Neighborhood Effect and Regional Poverty Trap in Rural China

Yingfeng Fang, Wei Zou

China & World Economy,2014,Vol.22(1):83-102

Abstract: We construct a multilevel econometric model to initiate an investigation on regional poverty trap in rural China from the viewpoint of neighborhood effect. The group-level factors have been found to present significant effect on individual income. It is more difficult for an individual to escape from chronic poverty in neighborhoods with higher proportion of agricultural population, lower education, and poorer infrastructure of transport or telecommunications. Neighborhood effect dominates when community income is low, while individual factors turn to be dominant in determining the way out of poverty when income surpasses a threshold level.

Key words: neighborhood effect, regional poverty trap, multilevel modeling

JEL Code: I25, I32, I38

1. Introduction

In an era of unprecedented fast economic growth in China during the past three decades, the number of people living below the poverty line has been significantly decreased, however, there are still considerable rural residents trapped in poverty that lasts for many years, or even their entire lifetime. In 2008, among 40.07 million people below poverty line, 26.49 million (66.1%) are living in western area, 10.04 million (25.1%) in central area; the poverty incidents are 7.8% and 3.4% in western and central areas, compared with 0.8% in eastern area. Moreover, 83.4% of people below poverty line are living in remote mountain areas and highlands, where poverty incident is as high as 10.8% (NSB, 2009). For the chronically poor, poverty is not simply about having a very low income, it is about multidimensional deprivation, such as lack of food, under-nutrition, illiteracy, unsafe drinking water, lack of access to basic health services, fewer job opportunities, social discrimination, physical insecurity and economic deficiency and vulnerability (Zou & Fang, 2011). Focusing on "neighborhood effect", this paper examines the causation and nature of regional poverty trap in rural China. We will take into account the correlation between individual and collective capability formations, establish a multilevel econometric model to formalize and measure the influence and dynamics of neighborhood effect on chronic poverty in rural China, and finally strive to produce policy recommendations to tackle chronic poverty.

The regional poverty trap mainly results from a self-reinforcing mechanism or a vicious cycle (Azariadis, 1996, Azariadis & Stachurski, 2006; Bowles, Durlauf & Hoff, 2006). The chronically poor are not a single distinct group. They include people who are discriminated against or socially marginalized; members of ethnic, religious, indigenous, and nomadic groups; migrants and informal laborers; disabled people; those with ill health or poor education background. Despite

this heterogeneity, we can identify multiple and overlapping causes that underpin chronic poverty. (1) Spatial disadvantage. The remoteness, historical backwardness, infertile and stony field, desperate living conditions, overexploitation of certain types of natural resource base, political exclusion and weak economic integration can all contribute to intra-country spatial poverty traps. (2) Vulnerability. The chronically poor are frequently those living in insecure environments with higher possibility of natural disasters (earthquakes, flooding or drought, debris flow etc.), and who have few assets or entitlements to cope with them. They are also more susceptible to individual- or household-level shocks (idiosyncratic shocks), especially ill health. Their coping strategies often involve trading long-term improvement in their life (e.g. assets accumulation and education of children) for short-term survival. (3) Constrained social network. Most rural residents below poverty line feel less reluctant to mobilize due to the restriction of Hukou (household registration) system or the unbearable post-mobility uncertainty and risks. In many poor rural areas, traditional kin system, instead of formal sector, provides social service for local residents and help to diversify risks (Hoff & Sen, 2004). However, the kin system may also deny them access to public and private goods, and local public services are based on gender, religious and ethnic identity, age etc. (4) Poor work opportunities. The chronically poor are often stuck in traditional farming or live on work which is insecure, low paid, unhealthy and unsafe, and have little scope to improve their situation. Such work allows day-to-day survival but does not permit asset accumulation, skill formation and children's education, and often increases health shocks.

Chronic poverty, usually having the attributes of geographical concentration and contiguous spreading-out, can thus be examined from the viewpoint of neighborhood effect[1]. Initially used in interdisciplinary context, neighborhood effect is a social interaction or an endogenous effect that influences the behavior or socioeconomic outcome of an individual. Neighborhood effects also include influences on individual behavior or outcomes due to the characteristics of an individual's neighborhood. The neighborhood component refers to the fact that these effects are typically defined in the context of a spatial relationship. Neighborhoods vary across time and space, and differ drastically in social pressure, paths of social change, and stability level of group members. On the one hand, living in a poor neighborhood may have influence on economic independence, living habit, cognitive ability of individual members (Wilson,1987); on the other hand, culture and structure of communities may also be affected by economic agglomeration and heterogeneity of members (Sampson & Groves, 1989; Bruhn, 2009). Manski (1993) analyzes how internal social effect can influence income inequality and persistent poverty. Others study how neighborhood effect can result in segregation among groups and inter-regional income disparity (Brock & Durlauf, 2002; Durlauf, 2004). They illustrate that the poverty trap of the bottom should be attributed to the effects of the characteristics of the group to which they belong, such as neighborhood living situation, quality of schooling, type of enterprises, race and religious beliefs.

