home (peo). These variables also affect the poverty status of family, but they are not the focus of this article, so put them in the control variables. Among them, the area is divided into coastal and inland areas; social subsidies and transfer income measure the assistance status of the family, and the amount of subsidy will affect the poverty status; the number of people eating at home reflects the family’s dependency ratio. The variable meanings and descriptive statistics are shown in Table 2.

Table 2. Key variable definitions and descriptive statistics

Variable	Definition	N	Mean	Sd	min	max
rmpi	The multidimensional poverty critical value K is set at 1 / 3, and the total deprivation score above k is assigned in a relative poverty state of 1, otherwise 0.	4,905	0.781	0.414	0	1
edu	Education level per capita (units: year).	4,905	5.523	3.080	0	19
outinc	Measured by the amount of the person send home (units: CNY).	4,905	11,710	19,074	0	200,000
edu_outinc	The interactive effect of education and labor mobility	4,905	71,451	146,100	0	3,200,000
area	The coastal area was assigned 1, and the inland area was assigned 0.	4,905	0.265	0.441	0	1
soc	Social subsidies received by families (units: CNY).	4,905	0.0169	0.129	0	1
trans	Total transfer income earned by the family. (units: CNY).	4,905	5,786	31,547	0	1,000,000
peo	The number of people in the family who usually eat.	4,905	3.599	1.816	1	21

2.4. Model

The explained variable of this article is whether it is in a multi-dimensional relative poverty state, which is a binary discrete variable, so this article uses the Logit Model for empirical analysis. First, express the relative poverty state of the explanatory variable in the form of probability:

$$\begin{cases} P(y=1|X) = F(x,\beta) \\ P(y=0|X) = 1 - F(x,\beta) \end{cases} \tag{3}$$

It is further expressed as the logit model as:

$$P_i = F(y_i) = F(\alpha + \beta x_i) = \frac{1}{1+e^{-y_i}} = \frac{1}{1+e^{-(\alpha+\beta x_i)}} \tag{4}$$

The explained variable is converted into probability through logistic probability distribution function F(y), and the above model is converted to obtain:

$$ln\frac{P}{1-p} = logit(P) = \beta_0 + \sum_{i=1}^{k} X_i\beta + \varepsilon \tag{5}$$

Among them, is defined as the chance ratio. In this article, it refers to the ratio of the probability of a family in relative poverty to the probability of not being in relative poverty. When estimating the model with maximum likelihood estimation, the dependent variable y obtained is not whether it is in relative poverty in this paper, but the logarithm of the chance ratio, also called odds ratio or odds ratio.

3. Results and Discussion

3.1. Regression Results

Table 3 reports the benchmark regression results of the logit model. Two regressions were performed according to whether the control variables were added. Among them, the robust standard errors are in parentheses. Model (1) does not add control variables, the left column reports the probability ratio, and the right column reports the variable coefficients.

From the results, both education (*edu*) and labor mobility (*outinc*) are very significant, and the interaction effect of education and labor mobility (*edu*outinc*) is also significant at the

0.1 level. Judging from the sign of the coefficient, the coefficients of the two core explanatory variables of education and labor mobility are both negative, indicating that the increase in the number of years of education and labor mobility will reduce the probability of rural families in relative poverty. The odds ratio (β) shows that for every increase in the average number of years of education of rural households by one unit, the probability of rural households in relative poverty is 0.69 times the original probability, that is, the probability of being in relative poverty drops by 31%. Although the odds ratio of family labor mobility is close to 1, it is still less than 1, indicating that labor mobility will also reduce the probability that rural families are in relative poverty.

The possible reason why the chance ratio of labor mobility in this article is close to 1 is that this article uses yuan as the unit of money sent home by migrant workers, so the regression results show this. But the regression result is still significantly negative, which does not affect our judgment. Therefore, the regression results of the core explanatory variables confirm the research hypothesis of this article: education, labor mobility, and the interactive effects of the two will reduce the probability of rural families in relative poverty.

