Evaluating the Effectiveness of Poverty Alleviation: Evidence from a Linear Quantile Mixed Model

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Abstract

Poverty alleviation remains one of the most pressing problems, and China has made considerable advancements toward poverty alleviation in recent years. Considering village as a random effect, this paper proposes a linear quantile mixed model to analyze the effects of household type and village type to test whether local governments equitably implement poverty alleviation measures among poverty and non-poverty-stricken villages. Results indicate that anti-poverty policies have been equally implemented among village-types on average, but there is unbalanced development of poor and non-poor households depending on village-type. Previously unidentified, marginally non-poor households are found to benefit disproportionately less from these policies.

Keywords: poverty alleviation; effectiveness evaluation; linear quantile mixed model; unbalanced development; marginally non-poor household

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1. Introduction

Promoting development, narrowing the rural-urban gap, eliminating poverty and achieving common prosperity are all objectives that have been regularly targeting by policy makers (Mani et al., 2013). However, as poverty alleviation remains a significant challenge to the global community (Tollefson and Jeff, 2015), external interference, such as poverty reduction policy, is vital (Haushofer and Fehr, 2014). By the end of 2018, China had contributed to over 70% of the reduction in global poverty, and has lifted more people out of poverty than any other country in the world[1].

Targeted poverty alleviation (TPA) established in 2013 aims to lift the remaining rural poor out of poverty by 2020. It had been a critical strategy in the rapid extreme poverty reduction of China (Li, Su and Liu, 2016). Six measures have been established to combat poverty; identification of objects (including poverty-stricken villages and poverty-stricken households), project arrangements, use of funds, implementation of aid measures, dispatch of responsible people, and effective poverty reduction (Liu, Guo and Zhou, 2018). The poverty alleviation program identified villages as poverty-stricken villages where incidence of poverty was twice that of the whole province, where per capita net income of the households was 60% lower that the provincial average value, and where the village had no collective economic income. Households with annual net household income below 2760 Chinese CNY (CNY) were identified as poverty-stricken households with all others identified as non-poverty-stricken households (Liu, Liu and Zhou, 2017). The Chinese government has invested significant resources to reduce poverty such as financial aid, support staff, and relative projects. For poverty-stricken villages, infrastructure projects such as road construction, were developed with the aim of propelling economic and agricultural development. For poverty-stricken households, a large number of policies on improving the living standards and incomes were designed, including medical treatment, education, housing, etc. Moreover, to eliminate absolute poverty in rural areas by 2020, local governments formed plans for when each poverty-stricken village and each poverty-stricken household would escape poverty.

As effective and sustained poverty alleviation is the core mission of poverty reduction, independent annual third-party poverty reduction evaluations by academic institutions and universities have been instrumental in ensuring the success of this mission (Yang et al., 2018). Poverty alleviation effectiveness

[1] https://www.un.org/development/desa/dspd/wp-content/uploads/sites/22/2018/05/31.pdf

evaluations have generally identified income above the poverty line, no worries about food and clothing, ensuring compulsory education, basic medical care, and safe housing (Wang, Chen and Yan, 2016) as uniform benchmarking criteria. Income has been the most important criterion, as only by achieving income growth can stable poverty alleviation be assured.

This paper contributes to the poverty alleviation literature in a few important ways. Using a linear quantile mixed model for household income, this paper evaluates the poverty alleviation effectiveness in a poverty-stricken southwestern Chinese county. This method suggests a test of whether local governments equitably implement poverty alleviation measures among poverty-stricken and non-poverty-stricken regions. Results indicate that the effect of village-type on income is not significant and thus anti-poverty policies have been equally implemented among poverty-stricken and non-poverty-stricken villages on average. However, there is unbalanced development of poor and non-poor households depending on village-type. Previously unidentified, marginally non-poor households are found to benefit disproportionately less from poverty alleviation policies irrespective of village-type. Additionally, income growth in non-poor households in the lower tail of the distribution has slowed compared to the similar group of e-poor households. The findings from this study provide a valuable reference for the further formulation and implementation of poverty alleviation measures.

The remainder of this paper is organized as follows. Section 2 gives an overview of previous poverty alleviation evaluations, Section 3 describes the data and methodology employed in the analysis, Section 4 reports the empirical results, and Section 5 concludes.

2. Literature Review

Poverty evaluations improve the understanding of poverty alleviation programs. More importantly, effectiveness assessments reveal policy deficiencies and assist policy makers. Over time, extensive and intensive poverty alleviation performance evaluation studies have been conducted using a range of different methods (Park and Wang, 2010). Optimization analyses have been one of the more widely used evaluation methods. Based on an analytic hierarchy process (AHP), Yong et al. (2017) build a poverty alleviation performance evaluation index system and then establishes a Bayesian spatial-temporal model to explore the space-time variability of poverty alleviation performances in poor areas. Wu et al. (2018) propose a modified three-phase data envelopment analysis (DEA) model to assess the performance efficiency of

photovoltaic poverty alleviation projects and explore their influencing factors. Mellor and Malik (2017) use a simplified growth accounting framework as well as multipliers to calculate the impact on poverty alleviation of increased agricultural production by small commercial farm households on rural non-farm households.

Statistical models are also widely used to explore the effectiveness of poverty alleviation programs over time. For example, Meng (2013) uses a regression discontinuity approach to evaluate the impact of the "8-7 Plan" in China. Islam (2014) combines multidimensional poverty measures with difference-in-difference matching estimators to measure the effectiveness of an anti-poverty program with multiple outcomes, and find that this was a more comprehensive poverty reduction measure than unidimensional measures. Gao, Yang and Li (2015) use a propensity score matching method to identify and compare non-participating and participating families to examine the targeted performance and anti-poverty effectiveness of China's primary urban poverty reduction program, Dibao (minimum living security). Liao and Fei (2019) conduct t-tests to determine whether there were any significant differences between solar potential and poverty in two counties based on whether or not the people had been included in a photovoltaic-based poverty reduction program. Agbola, Acupan and Mahmood (2017) employ a mixed method approach to evaluate the impact of micro-finance on poverty alleviation, health, education and living standard wellbeing measures in Northeastern Mindanao, the Philippines. Bosco (2019) uses quantile regression to evaluate the effects of poverty determinants on poverty alleviation, finding that the implementation of a common European Union policy against poverty should consider cross-country interquartile differences and avoid a uniform one-size-fits-all philosophy.

Focusing on household income growth has been a direct approach to the assessment of household poverty levels, with many researchers evaluating poverty alleviation effectiveness based solely on income (Agbola, Acupan and Mahmood, 2017; Park and Wang, 2010). Many previous studies have use traditional ordinary least square methods to investigate the effectiveness of poverty alleviation programs on household income based on the assumption that household income data followed a normal distribution. Income distribution data are usually skewed because of income variability, with the extreme values often indicating important information (Sutter, Bruton and Chen, 2019). Quantile regression has been found to be a very suitable approach for understanding poverty alleviation performances and different income levels and can provide more valuable information for policy makers (Koenker and Bassett, 1978).