[1] Neighborhood effect is sometimes referred to as group effect, community effect or peer effect. Without loss of general idea, we use these concepts interchangeably in this paper. The definitions of neighbor are usually based on availability of data set, ranging from 5-digit zip codes, counties or villages, to ethnic or language groups. We define a village or a living community as a neighborhood.

The theoretical models of externality and multiple equilibria in growth have provided a mechanism of how neighborhood effect can transmit to income inequality and chronic poverty. Benabou (1996) establishes an endogenous growth model to formalize the effect of a neighborhood or social structure on stratification and polarization of income distribution. Azariadis (1996) takes into account threshold externality to demonstrate the vicious cycle of "slow growth—low income and demand—low capital accumulation—even slower growth" and how it induces to regional poverty trap. Galor & Tsiddon (1997) argue that distribution of human capital can affect economic growth through two different mechanisms, one is "local home environment externality", which means individual human capital accumulation is an increasing function of human capital stock of parents; the other is "global technological externality", which means the average level of human capital changes proportionally with technological progress. When the former externality is the main factor in determining income distribution, stratification and polarization may occur, as what has been observed in earlier stages of development across countries. While in later stages of development, the latter externality dominates and leads to income convergence. Therefore, there is a threshold level of human capital; households with human capital above the threshold would escape from poverty, while those below would not.

Empirically, many have analyzed regional disparities in China based upon new growth theory hypotheses. Differing in econometric models, data sets or data processing methods, most researchers have studied the conditional convergence, club convergence in Chinese economy and regarded human capital as one of the major factors leading to income disparities (Shen & Ma, 2002; Lin & Liu, 2003; Yao & Zhang, 2008; Zou and Zhou, 2007a, 2007b, 2008; Zou & Liu, 2010, etc.). Unfortunately, these studies cannot distinguish temporary, sporadic poverty from persistent, spreading-out poverty, and they simply assume poverty can be alleviated with the passage of time. Furthermore, the aggregate regional data may be used to test the existence of poverty trap, but cannot provide information of whether the great divergence in income levels arises from individual wealth accumulation or from geographical externality. Jalan & Ravallion (2002, 2004) study the effect of regional capital accumulation on individual capital formation based on a micro model of consumption growth. They find out that regional poverty trap does exist in rural China, and the geographical externality and the increasing returns to scale of individual wealth accumulation have been the driving forces of great divergence. Some researchers emphasize that underdevelopment of education in rural China has led to poverty trap (Knight, Li & Deng, 2010), others try to analyze the multi-generational neighborhood effects on cognitive ability and the legacy of poverty (Brooks-Gunn, et. al., 1997; Sharkey & Elwert, 2011).

OLS regression parameter for the neighborhood effect is usually biased and inconsistent due to endogenous independent variables and omitted variables. Mckenzie & Rapoport (2007) use instrument variables to deal with the problems of estimator bias and omitted variables in their research of migration and income inequality within or across groups. However, neither linear model nor standard panel regression can identify the endogenous effect and context effect, let alone further specify robustly the correlation between group and individual behaviors (Manski,

1993; Brock & Durlauf, 2001; Durlauf, 2001). Multilevel econometric model has recently been used to study how neighborhood effect presents influence on individual activities, income levels or health positions (Johnson, 2009; Nguyen et al, 2010). Studying data at individual and group levels simultaneously, multilevel modeling can test both individual and context variables; moreover, it need not assume independence of observables in the dataset, and therefore can amend parameter estimator biases resulted from non-independence of observables. Multilevel model suits well with longitudinal data to reveal inter- and intra-group differences overtime, deal with omitted observables and unbalanced data, and provide estimations with maximum likelihood (ML) or restricted maximum likelihood (RML) methods (Goldstein, 1987; Garner, & Raudenbush, 1991; Evans, Oates & Schwab, 1992; Duncan & Jones, 2000).

This paper uses China Health and Nutrition Survey (CHNS) data, and establishes a multilevel econometric model to investigate the dynamic evolution of individual living standard and income inequality across groups and shed light on how neighborhood effect has transmitted to chronic poverty in rural China. Our research shows that: (1) there are complementarities between individual and collective capability formations. The individual living standard and regional income levels depend not only on individual physical and human capital accumulation, but also on group-level factors, such as group-average education level, externality of communication and transport. (2) it is more difficult for an individual to escape from poverty in neighborhoods with higher proportion of agricultural population, lower average education, and poorer public infrastructure. (3) group-level factors have stronger effect than individual factors when community income is low, while individual effect will be dominant in escaping from poverty when community income has surpassed a threshold value.

The remaining sections of the paper are organized as follows: Section 2 establishes multilevel econometric model in the context of neighborhood effect. Section 3 discusses the characteristics of CHNS data set, and tests the hypothesis of poverty trap through regression and income dynamics. Section 4 produces empirical results and specifies how neighborhood effect has contributed or reinforced regional poverty trap. Section 5 concludes with policy implications.