Table 3. Regression results

	(1)		(2)	
Varibales	Odds ratio	β	Odds ratio	β
edu	0.6913638***	-0.369***	0.7026641***	-0.353***
		(0.0165)		(0.0167)
outinc	0.9999792***	-0.0000208***	0.9999772***	-0.0000228***
		(0.00000492)		(0.0000049)
edu_outinc	1.000001*	0.00000117*	1.0000001**	0.00000135**
		(0.000000632)		(0.000000622)
area			0.8189709**	-0.200**
				(0.0850)
soc			2.3567713**	0.862**
				(0.416)
trans			0.9999973**	-0.00000266**
				(0.00000127)
peo			1.099234***	0.0946***
				(0.0238)
Constant	43.2503***	3.767***	30.16122***	3.407***
		(0.126)		(0.161)
Observations		4,905		4,905
chi-square	877.43***		909.33***	
	(0.000)		(0.000)	
H-L chi2	12.68		14.36	
	(0.1232)		(0.0729)	

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Model (2) is the regression result after adding control variables. Compared with model (1), the original estimation results are not changed after the control variables are added, and the results are still significant on the core variables. In terms of chance ratio, the chance ratio of model (2) is reduced, that is, the probability of being in relative poverty is reduced, but the results of the two models are not much different. The control variables are basically significant, indicating that the model has a better fitting effect.

The area variable is added to the control variable to judge the regional heterogeneity of the result. The area (*area*) is represented by two values, 1 is the coastal area, and 2 is the inland area. The β coefficient of Area is less than 0, and the probability ratio is less than 1. This shows that the probability of rural households in the coastal areas (*area* = 1) being relatively poor is 0.82 times that of the rural households in the inland areas (*area* = 0). This result may be related to the economic differences between the coastal and inland areas. Compared with the inland areas, the coastal areas have a higher level of economic development, and even the probability of rural poverty is lower than that in the inland areas.

In order to make the results of this paper more convincing, the overall effect of the model is tested here. From the chi-square value of LR, the chi-square of the two models is significant, and the overall fitting effect of the model is better. The model is then subjected to the *Hosmer & Lemeshow* test (*H-L test*). The H-L test is based on the difference between the predicted value obtained by the model and the actual observed data to determine whether it is significant. The larger the Sig obtained by H-L test, the better the overall fitting effect of the model. According to Table 3, Sig = 0.1232 > 0.5 for model (1), Sig = 0.0792 > 0.05 for model (2). The test values of neither model reached the significance level of 0.05, indicating that the overall model was well adapted.