As individual level observations are taken from several villages/counties/cities, the data are generally clustered; therefore, appropriate statistical analyses are needed to account for the within-participant effects to ensure the results are repeatable and translatable to real-world applications (Staynor et al., 2019). Mixed effects models, which contain both random and fixed effects, are therefore useful in settings where the measurements are made based on related clustered observations (Schnell and MaitreyeeBose, 2019). Linear quantile mixed models have the advantages of both quantile regression and mixed models as they are able to simultaneously consider both individual and distributional heterogeneity.

3. Research Design

This section describes the research study design, the survey area, participant selection, the data and the models estimated.

3.1. Survey area and participant selection

This study evaluates the poverty alleviation effectiveness in China in 2017, taking a county in south-western China as an example. Covering an area of 3,903 square kilometers, the county is home to 168,552 households with a population of 498,200. These households are clustered in 294 villages (including 87 poverty-stricken villages), which are further organized into 14 townships.

Sixty-nine university teachers and college students were appointed by the provincial government to investigate the standards of living of the selected households. Stratified random sampling was first employed to select 0.59% of the households (i.e. 1006), 625 of which were from poverty-stricken villages. Finally, the sample was made up of households from 20 villages and 6 towns; 505 non-poverty-stricken households and 501 poverty-stricken households (including 427 households having been lifted out of poverty and 74 households being still poverty-stricken by 2017). Household data were collected in face-to-face interviews with the household head and sometimes with their spouse. After the six-day field survey period, 1006 questionnaires on various aspects of the household economic situation had been collected.

The survey questionnaires included 239 questions for the poverty-stricken households, involving information on household's basic information, quality of life, incomes from all source, implementation of policies, acceptance of targeted poverty alleviation, and procedures for identifying as well as lifting out of poverty-stricken households. Of these questions, there were 22 items on incomes, including wage income,

family business income, property income and transfer income. Referencing the account books provided by the government, the investigators recalculated and verified household income. Incomes from all grains and livestock were calculated at local prices. There were 139 questions for non-poverty-stricken households involving all the questions for poverty-stricken households except implementation of policies and procedures for identifying as well as lifting out of poverty-stricken households.

3.2. Data and definitions

Income is the most important criteria to judge whether the poverty-stricken households escape from poverty. There were two types of poverty-stricken households: those who had been lifted out of poverty by 2017, which were defined as "e-poor households", and those who were still poverty-stricken by 2017, which were defined as as "poor households" in this paper. If the poverty alleviation policies have been effective the e-poor households are lifted out of poverty. It is expected that these e-poor households have higher incomes than the poor households and the poverty line so the information of household type should be added to model. Poverty-stricken villages receive greater support for infrastructure construction such as road repairs; but at the household level, poverty-stricken households have access to the same policy assistance regardless of where they live.The poverty-stricken households in non-poverty-stricken villages often do not get the same attention as those in poverty-stricken villages because of less detailed poverty alleviation policies for non-poverty-stricken villages. Thus, to test whether the local government treated the poverty-stricken households in non-poverty-stricken villages differently from those in poverty-stricken villages, the information of village type is also accounted for in the model.

Household income is the dependent variable and is measured by annual net income per capita, with the main variables of interest being household type and village type. Household type was taken as a categorical variable; that is, poor households, e-poor households and non-poor households, and two dummy variables were used to analyze the effects, which were respectively labeled *E-Poor*; 1 if the poverty-sticken household had been lifted out of poverty by 2017 and 0 otherwise; and *Non-Poor*; 1 if the household had not been poor before and in 2017 (known as non-poverty-stricken households) and 0 otherwise. Village type was also a categorical variable; poverty-stricken villages and non-Poverty-stricken villages. A dummy variable was created labeled *Non-Poverty*, which was 1 if the household was not from a poverty-stricken village and 0 otherwise. The details are shown in Table 1.

Table 1: Variable definitions

Variable	Definition	Variable type
Income	Annual net household income per capita	Continuous variable
Poor	Households with annual net income per capita lower than the poverty line (2760 CNY) of 2014 and and planned to be lifted out of poverty after 2017	Dummy variable
E-Poor	Households with annual net income per capita lower than the poverty line (2760 CNY) in 2014 and planned to be lifted out of poverty before and in 2017	Dummy variable
Non-Poor	Households with annual net income per capita higher than the poverty line in 2014	Dummy variable
Poverty	Villages recognized as poverty-stricken in 2014	Dummy variable
Non-Poverty	Villages not recognized as poverty-stricken in 2014	Dummy variable

Summary descriptive statistics are located in Table 2. The mean and median incomes in the poor households (5265.85 CNY and 4097.85 CNY respectively) were lower than in the e-poor households (9042.47 CNY and 7392.7 CNY respectively) and the non-poor households (12537.72 CNY and 7729.29 CNY respectively). The mean and median incomes of the households in the poverty-stricken villages (9595.25 CNY and 7392.7 CNY respectively) were lower than in the non-poverty-stricken villages (12034.97 CNY and 8375 CNY respectively). All the mean values were obviously larger than the medians, indicating that the distribution of income was right skewed so that it would be inappropriate to rely on the mean values to describe the distribution center. The distributions of all variables were skewed (skewness $\gg 0$), with the kurtosis (kurtosis $\gg 0$) showing that these six series distributions were more concentrated than a normal distribution and had longer tails. A Shapiro-Wilk test was calculated and the results are contained at the bottom of Table 2. This test is a correlation-based algorithm in which the closer the value is to 1, the closer the data distribution is to a normal distribution. The results indicate that the null hypothesis of normality is rejected at the 1 percent confidence level, ($p < 0.0001$). These results provided evidence and further support that quantile regression is a more appropriate tool for estimation and hypothesis testing. For asymptotically non-normal data this has obvious advantages over ordinary least square (OLS) regression, which relies on the assumption that the error term is distributed normally.

Table 2: Descriptive statistics

	Income	Household Type			Village Type	
		Non-Poor	E-Poor	Poor	Non-Poverty	Poverty
N	1006	505	427	74	381	625
Mean	10,519.24	12,537.72	9,042.47	5,265.84	12,034.97	9,595.25
Std dev.	1,0424	13,381	5,536	3,457	13,979	7,330
Median	7,729.29	8,838.53	7,392.70	4,097.85	8,375.00	7,392.70
Minimum	1,478.00	1,478.00	2,313.67	1,505.71	1,980.00	1,478.00
Maximum	160,000	160,000	46,959.25	19,509.18	160,000	65,533
Skewness	5.9608	5.0784	2.6484	2.1611	5.6590	2.7834
Kurtosis	59.4324	39.5953	10.6234	5.2433	44.3100	11.6234
Shapiro-Wilk	0.5628*** (0.0000)	0.5781*** (0.0000)	0.7617*** (0.0000)	0.7648*** (0.0000)	0.5034*** (0.0000)	0.7456*** (0.0000)

Note: *** denotes significance at the 1% level.