2. The Multilevel Econometric Model

We construct a three-level econometric model to examine what a role neighborhood effect has played in regional poverty trap in China. In level 1, we trace the trajectory of individual income change, the unit of analysis is time (year); in level 2, we study how individual characteristics affect individual income, the unit of analysis is individual; while in level 3 in which the unit of analysis is group (community or village), we analyze how group characteristics affect individual income. The specific models at different levels are as follows:

Level 1 (within individual) model:

$$\ln(y_{tij}) \quad {}_{0ij} \quad {}_{1ij}Year_{tij} \quad \sum_{p=2}^{P} {}_{pij}W_{ptij} \quad e_{tij} \tag{1}$$

Where y_{tij} is income for individual i (within level 2) of group j (within level 3) in year t (within

level 1), β_{0ij} is intercept, representing the initial individual income level, β_{1ij} is slope representing annual growth rate of income. $Year_{tij}$ is time variable, W_{ptij} is a series of time-related variables, like age. e_{tij} is idiosyncratic errors, and assumed to be independent and conform to normal distribution with mean of 0 and variance of σ^2.

Level 2 (among individuals) model:

$$\begin{aligned} \beta_{0ij} &= \gamma_{00j} + \sum_{q=1}^{Q} \gamma_{0qj} X_{qij} + \sum_{r=1}^{R} \gamma_{0rj} Y_{rij} + u_{0ij} \qquad u_{0ij} \sim N(0, \sigma^2_{u_{0ij}}) \\ \beta_{1ij} &= \gamma_{10j} + \sum_{q=1}^{Q} \gamma_{1qj} X_{qij} + u_{1ij} \qquad u_{1ij} \sim N(0, \sigma^2_{u_{1ij}}) \\ \beta_{pij} &= \gamma_{p0j}, \quad p = 2,\ldots,P \end{aligned} \tag{2}$$

Where Y_{rij} is a vector of individual-level, time-invariant variables, including gender, region etc.. X_{qij} is a vector of individual-level, time-variant variables, including education, marriage status, possession of durables like telephone, television, vehicles. In our research, we calculate the differentials of individual value and group mean to take place X_{qij} with $\tilde{X}_{tij}$, where $\tilde{X}_{tij} = X_{tij} - \overline{X_{t\bullet j}}$, and $\overline{X_{t\bullet j}}$ is mean of year t in group j. The above centering process can make interpretation of intercept and slope more meaningful, and can reduce multi-collinearity and improve robustness of estimation. Moreover, the centering will make the estimates reflect both individual effect and context effect, and help to eliminate the estimate bias induced by endogeneity of individual variables (Grilli & Rampichini, 2006; Corrado & Fingleton, 2011).

Level 3 (among groups) model:

$$\begin{aligned} \gamma_{00j} &= \gamma_{000} + \sum_{s=1}^{S} \gamma_{00s} Z_{sj} + v_{00j} \qquad v_{00j} \sim N(0, \sigma^2_{v_{00j}}) \\ \gamma_{10j} &= \gamma_{100} + \sum_{s=1}^{S} \gamma_{10s} Z_{sj} + v_{10j} \qquad v_{10j} \sim N(0, \sigma^2_{v_{10j}}) \\ \gamma_{0qj} &= \gamma_{0q0} \quad \gamma_{1qj} = \gamma_{1q0} \quad \gamma_{p0j} = \gamma_{p00} \quad \gamma_{0rj} = \gamma_{0r0}, \quad p = 2,\ldots,P \quad q = 1,\ldots,Q \end{aligned} \tag{3}$$

Where Z_{1j} is a vector of group-level variables, including possession rate of TV, telephone, average education level, the proportion of group members with occupation as farmers.

We substitute level-3 model (3) into the modified level-2 model (2), and combine with (1) to get the reduced model as follows:

$$\begin{aligned} \ln(y_{tij}) = {} & \gamma_{000} + \gamma_{100} Year_{tij} + \sum_{p=2}^{P} \gamma_{p00} W_{ptij} + \sum_{q=1}^{Q} \gamma_{0q0} X_{qij} + \sum_{r=1}^{R} \gamma_{0r0} Y_{rij} + \sum_{s=1}^{S} \gamma_{00s} Z_{sj} \\ & + \sum_{s=1}^{S} \gamma_{0s0} Z_{sj} Year_{tij} + \sum_{q=1}^{Q} \gamma_{1q0} X_{qij} Year_{tij} \\ & + v_{00j} + u_{0ij} + (v_{10j} + u_{1ij}) Year_{tij} + e_{tij} \end{aligned} \tag{4}$$

The first two rows of (4) specify the fixed effect. The third row specifies random effect, where e_{tij} is idiosyncratic error, and v_{00j} and u_{0ij} are group random intercept and individual random intercept respectively; v_{10j} and u_{1ij} are random portion of time trends at group level and

individual level respectively[2].