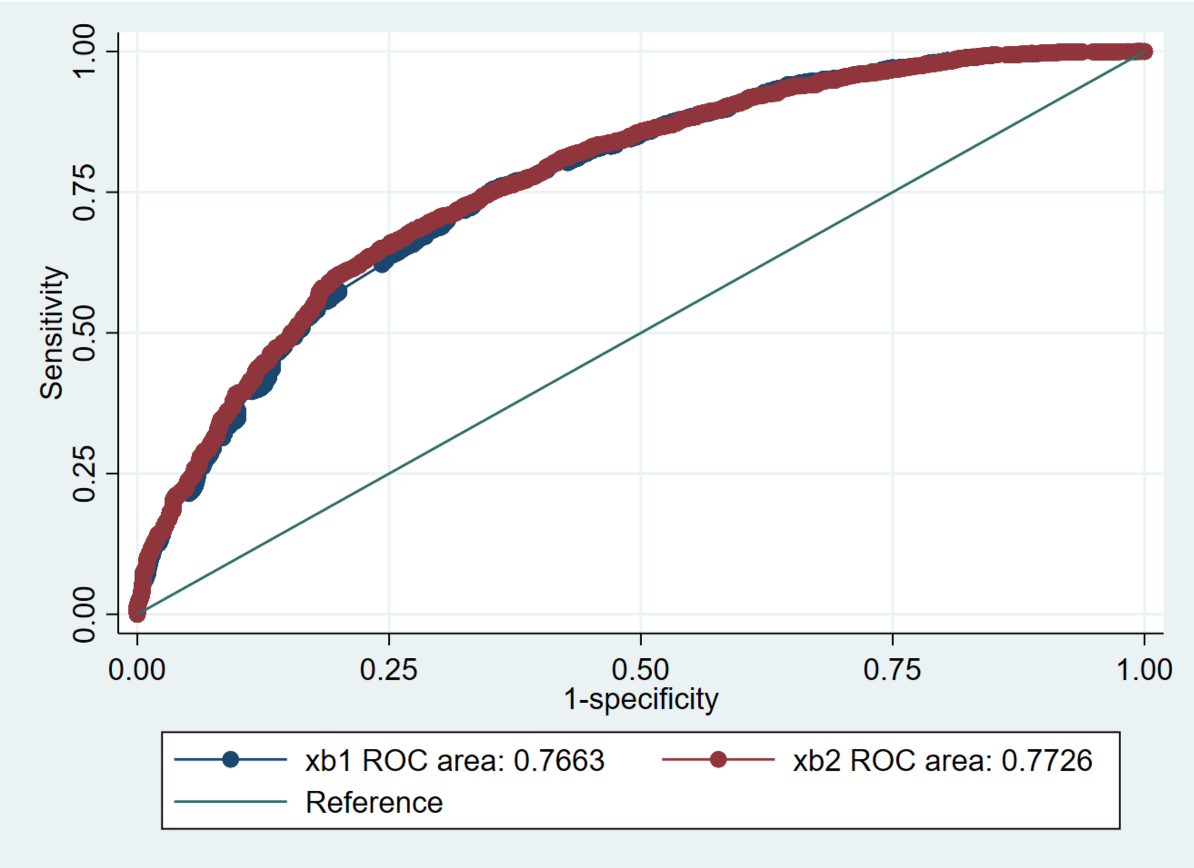

Figure 1. The ROC curve and the AUC value of models (1) and (2)

Figure 1 shows the ROC curves and AUC values for the two models. Blue curve indicates model (1) and AUC = 0.7663. Red curve indicates model (2) and AUC = 0.7726. It can be seen that the AUC value of both models is close to 8, indicating that the model has good regression quality as a whole.

3.2. Robust Test

In this paper, the robust test is carried out from the aspects of changing the model setting form and adjusting the measurement method of core variables, and all the results are shown in Table 4.

Change the model setting. OLS regression was used while adjusting the measure of relative poverty. The relative poverty in this paper was determined using 1/3 of the deprivation score as the cut-off value, and for robustness testing, OLS regression was performed directly using the deprivation score as the explanatory variable. The results are reported in the model (3) of Table 4, and all variables pass the significance test and the coefficient symbols are as expected. The research hypothesis in this paper is tested.

Adjust the measurement of the number of years of schooling per household. The number of years of schooling of children in a family may not yield economic returns due to time, which in turn affects the relative poverty of the family. Therefore, the average number of years of schooling of adults in the family can be used to measure the educational level of rural families, and the age boundary between adults and children is divided into 16. The result table is shown in model 2 (4), and the significance test of each variable is passed, and the size of the chance ratio is also as expected. The research hypothesis in this paper is tested.

Adjust how labor mobility is measured. Labor mobility is measured using the binary variable of whether rural households are migrant workers, and the results are shown in the model in Table 4 (5). Except for the insignificant interaction, the other variables passed the significance test, which basically verified the research hypothesis in this paper.

Table 4. Robustness test

	(3)	(4)	(5)
Varibales	β	Odds	Odds
edu	-0.0282***	0.7321768***	0.7295707***
	(0.000828)	(0.0148)	(0.0251)
outinc	-0.00000195***	0.9999781***	1.102723*
	(0.000000263)	(0.00000517)	(0.0532)
edu_outinc	0.000000103***	1.000001**	0.9905793
	(0.0000000328)	(0.000000551)	(0.00714)
area	-0.0182***	0.8084854**	0.8075469**
	(0.00583)	(0.0839)	(0.0848)
soc	0.0370**	2.397849**	2.515133**
	(0.0174)	(0.442)	(0.416)
trans	-0.000000339***	0.9999971**	0.9999974**
	(0.0000000939)	(0.00000126)	(0.00000125)
fp2	0.00738***	1.197105***	1.081077***
	(0.00132)	(0.0231)	(0.0233)
Constant	0.637***	21.95543***	18.87656***
	(0.00788)	(0.150)	(0.216)
Observations	4,905	4,905	4,905
R-squared	0.230		

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

4. Conclusions

Based on the sample data of rural households in CFPS 2018, this paper studies the impact of education and labor mobility on the relative poverty of rural households. Through literature review, the theoretical model of dynamic game with incomplete information is established and the research hypothesis of this article is put forward. Subsequently, an empirical analysis was carried out. First, the A-F double critical value method was used to measure the relative poverty of rural households in multiple dimensions. In the construction of multidimensional poverty indicators, the income dimension uses the relative poverty indicator of income. The specific method is to use 50% of the national per capita disposable income as the critical value. Subsequently, a dual choice model was constructed, and the Logit model was used to establish an econometric model for empirical testing.

The results of the study show that: (1) Per capita years of education and labor mobility will significantly reduce the probability of rural households falling into multi-dimensional relative poverty, and the interactive effect of education and labor mobility will also affect the relative poverty; (2) Education and labor force reduction The poverty effect has regional heterogeneity. The mitigation effect of education and labor mobility on relative poverty is lower than that of inland areas, and education and labor mobility in inland areas greatly reduce the probability of relative poverty.

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