3.3. Models

To evaluate the efficiency of poverty alleviation, a two-way analysis of variance model is constructed according to Equation 1.

$$\begin{aligned} \text{Income}_j &= \beta_0 + \beta_1 \text{Non-Poor}_j + \beta_2 \text{E-Poor}_j + \beta_3 \text{Non-Poverty}_j \\ &+ \beta_4 \text{Non-Poor}_j * \text{Non-Poverty}_j + \beta_5 \text{E-Poor}_j * \text{Non-Poverty}_j + e_j \end{aligned} \tag{1}$$

The dependent variable Income_j is the annual net income per capita for observation j, and $e_j \sim N(0, \sigma^2_{\text{res(anova)}})$ is a sequence of residual errors. The poverty-stricken households which were still poor in poverty-stricken villages are the reference group and with Non-Poor_j, E-Poor_j, Non-Poverty_j as dummy variables (see Table 1).

As traditional regression techniques focus on the mean effects, the relevant coefficient can be under or over- estimated and important relationships may not be detected (Binder and Coad, 2011). However, quantile regression (Koenker and Bassett, 1978) is robust to outliers and relatively skewed distributions. As above stated, quantile regression is more appropriate than OLS regression because the moment conditions for these series do not conform to a normal distribution. The ANOVA conditional quantile for

$y_i|x_i$ is defined by Equation 2.

$$\begin{aligned} \mathrm{Q}_\tau(\text{Income}_j) &= \beta_0^\tau + \beta_1^\tau \text{Non-Poor}_j + \beta_2^\tau \text{E-Poor}_j + \beta_3^\tau \text{Non-Poverty}_j \\ &+ \beta_4^\tau \text{Non-Poor}_j * \text{Non-Poverty}_j + \beta_5^\tau \text{E-Poor}_j * \text{Non-Poverty}_j + e_j^\tau \end{aligned} \tag{2}$$

Here $\mathrm{Q}_\tau(\text{Income}_j)$ is the annual net income per capita at the τ-quantile for household j, and $e_j^\tau \sim N(0, \sigma^2_{\tau(\text{anova})})$.

When analyzing clustered data, it is necessary to account for the correlations between the multiple groups of observations (Parker and Browne, 2014). As Model (1) did not consider the unobserved heterogeneity of the villages, the development differences among the villages could have affected the household incomes. Therefore, a mixed effects model is considered, which makes it possible to estimate the conditional heterogeneous covariance effects of the household income drivers. The linear mixed model was defined by Equation 3.

$$\begin{aligned} \text{Income}_{ij} &= \beta_0 + \text{village}_i + \beta_1 \text{Non-Poor}_{ij} + \beta_2 \text{E-Poor}_{ij} + \beta_3 \text{Non-Poverty}_{ij} \\ &+ \beta_4 \text{Non-Poor}_{ij} * \text{Non-Poverty}_{ij} + \beta_5 \text{E-Poor}_{ij} * \text{Non-Poverty}_{ij} + e_{ij} \end{aligned} \tag{3}$$

Income_{ij} is the annual net income per capita for household j in village i, and where village_i is distributed $N(0, \sigma^2_{\text{vil(mixed)}})$ and is the deviation in the intercept for a specific village from the average intercept in the group to which that household belonged. Additionally, $e_{ij} \sim N(0, \sigma^2_{\text{res(mixed)}})$.

To account for the heterogeneity between villages and the asymmetry of the income distributions, a quantile mixed model is introduced, which can filter the heterogeneity between villages and can examine the determinants of household income throughout the conditional distribution. This is especially important in the households with the least income (Koenker, 2004; Wang and Lin, 2009; Han, Powell and Pugach, 2011; Ma, Renwick and Greig, 2019). The linear quantile mixed model is given by Equation 4.

$$\begin{aligned} \mathrm{Q}_\tau(\text{Income}_{ij}) &= \beta_0^\tau + \text{village}_i^\tau + \beta_1^\tau \text{Non-Poor}_{ij} + \beta_2^\tau \text{E-Poor}_{ij} + \beta_3^\tau \text{Non-Poverty}_{ij} \\ &+ \beta_4^\tau \text{Non-Poor}_{ij} * \text{Non-Poverty}_{ij} + \beta_5^\tau \text{E-Poor}_{ij} * \text{Non-Poverty}_{ij} + e_{ij}^\tau \end{aligned} \tag{4}$$

$\mathrm{Q}_\tau(\mathrm{Income}_{ij})$ is defined as the annual net income per capita for the household j in village i such that $\mathrm{village}_i^\tau \sim N(0, \sigma^2_{\mathrm{vil(lqmm)}})$ and $e_{ij}^\tau \sim N(0, \sigma^2_{\tau(\mathrm{lqmm})})$

For poverty-stricken villages, Model (4) is reduced to

$$\mathrm{Income}_{ij}^\tau = \beta_0^\tau + \mathrm{village}_i^\tau + \beta_1^\tau \mathrm{Non\text{-}Poor}_{ij} + \beta_{2\tau} \mathrm{E\text{-}Poor}_{ij}, \tag{5}$$

where the parameter β_0^τ is the estimated income of poor households in poverty-stricken villages in the τ percentile. β_1^τ and β_2^τ are the income differences between the households being poor in a poverty-stricken village and the household being non-poor (β_1^τ) as well as the household being e-poor (β_2^τ) in a poverty-stricken village in a given τ percentile.

Similar to Equation 7, for non-poverty-stricken villages we can model

$$\mathrm{Income}_{ij}^\tau = \beta_0^\tau + \mathrm{village}_i + \beta_1^\tau \mathrm{Non\text{-}Poor}_{ij} + \beta_2^\tau \mathrm{E\text{-}Poor}_{ij} + \beta_3^\tau + \beta_4^\tau \mathrm{Non\text{-}Poor}_{ij} + \beta_5^\tau \mathrm{E\text{-}Poor}_{ij}, \tag{6}$$

where $\beta_0^\tau + \beta_3^\tau$ is the estimated income of poor households in non-poverty-stricken villages in the τ percentile, and β_3^τ is the difference in income in the τ percentile between poor households in non-poverty-stricken villages and those in poverty-stricken villages.

For non-poor households in poverty-stricken villages and in non-poverty-stricken villages, the estimated incomes in the τ percentile amount to $\beta_0^\tau + \beta_1^\tau$ and $\beta_0^\tau + \beta_1^\tau + \beta_3^\tau + \beta_4^\tau$ respectively, so that the village type gap of income for non-poor households is the sum of the village type income gap for poor households, β_3^τ and β_4^τ. β_4^τ indicates how much the village type income gap for non-poor households differed from the gap for poor households. Similarly, the village type income gap for e-poor households is equal to $\beta_3^\tau + \beta_5^\tau$. β_5^τ indicates how much the village type income gap for e-poor households differs from the gap for poor households.

4. Results

This section discusses the effectiveness of the poverty reduction based on the linear quantile mixed model results. Nine representative quantile points (i.e., 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, and 90th) were selected to implement the regression estimation. To test the advantages of the linear

quantile mixed model, a comparison analysis with a two-way analysis of variance (ANOVA) model, a linear mixed model, and a quantile regression model were conducted (Table 3 and Table 5 and Figure 4).