Before studying multilevel model, we need to test whether dependent variables differ significantly across groups. Usually, intra-class correlation coefficient (ICC, represented by) is established to measure the ratio of between-group variance and the whole variance:

$$\frac{\sigma_b^2}{\sigma_b^2 + \sigma_w^2} \tag{5}$$

Where σ_b^2 and σ_w^2 are between-group variance and within-group variance respectively. When ICC approaches 0, there is no significant difference in dependent variables across groups, thus multilevel model is not applicable. When ICC approaches 1, every individual within a group is indifferent. To make a judgment of whether the between-group differences are significant, we refer to the following rule (Cohen, 1988): the correlation is low if $0.059 \le \rho \le 0.01$, middle if $0.138 \le \rho \le 0.059$ and high if $\rho \ge 0.138$. Therefore, as long as $\rho \ge 0.059$, we think the between-group difference is not ignorable and the multilevel model is applicable. The calculation of ρ is based upon the "null model". Corresponding to our three-level model, the null model is given as:

$$\begin{aligned} \ln(y_{tij}) &= \pi_{0ij} + e_{tij} \\ \pi_{0ij} &= \beta_{00j} + u_{0ij} \\ \beta_{00j} &= \gamma_{000} + v_{00j} \end{aligned} \tag{6}$$

The reduced form is:

$$\ln(y_{tij}) = \gamma_{000} + v_{00j} + u_{0ij} + e_{tij} \tag{7}$$

Accordingly, the variance is:

$$Var(\ln(y_{tij})) = Var(\gamma_{000} + v_{00j} + u_{0ij} + e_{tij}) = \sigma_{v_{00j}}^2 + \sigma_{u_{0ij}}^2 + \sigma^2 \tag{8}$$

Where π_{0ij} is the mean of logarithm income of all individual in year j, which amounts to individual permanent income. e_{tij} is residual, and can be regarded as temporary income. β_{00j} is the mean of logarithm income of all members in group j. u_{0ij} is individual-level random intercept coefficient. γ_{000} is the mean of all individual logarithm income, v_{00j} is the group-level random intercept coefficient. Thus ICCs of each level are as follows:

$$group = \frac{\sigma_{v_{00j}}^2}{\sigma_{v_{00j}}^2 + \sigma_{u_{0ij}}^2 + \sigma^2}, \quad individual = \frac{\sigma_{v_{00j}}^2 + \sigma_{u_{0ij}}^2}{\sigma_{v_{00j}}^2 + \sigma_{u_{0ij}}^2 + \sigma^2} \tag{9}$$

3. Data

We use individual and household data from China Health and Nutrition Survey (CHNS), which has been implemented 8 times, i.e. in years of 1989, 1991, 1993, 1997, 2000, 2004, 2006, and 2009. Eight provinces (Liaoning, Shandong, Jiangsu, Henan, Hubei, Hunan, Guizhou and Gunagxi) have been covered before 1997, while Heilongjiang was used in place of Liaoning in 1997, and all the nine provinces have been covered consistently since 2000. Located in different areas of China, the nine provinces vary substantially in geography, public service, natural resources, income level, and health indicators. A multi-stage, random cluster sampling process has been used to draw the

[2] For the detail of estimation methods, please refer to the Appendix A.

sample counties for survey in each province. Counties in each province were stratified by income (from low to high), and a weighted sampling scheme was used to randomly select four counties (cities) in each province. Villages (or townships) within the selected counties, and urban or suburban communities within the selected cities were further selected randomly. There are about 4400 household, and around 19000 individuals each survey year in the data. The CHNS data does not satisfy independence between observables, we thus establish multilevel model instead of normal regression model. In order to keep consistency and comparability of samples, we focus our study on rural survey data in years of 2000, 2004, 2006, and 2009.

Due to migration, natural death and the formation of new household, there are many missing data in CHNS, which can lead to biases in estimation. We filter out a sample household if data of most main variables of the household are missing. Finally, we obtain 19856 rural samples, among which there are 143 groups (villages or communities) in 2000 and 2004 respectively, and 145 in 2006 and 2009 respectively; the samples in the four survey years include 5648, 4371, 4533, and 4944 individuals respectively. The data used here are unbalanced panel data in the view of groups or years, which will not substantively affect estimation in random effect model, or affect within-group estimation in fixed effect model. We thus do not adjust the data into balanced data in order to maintain the properties of large samples and avoid random deletion of samples[3].

CHNS provides multilevel data across provinces and years, at levels of groups (villages or communities), households, and individuals. Group data include physical infrastructure, public environment etc.. Household data include family income and its composition, family size, source of drinking water, sanitary facilities, possession of durables etc.. Individual data include individual income, occupation, education level etc.. Table 1 provides partial correlation of variables with household income in each survey year. We can find out that, education level is significantly correlated with household income, yet the coefficients fluctuate from year to year. Possession of automobile has higher correlation coefficient with household income and the coefficient increases overtime. The possession of telephone and motorcycle has been significantly correlated with household income, yet the coefficients have been decreasing. The effect of TV possession on household income is lower and less significant.

Table 1. The partial correlation of variables with household income

Partial correlation coefficient with household income	Possession of durables				Education level	Number of samples
	telephone	TV	motorcycle	automobile		
2000	0.1466***	0.0763***	0.1627***	0.1064***	0.0431***	5648
2004	0.1271***	0.0165	0.1506***	0.1692***	0.1065***	4731
2006	0.0525***	0.0367**	0.1257***	0.1938***	0.1082***	4533
2009	0.0518***	0.0257*	0.0496***	0.2102***	0.0999***	4944
pooled	0.0934***	0.0387***	0.0992***	0.1811***	0.0799***	19856

[3] Please refer to the Appendix B for the statistical description of variables.

