EXAMINING MULTI-LEVEL POVERTY-CAUSING FACTORS OF FARM HOUSEHOLD

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ABSTRACT:

In view of the current research on the factors of poverty at home and abroad, most of them have less background effects on scale and the mechanism. This study uses a multi-level linear regression model and a geographic detector to jointly detect the poverty influencing factors in the study area. This study mainly draws the following three conclusions: (1) There are background effects on the scale of the poverty-stricken factors in the study area, and the background effects have a great impact. (2) At different scales there are significant poverty-stricken factors. (3) Different research methods lead to differences in research results.

1. INTRODUCTION

The eradication of poverty is an important dimension of the UN's 2030 sustainable development goals and an important guarantee for the task of building a well-off society in an all-round way. China is the largest developing country in the world, and its poverty reduction efforts have a pivotal impact on global poverty reduction (Liu, et al., 2016). Farmers' poverty has always been a key consideration for the Chinese government to formulate a series of poverty alleviation policies (Zhou et al., 2018). In order to solve a series of poverty problems, it is crucial to accurately explore the causes of poverty. So far, many experts and scholars at home and abroad have explored the factors of poverty from different angles (Carneiro et al., 2016; Wang & Qian, 2017; Aristondo, 2018). However, on the one hand, most research methods use traditional linear regression models to explore poverty factors from a single scale (Ibrahim et al., 2016; Du et al., 2018; Guo Et al., 2018), not considering the geographical background factors of the research object. On the other hand, due to data acquisition restrictions and other reasons, most studies are based on provinces, cities, counties, villages, etc. Geographic unit scale as the evaluation object (Wang & Chen, 2017; Liu et al., 2018; Michalek & Madajova, 2019), and the detection of poverty-reducing factors from a more elaborate scale is more conducive to the precision of poverty alleviation. In view of this, this paper selects Fugong County of China as the research area and takes the poor households as the research unit. From the perspective of the new research of the individual effects and background effects of the comprehensive detection of influencing factors, the multi-level linear model and the geo-detector are used to achieve a more accurate detection of the cause of poverty.

2. RESEARCH AREA AND DATA

This paper selects Fugong County of Yunnan Province as the research area. Fugong County is one of the key counties for poverty alleviation in the country. It has has a wide range of poverty, a high proportion of poverty, a deep degree of poverty and a great difficulty in getting rid of poverty. The poverty problem in Fugong County needs to be solved urgently. The data in this paper are survey data of poor farmers and basic statistics of villages. A total of 1,000 valid samples were taken from the survey data of farmers, covering 57 villages in the county.

3. RESEARCH METHODS

3.1 Index system construction

Based on the actual situation of the study area, referring to the existing related research, considering the typicality, representativeness and accessibility of the indicators, a total of 21 impact factors (including household level factors and village level factors) of 9 dimensions are selected to constitute a candidate set of indicators. Then, the coefficient of variation method and the complex correlation coefficient method are used to screen all the indicators in the candidate set, and finally 20 influencing factors are retained to participate in the calculation. The constructed indicator system and screening results are shown in Table 1.

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Type	Variable	Variable interpretation	Coefficient of variation	(
ident variable	*Y_poverty*	Poverty level	—	
ographical ocation	X_1	Distance from the main road	retain	
	X_2	Road access type	retain	
Family racteristics	X_3	Ratio of healthy family members（%）	retain	
	X_4	Ratio of family labor force（%）	retain	
	X_5	Ratio of population with education below high middle school excepting students（%）	retain	
	X_6	Ratio of non-compulsory education students in family（%）	retain	
ial Security	X_7	Ratio of population enrolled in the new rural cooperative medical insurance of China in the family（%）	retain	
	X_8	Ratio of population enrolled in urban and rural basic pension insurance in the family（%）	retain	
conomic velopment	X_9	Per capita annual income of family (yuan)	retain	
ographical vironment	Y_1	Terrain relief	retain	
	Y_2	Altitude	retain	
	Y_3	Slope	retain	
	Y_4	Per capita cultivated land area	retain	
rastructure	Y_5	Road access ratio（%）	retain	
	Y_6	Education (whether there is a primary school in the village, yes=1, no=0)	retain	
or situation	Y_7	Ratio of village labor force（%）	retain	
	Y_8	Proportion of migrant workers in the village（%）	retain	
ial Security	Y_9	Ratio of population enrolled in the new rural cooperative medical insurance of China in the village（%）	retain	
	Y_{10}	Ratio of population enrolled in urban and rural basic pension insurance in the village（%）	retain	
conomic velopment	Y_{11}	Per capita annual income of the village (yuan)	retain	
	Y_{12}	Collective income of the village (yuan)	retain	