Table 3 shows the effect of both household type and village type as well as their interactions with household income based on the models described by Model (3) and Model (4). Columns 2-10 in Table 3 show the results of the linear quantile mixed model at the different quantile levels, and column 11 reports the results of the linear mixed model and the ordinary least squares (OLS) method. Table 5 shows the results from Model (2) and Model (1), in which Columns 2-10 report the results of the linear quantile model, and column 11 reports the results of the two-way ANOVA.

Under the assumption that all other factors were fixed (in each plot in Figure 1), the regression coefficient at a given quantile indicates the effect on household income of a unit change in that factor. The intercept is interpreted as the estimated conditional quantile function of the income distribution of a poor household in a poverty-stricken village (the first plot in Figure 1). The remaining subfigures reveal the marginal effects of different variables on household income at different quantile levels, which are discussed further below.

4.1. Effect of household type on household income

The effect of household type on household income is statistically significant at every quantile level (Table 3). The e-poor households tended to have significantly higher incomes than the poor households ($p < 0.001$), especially in the upper tail of the income distribution (the third plot in Figure 1). In addition, as the income distribution quantile increased, the income gap between the two groups grew larger. When $\tau = 0.1$, the estimated incomes of the e-poor households in the poverty-stricken villages and in the non-poverty-stricken villages were 4453.05 CNY and 4442.66 CNY respectively. This is higher than the poverty line (3300 CNY in 2017) and indicates that the e-poor households had been lifted out of poverty and implies that poverty alleviation policies have been effective in this sample.

The non-poor households are found to have lower incomes than the e-poor households in the lower distribution tail (Table 3). Specifically, in the 10th percentile, the estimated income of the e-poor households in the poverty-stricken villages (4453.05 CNY) is nearly 500 CNY more than the estimated income of the non-poor households (3784.09 CNY) and 259.77 CNY higher than in the non-poverty-stricken villages. In the 20th percentile, the gaps are 573.11 CNY in the poverty-stricken villages and −144.32 CNY

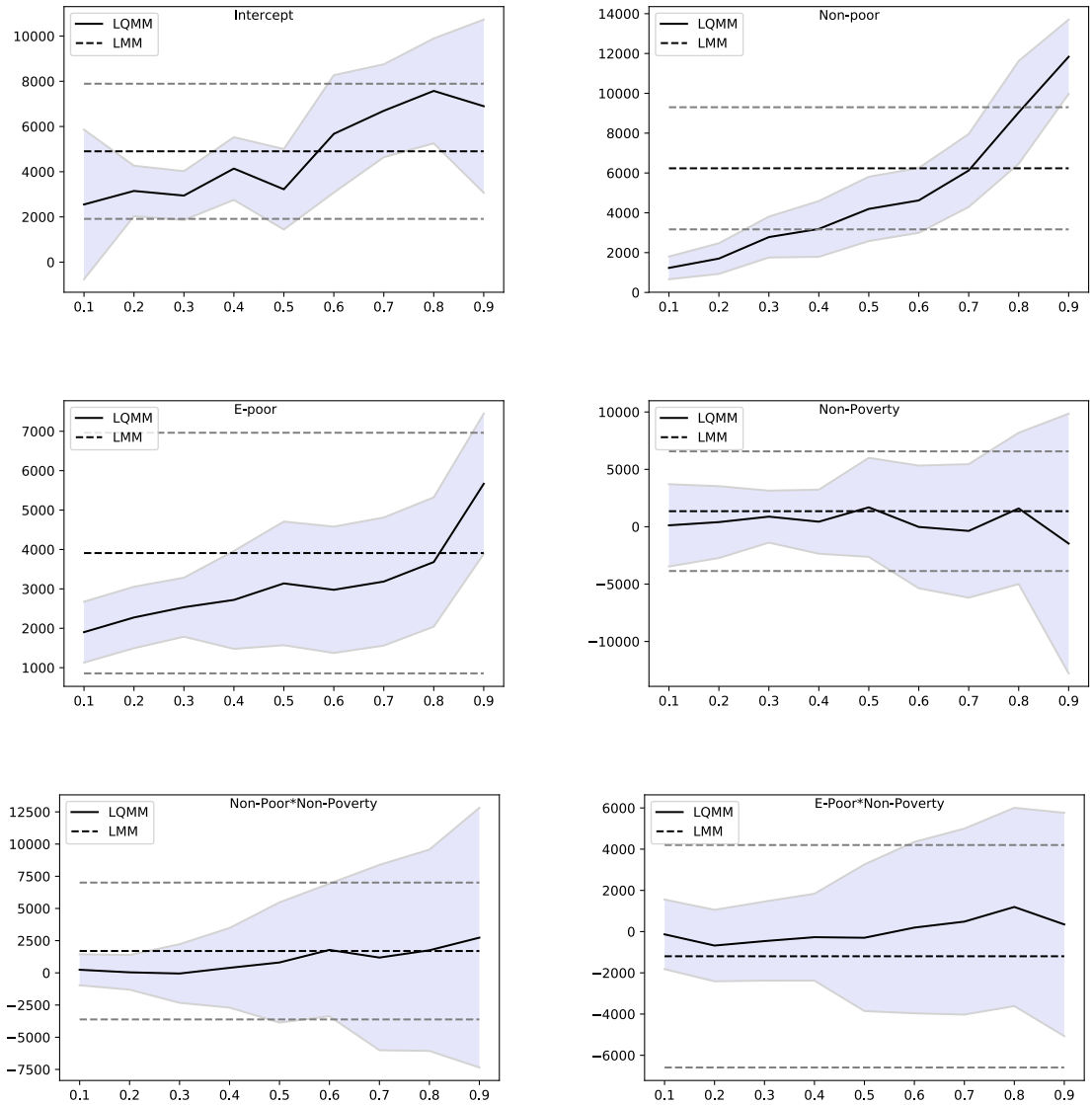


Fig. 1: Estimated parameter for income with 95% confidence bands using lqmm and lmm

in the non-poverty-stricken villages. This implies that the income growth in the non-poor households in the lower tail of the income distribution is slower than in the e-poor households.

The non-poor households with incomes just above the poverty line are identified as marginally non-poor households. To show the dilemma of marginally non-poor households more intuitively, Model (7) is built with e-poor as the reference group. Estimated incomes in different quantile levels show that non-poor households are significantly lower than that of e-poor household in poverty-stricken villages in the 10th ($p = 0.0078$) and 20th ($p = 0.0735$) percentiles (Table 4).

$$\begin{aligned} \mathrm{Q}_\tau(\mathrm{Income}_{ij}) =& \beta_0^\tau + \mathrm{village}_i^\tau + \beta_1^\tau \mathrm{Non\text{-}Poor}_{ij} + \beta_2^\tau \mathrm{Poor}_{ij} + \beta_3^\tau \mathrm{Non\text{-}Poverty}_{ij} + \\ & \beta_4^\tau \mathrm{Non\text{-}Poor}_{ij} * \mathrm{Non\text{-}Poverty}_{ij} + \beta_5^\tau \mathrm{Poor}_{ij} * \mathrm{Non\text{-}Poverty}_{ij} + e_{ij}^\tau, \end{aligned} \tag{7}$$

where $\mathrm{Q}_\tau(\mathrm{Income}_{ij})$ is defined as the annual net income per capita for the household j in village i, $\mathrm{village}_i^\tau \sim N(0, \sigma^2_{\mathrm{vil(epoor)}})$ and $e_{ij}^\tau \sim N(0, \sigma^2_{\tau(\mathrm{epoor})})$.