Notes: (1)***, **, * represent significance of degree 1%, 5% and 10% respectively. (2) Household income has been adjusted to 2009 price level. (3) Education level is the highest education acquired by family members.

The possession of durables may increase the possibility of household to get access to and make use of public infrastructure. To specify the complementarities between group factors and individual factors in determining individual income[4], we take into account not only schooling years, possession of TV, telephone and vehicles at individual level, but also average schooling, average possession of TV, telephone, and vehicles, and the proportion of members with occupation as farmers at group level. To avoid the estimation bias induced by endogeneity, we treat individual-level variables through centering (scalar) process, i.e. calculating and using the differences between each individual variable and the corresponding group mean.

Before analyzing income disparity and neighborhood effect, we need to test whether there is regional poverty trap. As usual, auto-regression of logarithm income can be used to test whether there is non-convexity of income dynamics. The polynomial regression equation is as follows (Jalan & Ravallion, 2004; Antman & Mckenzie, 2007):

$$y_{i,t} \quad . \quad t \quad {}_1 y_{i,t-1} \quad {}_2 y_{i,t-1}^2 \quad {}_3 y_{i,t-1}^3 \quad i \quad {}_{i,t} \tag{10}$$

Where $y_{i,t}$ is average income of community i in year t. We calculate logarithm community income and use quasi-differentials to avoid the endogenous effect of group-level variables, and the results of random effect GMM estimation are listed in Table 2. No matter the time trends are taken into account or not, all the coefficients are significant and sign of coefficient of Square $\ln(y_{t-1})$ is positive, sign of coefficient of Cubic $\ln(y_{t-1})$ is negative. The results demonstrate that the group-level income dynamics present non-convex, "S-shaped" curve, which is the pre-requisite of the existence of multiple equilibia and a poverty trap.

Table 2. Logarithm of group-level income and the lagged income

		Time trends	$\ln(y_{t-1})$	Square $\ln(y_{t-1})$	Cubic $\ln(y_{t-1})$	Constant
$\ln(y_t)$	Coefficient		-15.3453	1.8188	-0.06867	50.0525
	t-value		-2.38**	2.45**	-2.42**	2.68***
$\ln(y_t)$	Coefficient	0.0820	-12.3415	1.4717	-0.0560	41.2633
	t-value	8.32***	-2.03**	2.11**	-2.10**	2.35**

Note: $\ln(y_t)$ and $\ln(y_{t-1})$ are logarithm group-level average incomes at current year and previous survey year respectively. ***, ** represent confidential level at 1% and 5% respectively.

Figure 1 presents the scatter diagram of community income between two adjacent survey years, the vertical and horizontal lines represent the lower 40% cut-off lines at different years. There are

[4] Due to data availability, we use household income (adjusted with 2009 CPI) divided by family size to calculate individual income.

a considerable communities located below the 40% cut-off lines between two survey years. We calculate the frequency and numbers of communities living below 40% of average income in the four surveys from 2000 to 2009, and find that among the 147 communities, 20 (13.61%) live below 40% cut-off line in four survey years (lasting 10 years), 29 (19.73%) live below 40% cut-off line in three survey years (lasting 6-8 years). We regard these communities as living in relatively deep poverty.

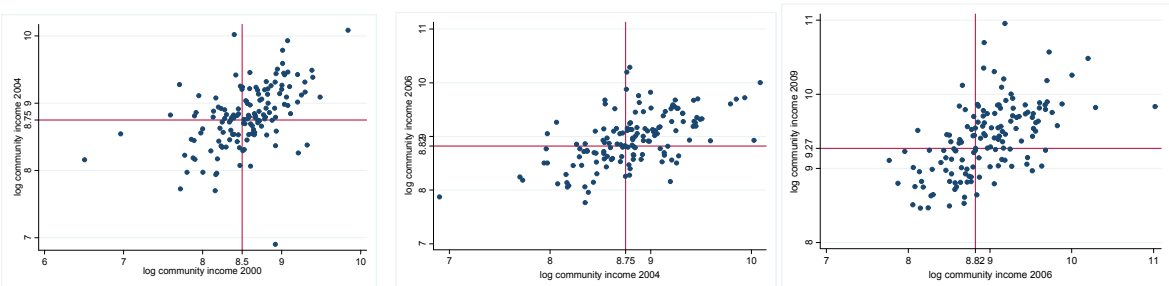

Figure 1. The scatter diagram of community income between adjacent survey years

We measure Gini coefficients at individual- and group-level respectively (Table 3). It turns out that the Ginis of community mean income increases, from 0.236 in 2000 to 0.295 in 2006, and decreases slightly in 2009. However, the Ginis at individual-level are much higher and increasing consistently. i.e. from 0.410 in 2000 to 0.476 in 2009. We further trace the income dynamics through establishing Kernel density function of logarithm income (see Figure 2(a), 2(b))[5]. On one hand, the curves move to the right overtime, representing an increase in income at individual and community levels; on the other hand, the distribution of individual income has been more diversified, representing much higher inequality at individual level.