Tab.1 Indicators of household-village

Note: The dependent variable is the poverty level (Y), expressed as the per capita income level. According to the national poverty line and relevant documents of the study area, the following grades are divided into: 1067 yuan (including 1067 yuan) for absolute poverty, assigned value 5; 1067-2300 yuan for deep poverty, assigned value 4; 2300-2800 yuan for medium Poverty, assigned value 3; 2800-3500 yuan for mild poverty, assigned value 2; more than 3,500 yuan for poverty, assigned value 1. For the entry type indicator, the scoring system is adopted, the asphalt road is assigned value 1, the cement road is assigned value 0.75, the sand road is assigned value 0.5, and the ordinary soil road is assigned value 0.25

3.2 Introduction to the method

In this paper, two methods are used to detect the poverty-reducing factors in the study area, namely multi-level linear regression model and geographic detector. Multi-level linear regression model is a statistical method for processing data with nested structure. It can effectively solve the problem of background effect and analyze the influence of independent variables on dependent variables from different levels (Raudenbush & Bryk, 2002; Wang et al., 2019). Geo-detectors can detect spatial stratification heterogeneity of variables and detect how a factor interprets the spatial differentiation of the variable. Because the data in the study area is nested on the scale, that is, the household is embedded in the village, and there may be spatial differences in the poverty factors of farmers in different villages. Therefore, both methods are applicable to this study. At the same time, two methods are used for research. On the one hand, the results can be mutually verified. And on the other hand, it can be more comprehensive to detect the significant poverty factors. The principle introduction of the two methods is shown in Table 2.

Multi-level linear regression model	Geographic detector
Household level: $Y = \beta_{0j} + \beta_{1j} X_{ij} + r_{ij}$ Village level: $\beta_{0j} = \gamma_{00} + W_j + \mu_{0j}$ $\beta_{1j} = \gamma_{10} + \mu_{1j}$	$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST}$
Note: i represents the household and j represents the village; X_{ij} is explanatory variable of the household layer, W_j is explanatory variable of the village layer; β_{0j} is the average value of Y, and β_{1j} is the regression slope of the household variable; γ_{00} and γ_{10} are the average values of β_{0j} and β_{1j}, respectively, which are fixed effects; μ_{0j} and μ_{1j} are random effects of β_{0j} and β_{1j}, respectively, representing the variation of the village layer.	Note: L is the stratification of the independent variable or dependent variable, N_h and N are the number of elements of layer h and the whole area, respectively; σ_h^2 And σ2 are the variance of the dependent variable in layer h and the whole region, respectively; SSW represents the sum of the variance within the layer, and SST represents the total variance of the whole region. The larger the q value, the stronger the explanatory power of the independent variable to the dependent variable.

Tab.2 Method introduction

4. RESULTS AND ANALYSIS

Before constructing a multi-level model with independent variables, construct a null model (without any independent variables), and combine the variance ratio calculation formula to detect whether there is a scale background effect on the poverty-reducing factors of the research object. Table 3 shows the estimation results of the null model and the calculation results of the variance ratio and the q statistics calculated by the administrative village as a partition with the geo-detector. The results are shown in Table 3.

The null model				Geographic detector
Level	Variance	Formula for calculating the variance ratio	Variance ratio	q value
Household level	1.1589	$\rho_1 = \frac{\sigma_{eo}^2}{\sigma_{eo}^2 + \sigma_{uo}^2}$	78.16%	0.28
Village level	0.3239	$\rho_2 = \frac{\sigma_{uo}^2}{\sigma_{eo}^2 + \sigma_{uo}^2}$	21.84%	

Note: σ_{eo}^2 is the household level variance, σ_{uo}^2 is the variance of the village; ρ_1 is the proportion of the household variance, and ρ_2 is the proportion of the village variance.