4.2. Effect of village type on household income

The effect of village type on household income was statistically insignificant as the household incomes in the non-poverty-stricken villages and those in the poverty-stricken villages were not found to have any substantive difference at any chosen quantile ($p > 0.1$, Table 3). The fourth plot in Figure 1 gives visual evidence that the income difference is relatively small and is distributed around 0 at all quantile levels. This further supports that household income is not related to whether or not a given household comes from a poverty-stricken village.

4.3. Effect of interaction on household income

When $\tau = 0.1$, household income for poor households in poverty-stricken villages is 2552.33 CNY (β_0). This is 1232.76 CNY (β_1) lower than the non-poor households (3785.09) and 1901.72 CNY (β_2) lower than the e-poor households (4454.05) in poverty-stricken villages. The estimated value for the variable non-poverty (122.13, not significant) is the village-type gap for the poor households. When added to 2552.33, the estimated income for the poor households in non-poverty-stricken villages is 2674.46 CNY. The village-type gap for non-poor households is 362.8 CNY (122.13 CNY plus the interaction effect of 240.67 CNY). Similarly, the village type gap for the e-poor households is −10.39 CNY (122.13 CNY plus

Table 3: The estimated income in different quantile level for those household being poor(β_0) and the differences with those household being non-poor and being e-poor in poverty-stricken villages (β_1 and β_2) and in non-poverty-stricken villages($\beta_3 + \beta_4$ and $\beta_3 + \beta_5$)

	Quantile Level									LMM
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90	
(fixed effects:)										
Intercept(β_0)	2551.33 (0.1276)	3149.71*** (0.0000)	2944.10*** (0.0000)	4139.55*** (0.0000)	3221.73*** (0.0006)	5674.39*** (0.0000)	6695.05*** (0.0000)	7574.56*** (0.0000)	6898.32*** (0.0006)	4902.96*** (0.0048)
Non-poor (β_1)	1232.76*** (0.0000)	1701.11*** (0.0000)	2779.98*** (0.0000)	3189.55*** (0.0000)	4195.56*** (0.0000)	4622.25*** (0.0000)	6125.12*** (0.0000)	9042.29*** (0.0000)	11836.37*** (0.0000)	6235.18*** (0.0000)
E-poor(β_2)	1901.72*** (0.0000)	2274.22*** (0.0000)	2534.72*** (0.0000)	2720.07*** (0.0000)	3139.19*** (0.0002)	2976.54*** (0.0005)	3186.05*** (0.0003)	3681.25*** (0.0000)	5666.72*** (0.0000)	3909.10** (0.0123)
Non-Poverty (β_3)	122.13 (0.9457)	403.30 (0.7968)	879.26 (0.4391)	438.68 (0.7534)	1689.42 (0.4350)	−18.58 (0.9945)	−365.88 (0.8999)	1594.20 (0.6292)	-1465.71 (0.7957)	1354.14 (0.6108)
Non-Poor*Non-Poverty (β_4)	240.67 (0.6899)	40.74 (0.9517)	−51.38 (0.9640)	391.17 (0.8002)	805.87 (0.7300)	1781.27 (0.4902)	1186.34 (0.7418)	1753.00 (0.6542)	2732.01 (0.5885)	1696.40 (0.5316)
E-Poor*Non-Poverty (β_5)	−132.52 (0.8753)	−676.69 (0.4366)	−459.73 (0.6318)	−270.36 (0.7977)	−298.21 (0.8669)	194.63 (0.9254)	484.79 (0.8299)	1195.83 (0.6195)	348.01 (0.8978)	−1196.07 (0.6641)
(variance of the random effect:)										
Village	93546	317840	948323	1029384	1832008	3810052	6544592	8492536	46845280	2108917
Residual variance:	488740.81	1670039.29	3181585.69	4760687.61	6147424.36	7055929.69	7208688.01	6030462.49	3527635.24	100810000
ICC	0.1607	0.1599	0.2296	0.1778	0.2296	0.3506	0.4759	0.5848	0.9300	0.0205

Note: ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Table 4: The estimated income in different quantile level for those household being e-poor(β_0) and the differences with those household being non-poor and being poor in poverty-stricken villages (β_1 and β_2) and in non-poverty-stricken villages($\beta_3 + \beta_4$ and $\beta_3 + \beta_5$)

	Quantile Level									LMM
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90	
(fixed effects:)										
Intercept(β_0)	4450***	5422***	6226***	6925***	7682***	8670***	9876***	11236***	12565***	8812***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0000)	(0.0000)	(0.0006)	(0.0048)
Non-poor (β_1)	−670***	−572*	−60	530	1071**	1605***	2944***	5312***	6170***	2326***
	(0.0078)	(0.0735)	(0.8979)	(0.2693)	(0.02367)	(0.0043)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
poor(β_2)	−1895***	−2271***	−2332***	−2641***	−2749***	−2962***	−3181***	−3642***	−5667***	−3909**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0007)	(0.0006)	(0.0002)	(0.0003)	(0.0000)	(0.0123)
Non-Poverty (β_3)	24	−271	−225	145	95	157	125	2830	−1103	158
	(0.9742)	(0.7253)	(0.7752)	(0.8734)	(0.9251)	(0.9001)	(0.9415)	(0.2420)	(0.6693)	(0.9004)
Non-Poor*Non-Poverty (β_4)	345	715	747	685	1176	1648	698	606	2369	2892**
	(0.4842)	(0.2714)	(0.3457)	(0.4139)	(0.1944)	(0.1309)	(0.7661)	(0.7905)	(0.3996)	(0.0386)
Poor*Non-Poverty (β_5)	97	673	549	415	18	−231	−490	−1276	−363	1196
	(0.9087)	(0.4354)	(0.5431)	(0.7444)	(0.9920)	(0.9099)	(0.8181)	(0.5911)	(0.8982)	(0.6641)
(variance of the random effect:)										
Village	91993	317125	702787	1262321	2235416	3881177	6545429	8593997	46838650	2108917
Residual variance:	488741	1670039	3181586	4760688	6147424	7055930	7208688	6030462	3527635	100810000
ICC	0.1584	0.1596	0.1809	0.6040	0.2667	0.3549	0.4759	0.1240	0.5680	0.0205

Note: ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

the interaction effect -132.52 CNY). At $\tau = 0.1$, the non-poor households in the non-poverty-stricken villages is 4147.89 CNY ($2551.33 + 1232.76 + 122.13 + 240.67$) and the income for the e-poor households in non-poverty-stricken villages is 3773.7 CNY ($2551.33 + 1232.76 + 122.13 - 132.52$). For the other quantile levels, the calculations are analogous to $\tau = 0.1$.