Table 3. Gini Coefficients of individual income and community mean income (2000-2009)

Year	2000	2004	2006	2009
Ginis of individual income	0.410	0.434	0.473	0.476
Ginis of community mean income	0.236	0.254	0.295	0.271

Source: Calculated by authors with CHNS data.

[5] In Figure 2(a), 2(b), we use Gaussian Kernel: $K(z) = (2\pi)^{-0.5} \exp(-z^2/2)$, where N is sample size. The bandwidth is the optimal one h^*: $h^* = [\int z^2 K(z)dz]^{-2/5} [\int K(z)^2 dz]^{1/5} [\int f''(x)^2 dx]^{-1/5} N^{-1/5}$.

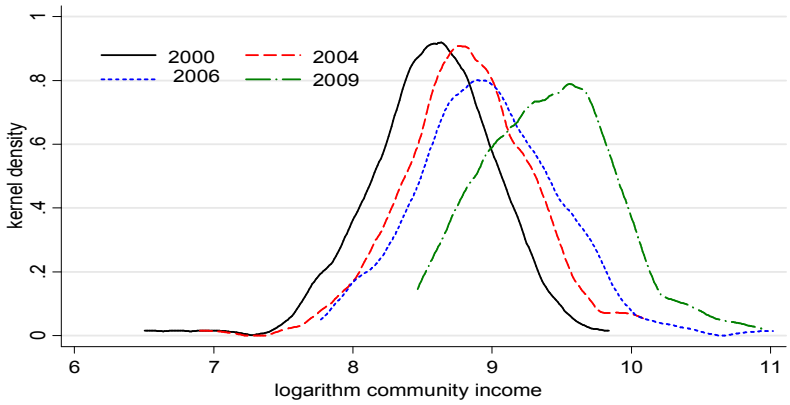

Figure 2(a) Income dynamics at community level (2000-2009)

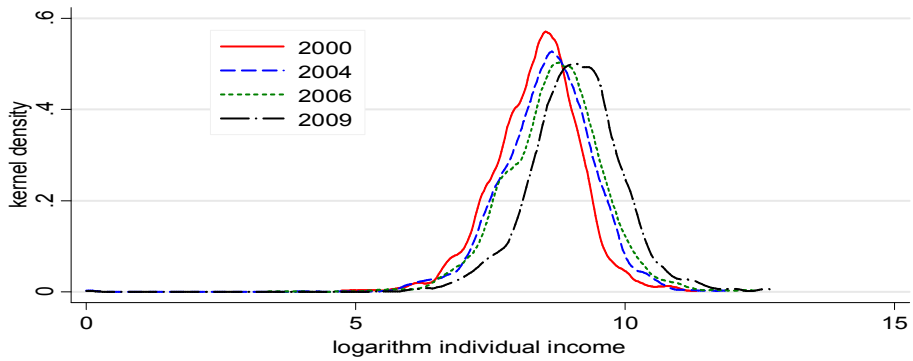

Figure 2(b) Income dynamics at individual level (2000-2009)

Why the income distribution differs at individual and community levels? The increasing Ginis in China indicates a deteriorating inequality accompanying fast economic growth, and there is still a long way to go to reach the turning point of traditional Kuznets inverted-U curves (Galor & Tsiddon, 1997). Furthermore, what roles have individual and community factors played in determining income distribution? What a threshold level has community infrastructure provided at earlier stage of development, and how the individuals can benefit from the threshold externality? In the next section, we will analyze the complementarities between individual and group factors, and shed light on regional chronic poverty in rural China.

4. The Empirical Results

We start with testing the null model and calculating ICCs (results reported in Table 4). In Model 1, ICC value is 0.1673, which means the income differences at community level can explain 16.73% of the whole income differences; while in Model 2 with time trends added, the ICC value increases to 0.3081. According to the rule given in Section 2, the differences across groups are high enough, and thus the three-level model applies well. In Model 2 with time trends, the average

logarithm income of all individuals is 8.2273, increasing consistently at a rate of 0.0795, both are empirically significant. The community-level intercept is negatively correlated with time, while the individual-level intercept is positively correlated with time, which means that as time goes on, the neighborhood effect turns to weaken, and individual-level effect turn to strengthen. Model 2 fits better based on likelihood-ratio test and the significance of all random coefficients. According to the variances of year at individual and community levels in random effect model, we can calculate standard deviations at the two levels, 0.0476 and 0.0222 respectively. Therefore the average growth rate of group mean income is 0.0795+0.0476=0.1271, while the average growth rate of individual income is 0.1271+ 0.0222=0.1493.

Table 4. The Null model and calculation of ICC

	Model 1	Model 2
Fixed-effect part		
intercept	8.6766 (0.0306)	8.2273 (0.0398)
Year		0.0795 (0.0042)
Random-effect part		
Variance of residual	0.5540 (0.0072)	0.4340 (0.0057)
Variance of individual intercept	0.0973 (0.0061)	0.0501 (0.0064)
Variance of *Year*		0.0005 (0.0001)
Covariance of year and intercept		0.0050 (0.00028)
Variance of group intercept	0.1309 (0.0161)	0.2155 (0.0275)
Variance of *Year*		0.0023 (0.0003)
Covariance of year and intercept		-0.0136 (0.0025)
ICC (group)	0.1673	0.3081
ICC (individual)	0.2917	0.3797

Note: The numbers in parentheses are standard errors.