Tab.3 Background effect detection results

From the calculation results of the variance ratio in Table 3, the household-level variance ratio is 78.16%, indicating that the household-level factors are dominant. And the village-level variance ratio is 21.84%, indicating that the village-level factor cannot be ignored. From the q value of the geo-detector, the village factor is 28%. On the whole, there is a background effect on the scale of the poverty-stricken factors in the study area, which needs to be detected by multi-level linear regression model and geographic detector.

The household level factor is added to the first level of the multi-level model, and the village level factor is added to the second level of the multi-level model to explore the impact of the multi-level scale influencing factors on poverty. Calculate the q value directly using the geo-detector. The results are shown in Table 4.

Analysis of results: From the data in Table 4, (1) it is found that the significant influencing factors obtained by the multi-level linear model and the geo-detector are consistent in general, indicating that these two methods have certain rationality in detecting the significant poverty-reducing factors. However, the two methods show different degrees of significance in the estimation results, which may be related to the different methods of estimation of them. It can be verified by field research. It can be seen that in the research process, it is necessary to use different methods for comparison, which is beneficial to improve the accuracy of the results. (2) The common household-level significant factors obtained by the two methods are X_4, X_8 and X_9, with the exceptions X_2 and X_5. (3) The main poverty-reducing factors obtained by the two methods are: Y_1, Y_3, Y_4, Y_5, Y_{10}, Y_{11}, except that Y_2, Y_6, Y_9, Y_{12} is not detected as significant factors by two methods.

	Multi-level linear model			Geographic detector		
	Estimate	Coefficients	P value	Estimate	Q value	P value
Household factor	(Intercept)	3.481	4.618	-	-	-
	X_1	-0.014	0.433	X_1	0.010	0.488
	X_2	-0.033	0.054	X_2***	0.032	0.000
	X_3	0.087	0.308	X_3	0.005	0.910
	X_4***	-0.201	0.008	X_4***	0.032	0.000
	X_5**	0.412	0.016	X_5*	0.012	0.054
	X_6	-0.074	0.450	X_6	0.002	0.448
	X_7	0.490	0.500	X_7	0.001	0.963
	X_8***	-9.997	0.000	X_8***	0.053	0.000
	X_9*	-0.182	0.095	X_9***	0.583	0.000
Village factor	Y_1***	-0.380	0.000	Y_1***	0.086	0.000
	Y_2	0.159	0.300	Y_2	0.036	0.000
	Y_3**	1.395	0.011	Y_3***	0.036	0.000
	Y_4**	-9.192	0.030	Y_4***	0.040	0.000
	Y_5**	8.703	0.036	Y_5***	0.029	0.000
	Y_6	-0.098	0.417	Y_6***	0.033	0.000
	Y_7	-0.057	0.159	Y_7***	0.067	0.000
	Y_8**	-0.330	0.022	Y_8**	0.011	0.024
	Y_9	-0.625	0.523	Y_9***	0.155	0.000
	Y_{10}*	-0.072	0.007	Y_{10}***	0.037	0.000
	Y_{11}***	-0.390	0.000	Y_{11}***	0.052	0.000
	Y_{12}	-0.137	0.878	Y_{12}	0.002	0.791

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Tab.4 Calculation results of multi-level linear model and geo-detector

5. CONCLUSION

The comparison test results of two detection methods show that: (1) There are scale effects of the poverty alleviation factors in the study area, and the background effect has a large impact and can be studied using a multi-level model.; The q value of the geo-detector of household poverty level is 0.28. Both methods indicate that about 25% of poverty-stricken households are caused by village-level factors. (2) Significant poverty factors at different scales are different. The main factors causing poverty at the household level are: ratio of family labor force, ratio of population enrolled in urban and rural basic pension insurance in the family, and per capita annual income of family; the significant poverty factors at the village level are: slope, per capita arable land, access rate and so on. At the household level, the detection results of the two methods are basically the same. At the village level, there are some differences in the detection results of the two methods, mainly because the sample size of the village level indicators is small and the variable types are complex. (3) The difference in research results due to different research methods indicates that it is necessary to use two or more methods to improve the accuracy of the research results. Field investigation is needed to verify the suitability of the method and the reliability of the results.

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