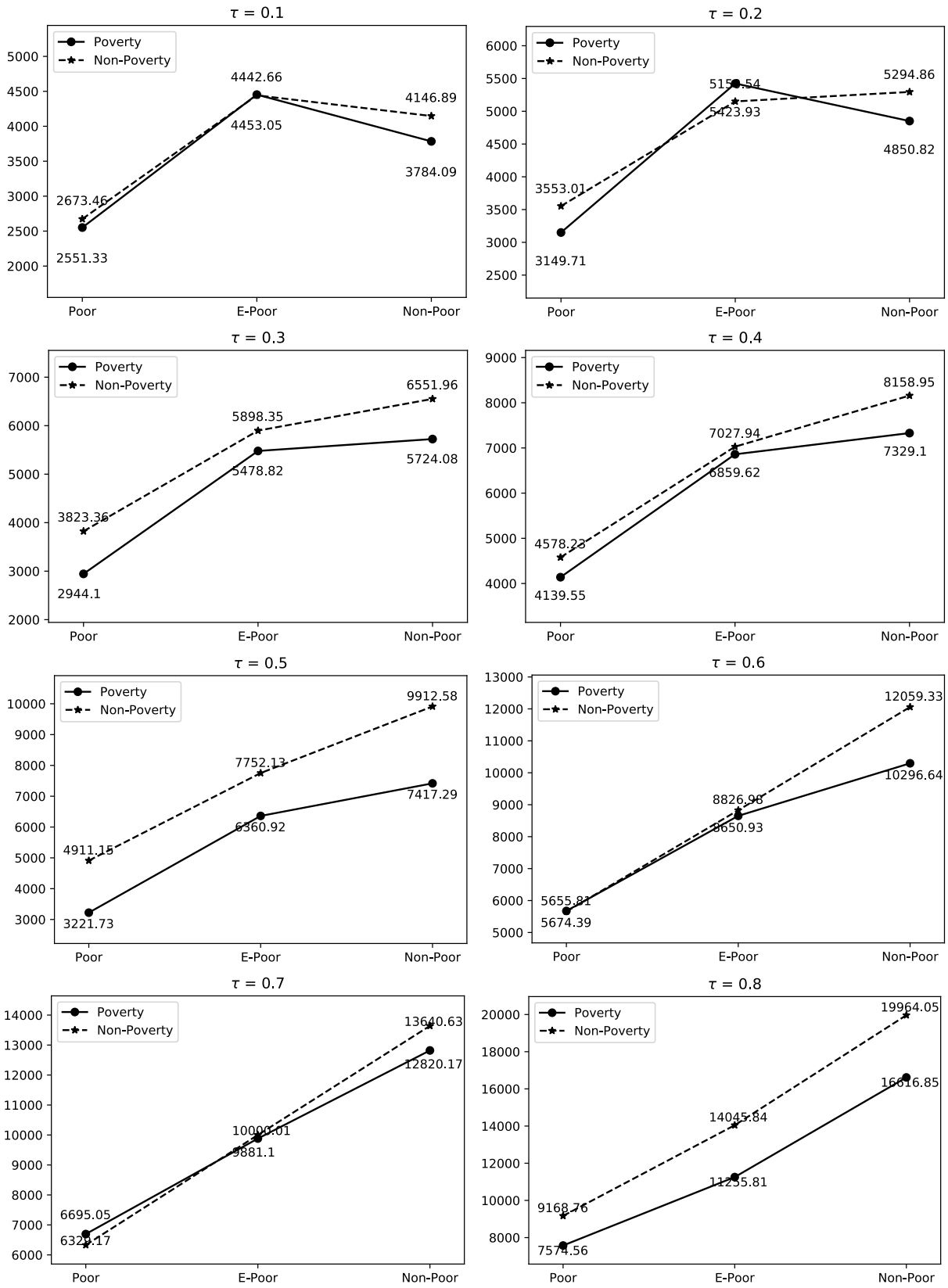
The village-type income gap is not found to be related to household type ($p > 0.1$), even though the gaps are smallest for the e-poor households in the lower tail of the income distribution ($\tau = 0.1 \sim 0.5$). For example, when $\tau = 0.1$, the gap is 122.13 CNY for poor households, -10.39 CNY ($122.13 - 132.52$) for the e-poor households and 362.8 CNY ($122.13 + 240.67$) for the non-poor households. However, the effects of the interactions are not statistically significant.

When $\tau = 0.1$ and $\tau = 0.2$, the poor households in the non-poverty-stricken villages are found to have a higher income than the poor households in the poverty-stricken villages. However, the e-poor households in the non-poverty-stricken villages have lower incomes than the e-poor households in the poverty-stricken villages (Figure 2), indicating that the upward income trend is steeper for the poor in poverty-stricken villages than the poor in non-poverty-stricken villages. Further analysis indicates that in the lower quantile, the effect of household type on household income is marginally greater (but statistically insignificant) for households in poverty-stricken villages than for households in non-poverty-stricken villages.

4.4. Comparison analysis

To illustrate the superiority of quantile regression in this context, this section shows the results of a comparison analysis with multiple models; a two-way ANOVA model, a mixed model, and a quantile regression model. The results of the two-way ANOVA model (Equation 1) show that mean incomes in the e-poor and non-poor households were significantly higher than the mean incomes in the poor households ($p < 0.01$). The mean income in the non-poor households was 6626.8 CNY higher than in the poor households, and the mean income in the e-poor households was 4465.49 higher than in the poor households (the last column of Table 5).

There were no statistically significant differences between the mean incomes of households in poverty-stricken villages and non-poverty-stricken villages ($p = 0.3278$). The village type income gap was not related to household type, and the interaction effect of household type and village type was statistically


τ = 0.1
Poverty
Non-Poverty
4442.66
4146.89
4453.05
3784.09
2673.46
2551.33
Poor
E-Poor
Non-Poor
τ = 0.2
Poverty
Non-Poverty
5294.86
5423.93
4850.82
3553.01
3149.71
τ = 0.3
Poverty
Non-Poverty
6551.96
5898.35
5724.08
5478.82
3823.36
2944.1
τ = 0.4
Poverty
Non-Poverty
8158.95
7027.94
7329.1
6859.62
4578.23
4139.55
τ = 0.5
Poverty
Non-Poverty
9912.58
7752.13
7417.29
6360.92
4911.15
3221.73
τ = 0.6
Poverty
Non-Poverty
12059.33
10296.64
8826.96
8650.93
5655.81
5674.39
τ = 0.7
Poverty
Non-Poverty
13640.63
12820.17
10000.01
9881.1
6695.05
6328.17
τ = 0.8
Poverty
Non-Poverty
19964.05
16016.85
14045.84
11255.81
9168.76
7574.56