We provide the regression outcome of null models in years 2000, 2004, 2006 and 2009 to figure out how the effect of group factors on individual income changes overtime. In Table 5, as time goes on, individual average income (represented by the individual intercept) increases gradually from 8.3442 to 9.0964. In random effect part, the ICCs are all high enough to present significant neighborhood effect on individual income based upon the rule given in Section 2, however, ICCs decrease overtime, representing a decreasing effect of group factors on individual income growth. This means when community average income has surpassed a threshold level, individual capability formation will take the place of group-level factors to be dominant in determining individual income.

Table 5. The regression results of null models and ICC (2000-2009)

	2000	2004	2006	2009
Fixed-effect part				
Individual intercept	8.3442 (0.0392)	8.5783 (0.0378)	8.6895 (0.0386)	9.0964 (0.0351)
Random-effect part				
Variance of residual	0.4412 (0.0084)	0.5157 (0.0108)	0.5895 (0.0126)	0.5752 (0.0117)
Variance of group intercept	0.2072 (0.0262)	0.1861 (0.0243)	0.1958 (0.0255)	0.1611 (0.0210)
ICC	0.3195	0.2652	0.2494	0.2188

Note: The standard errors are in parentheses.

Table 6 summarizes multilevel econometric analyses of Equation (4). The dependent variable is logarithm individual income, which has been increasing during the survey period. Among individual factors, age is found to present a non-linear and inverted U-shaped correlation with logarithm income, i.e., as an individual gets older, his/her logarithm income first increases, then decreases. The turning point is around age of 51.35, which is a reference point, because individual income is calculated by household income and family size, therefore turns to be lower with larger family size. However, the inverted U-shaped relation is significant in our model. We can use $e^{\square}$ to measure the effect of family size, for example, as family size increases by 1%, individual income may decrease by 11.17%. Marriage status has effect on individual income in the way that a married person has higher income than a devoiced, separated or widowed one. And an employed person significantly has higher income than an unemployed one.

Table 6. The regression results of the multilevel econometric model

Variables	Coefficient	*z*-value
Fixed effect part		
Constant	8.5507	54.24***
Year	0.0494	2.12**
Individual-level		
Age	0.0076	2.92***
Age squared	-0.000074	-2.80***
Family size	-0.1185	-29.29***
Single (Reference variable)		
Married	-0.1319	-5.56***
Divorced, widowed ,separated	-0.1897	-5.78***
Difference between individual education and group mean education	0.0560	5.81***

Difference between individual TV possession status and group TV owning rate	0.1212	4.62***
Difference between individual telephone possession status and group telephone owning rate	0.2212	8.19***
Difference between individual motorcycle possession status and motorcycle owning rate	0.1669	6.56***
Difference between individual automobile possession status and group automobile owning rate	0.3374	6.28***
Employed or not	0.1297	8.27***
Group (Community or village)-level		
East (Reference variable)		
Northeast	-0.2313	-3.76***
Middle	-0.3749	-6.83***
West	-0.2997	-4.91***
Mean education level of group	0.3642	5.88***
Owning rate of TV in group	0.1966	1.52
Owning rate of phone in group	-0.7873	-7.44***
Owning rate of motorcycle in group	0.3324	2.76***
Owning rate of automobile in group	0.3684	1.22
Proportion of group members engaging in farming	-0.3231	-3.44***
Interactive terms of the following variables with Time (Year)		
Difference between individual education and group mean education	0.0031	2.23**
Group mean education level	-0.0236	-2.78***
Difference between individual TV possession status and group TV owning rate	0.0101	1.74*
Group TV owning rate	-0.0400	-1.89*
Difference between individual telephone possession status and group telephone owning rate	-0.0013	-0.27
Group telephone owning rate	0.1479	8.38***
Difference between individual motorcycle possession status and motorcycle owning rate	-0.0016	-0.39
Group motorcycle owning rate	-0.0616	-3.72***
Difference between individual automobile possession status and group automobile owning rate	0.0233	3.07***
Group car owning rate	0.0530	1.32
Proportion of group members engaging in farming	0.0255	1.72*
Random effect part		
Time-level		
Random error	0.4149 (0.0054)	

Individual-level	
Variance of intercept	0.0288 (0.0056)
Variance of year	0.00035 (0.000087)
Covariance between intercept and year	0.0032 (0.000233)
Group (Community or village)-level	
Variance of intercept	0.1545 (0.0210)
Variance of year	0.0024 (0.0003)
Covariance between intercept and year	-0.0156 (0.0024)
LR test: VS. linear regression	chi2(6) = 2196.13 Prob. > chi2 = 0.0000

Note: The standard errors are in parentheses. ***, ** and * represent significance at 1%, 5% and 10% level respectively.