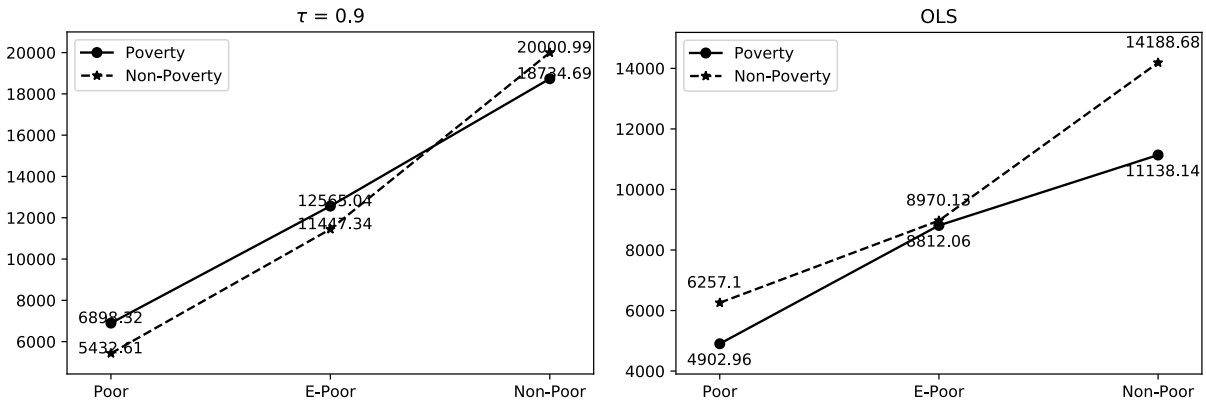


Fig. 2: The income in different quantile level of household being poor, e-poor and non-poor in poverty-stricken and non-poverty-stricken villages

insignificant ($p = 0.7554$ and $p = 0.4162$).

The residual variance of the two-way ANOVA model (102690000) is about 20 times larger than that of the linear quantile mixed model. This implies that the goodness of fit of the ANOVA model is worse than the LQMM (Table 3 and Table 5). More importantly, the ANOVA model is unable to detect the marginally non-poor households since it uses less information than the quantile regression estimation. The household income distribution is not normal, and the outliers are evenly weighted in the estimation (Figure 4). The intra-class correlation (ICC) of the mixed model (Equation 3) is 0.02, indicating that the 'village' factor only explains 2108917/100810000 = 2% of the total variability after the correction for household type and village type (the last column in Table 3). The small ICC implies that there is little variability between the villages, which suggests that the means are similar and a random intercepts model is not needed. However, when the random intercepts are omitted, the model degenerates into a two-way analysis of variance (Equation 1).

The results for (Equation 2) show that the effect of household type on household income is statistically significant at every quantile level ($p < 0.01$), indicating that the e-poor households have higher incomes than the poor households and have been lifted out of poverty (the columns 2-10 in Table 3 and Figure 3). The e-poor households are also found to have higher incomes than non-poor households in the lower tail. For non-poor households in the poverty-stricken villages, the estimated incomes when $\tau = 0.1$ and $\tau = 0.2$ is 677 CNY less than in the e-poor and 690.63 CNY less that in the non-poverty-stricken villages. When $\tau = 0.1$ and when $\tau = 0.2$ the non-poor household incomes are 500 CNY and 74.06 CNY less than in the e-poor households. Therefore, the quantile regression model is able to identify the marginally non-poor

households.

The variable *Non-Poverty* has a (marginally) significant effect on household income at higher quantile levels ($\tau = 0.8$, $p = 0.0372$ and $\tau = 0.9$, $p = 0.0818$ respectively), which indicates that poor households in non-poverty-stricken villages have significantly higher incomes than the poor households in poverty-stricken villages. This estimated gap is 5953.89 CNY when $\tau = 0.8$ and 7367.85 CNY when $\tau = 0.9$. The interaction effect for *E-Poor*Non-Poverty* is significant at $\tau = 0.8$ ($p = 0.0427$), which means that the village type income gap for the e-poor households ($221.91 = 5853.89 - 5631.98$) is smaller than the village type income gap for the poor households (5953.89). This also suggests that the incomes in the poor households are influenced by whether or not they live in a poverty-stricken village, which was in conflict with the analysis in subsection 4.3.

Intuitively, households in non-poverty-stricken villages have more income than those in poverty-stricken villages because there are less poverty-stricken households in non-poverty-stricken villages. However, at the village level there are more detailed poverty alleviation policies and more poverty reduction measurements in poverty-stricken villages. Here, development differences between village types are not significant. Surely, the larger economic environment plays some part in individual economic outcomes. In other words, the development difference among villages contributes to individual household income. All ICCs for each quantile level for the linear quantile mixed model are larger than 0.16, which means that the village factor explains 16% or more of the total variability at every quantile level[2] (the last row in Table 3). Therefore, if the village fixed effect were not introduced, the results would be misleading.

Overall, compared to the ANOVA, linear mixed model, and the quantile regression model, the linear quantile mixed model is found to be the most appropriate model for evaluating poverty reduction effectiveness.

5. Conclusion

Reducing the poverty rate is one of the most important aims in all countries. To ensure that the remaining rural poor will be out of poverty by 2020, China has had a targeted poverty alleviation strategy since 2013 which has had significant success. Taking a county in southwest China as an example, this

[2]It also implies that a random intercepts model is needed.

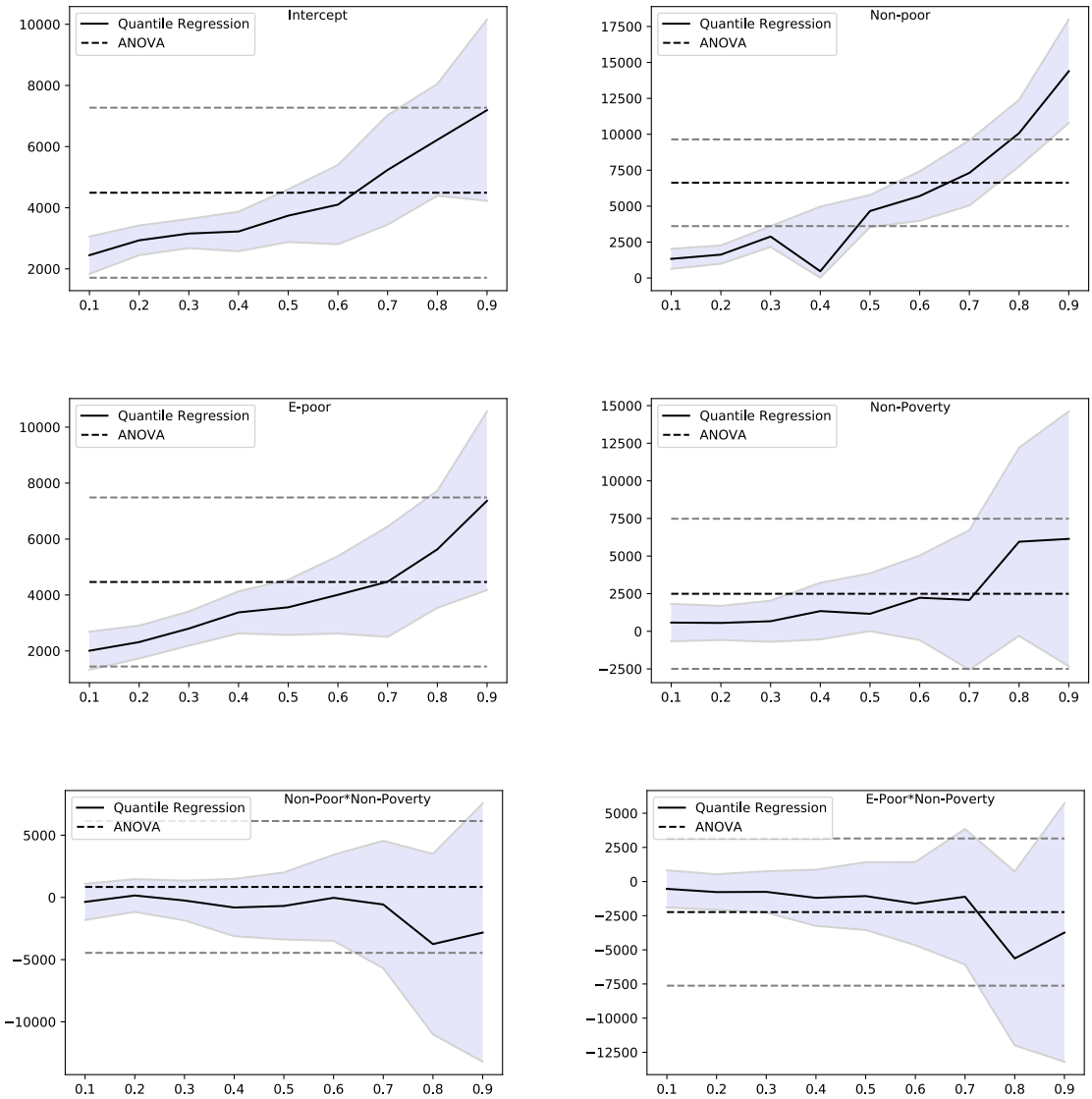


Fig. 3: Estimated parameter for income with 95% confidence bands using quantile regression and ANOVA

Table 5: The estimated income in different quantile level for those household being poor(β_0) and the differences with those household being non-poor and being e-poor in poverty-stricken villages (β_1 and β_2) and in non-poverty-stricken villages($\beta_3 + \beta_4$ and $\beta_3 + \beta_5$)

	Quantile Level									ANOVA
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90	
Intercept(β_0)	2447.75***	2933.5***	3156***	3223***	3741***	4101.2***	5237***	6220***	7191.63***	4491.30***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0016)
Non-poor (β_1)	1332.25***	1626.5***	2884***	4047***	4659***	5701.8***	7313***	10080***	14387.37***	6626.8***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
E-poor(β_2)	2009.25***	2317.13***	2800.83***	3378.25***	3560.21***	4007.02***	4474.05***	5631.67***	7367.85***	4465.49***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0038)
Non-Poverty (β_3)	578.75	553.88	667.41	1341.71	1565.09	2227.8	2082	5953.89**	6142.2*	2492.02
	(0.4647)	(0.3916)	(0.3193)	(0.1409)	(0.1918)	(0.1394)	(0.3595)	(0.0372)	(0.0818)	(0.3278)
Non-Poor*Non-Poverty (β_4)	−358.75	156.12	−247.41	−811.71	−686.09	−30.8	−569	−3753.89	−2826.2	2703.69
	(0.6732)	(0.3916)	(0.7604)	(0.4784)	(0.6085)	(0.9865)	(0.8134)	(0.26502)	(0.5108)	(0.7554)
E-Poor*Non-Poverty (β_5)	−535.75	−771.81	−756.57	−1194.05	−1064.80	−1616.62	−1111.32	−5631.98**	−3736.68	−2236.16
	(0.5025)	(0.2684)	(0.2853)	(0.1945)	(0.3990)	(0.3008)	(0.6338)	(0.0427)	(0.3369)	(0.4162)
Residual variance:	108463366	107416621	106240697	105113825	104243856	102661047	102665092	103335564	108276396	102690000

Note: ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

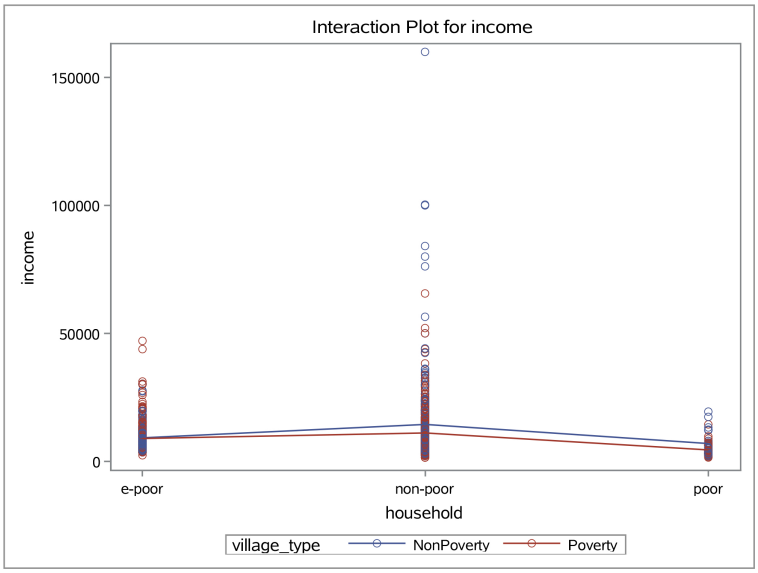


Fig. 4: Plot of Response by Household and Village type

study evaluated the effectiveness of poverty alleviation in 2017. Income measures, which included 22 items such as planting, breeding, wages, business and pensions, were aggregated in the evaluation process. The survey includes a stratified sampling of poor, e-poor and non-poor households in both poverty and non-poverty stricken villages. The individual and distributional heterogeneity of the data is confronted with a linear quantile mixed model to capture all available information. This analysis implies a test of whether local governments equally treat poor households in poverty-stricken and non-poverty-stricken villages when determining poverty alleviation measures.

The results above suggest some important conclusions. First, the effect of village-type on income is not significant. This implies that anti-poverty measures have been equitably implemented among poverty-stricken and non-poverty-stricken villages on average. There is somewhat unbalanced development between the poor and the e-poor households from poverty-stricken and non-poverty-stricken villages. Second, e-poor households have been lifted out of poverty over the sample period. Finally, there is a previously unidentified marginally non-poor household group that benefit disproportionately less from policy measures and are a risk of falling in the larger income distribution.

As the geographical scope of this study is limited to a county in southwest China, the poverty reduction effectiveness in other parts of China may have different results. This paper develops an analysis framework for the concrete evaluation of poverty reduction effectiveness inferred from income growth data. While publicly released growth rates of GDP in the Chinese economy are not necessarily trustwor-

thy for policy analysis, they still indicate a robust upward trend in growth over the short and long term. Whether the increasing standard of living is due to the poverty alleviation policy or some other cause is not perfectly identifiable here. Future research could explore the relationships between government regulatory frameworks and specific poverty reduction effectiveness in bringing about improvements in living standards.

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