According to equation (4), the marginal effect of individual variables can be defined as: $d\ln(y_{tij})/d\,X_{tij} = \gamma_{010} + \gamma_{110} Year_{tij}$. The specific effect of different individual variables vary across time, therefore we need to consider the interactive term of time (Year) with individual-level education, possession status of telephone, motorcycle, and car etc. to examine the dynamic effect on income. As we provide in Table 5, the differences between individual-level education, possession status of TV, and car and the corresponding group mean value show significantly positive interactive terms with time, which means as time goes on, individual-level human capital accumulation and possession of TV and car present higher and higher effect on individual income growth. However, the differences between individual possession of telephone and motorcycle and the corresponding group mean value exhibit negative, yet insignificant, interactive terms with time. The possible reason lies in that during the survey period, telephone and motorcycle have been necessities for most rural households in China, thus the possession of theses durables have been no longer influential in individual income.

Nevertheless, neighborhood effect differs from individual-level effect in many aspects. Firstly, the group average education, and the group owning rate of durables (like TV, motorcycle, and car) have positive effect on individual income growth. The neighborhood effect of the above variables turns out to be much more significant than individual effect. Secondly, the group owning rate of durables, like telephone and car, presents positive interactive terms with time, which means in the long run, the infrastructure of telecommunications and road systems will exhibit consistent and positive effect on poverty reduction. Thirdly, the group average education, and group owning rate of TV and motorcycle present negative interactive terms with time, which means the neighborhood effect of these variables turns to decline overtime. Actually, in random effect part, the covariance between group intercept and time is also negative, providing further evidence for declining neighborhood effect. Therefore, with economic growth, individual effect gets stronger, while neighborhood effect will be on the wane; as long as average income has surpassed a threshold level, individual income growth will no longer be constrained by local group network.

Geographical location also exhibits effect on rural poverty trap. Taking the east provinces (Jiangsu, Shandong) as reference points, living in the northeast (Liaoning, Heilongjiang), central (Henan, Hubei, Hunan) and west (Guizhou, Guangxi) does present very significant, negative effect on individual income, to different extent. Our model reveals that, the proportion of group members engaging in farming has significant and negative effect on individual income, while this group-level variable exhibits positive interactive term with time. The result reflects an increase in farmer's income, however, farming is still by far less profitable compared with non-agriculture sectors, and is not helpful in reducing chronic poverty overtime. Industrialization of agriculture and increase in non-agriculture employment will be more effective in fighting rural poverty trap.

According to our multilevel model defined in Section 2, γ_{0q0}, the coefficient of X_{tij}, represents individual-level effect; γ_{00s}, the coefficient of $Z_{sj}\overline{X_{t\bullet j}}$, represents group-level effect; and the difference between them, $\gamma_{00s}-\gamma_{0q0}$, represents context effect, i.e. the effect of some group variables on individual income in different groups. Putting aside interactive terms with time, we find out that there have been significant context effect induced by group variables such as group average education, group owning rates of telephone, TV, car and motorcycle, and for most group variables (owning rate of telephone is the only exception), neighborhood effect turns to be more influential in determining individual income than individual variables. However, when we take into account the interactive terms with time, we find out that the extent of neighborhood effect changes overtime. Take education for example, if education increases by 1% at individual and group levels respectively, after 10 years, the neighborhood effect of education would be: 0.3642-0.236=0.1282, while the individual effect of education would be: 0.056+0.031=0.087, i.e. even after 10 years, the neighborhood effect of education will still be dominant compared with individual education. Whereas the neighborhood effect of other factors, like the owning rate of TV and telephone, turns to decline continuously. After 10 years, individual possession of durables like TV and telephone will be dominant in determining individual income.

5. Conclusion

In this paper, we establish a multilevel econometric model to study the neighborhood effect and how it presents influence in regional poverty trap in rural China. We have found the following: (1) The effect of group variables, especially the group average education level, group owning rate of durables such as telephone and car, has been playing an important role in determining individual income. The lower group average education and poorer group infrastructure of communication or transport have been determinant factors in rural poverty trap. (2) Although farmer's income increases in China, the communities or villages with higher proportion engaging in farming are more prone to chronic poverty. (3) Group-level variables have been more influential in determining individual income than individual factors in the earlier stages of development, yet neighborhood effect turns to decline overtime. As average income surpasses a threshold level, individual capability formation (in term of human capital and physical capital accumulation) will

be dominant in determining individual income. In China, the complementarities between neighborhood effect and individual effect have been limited in fighting against poverty. The more capable individuals usually make more use of group-level factors (such as education facilities, road and telecommunication infrastructure etc.), and therefore the less capable and poorer ones can hardly benefit from group externality.

Drawing on our research, to eradicate chronic poverty in rural China, the policy priority should be given to providing social protection and public services. Publicly provided social protection, and particularly social assistance, is of great importance in reducing insecurity and increasing opportunities for the chronically poor to engage with the growth process. More public services in reproductive health care, education, and infrastructure of communication and transport can break the intergenerational transmission of poverty and have a dramatic effect on the prospects of the chronically poor households. Public services also can help asset accumulation for the poor. The more assets (physical, social and psychological) a household possesses, the more leverage it has in social networks and transactions, as well as in formal financial markets. Therefore the pro-poor growth strategy should involve space-indifferent public services, which can in turn promote individual capability formation. In earlier stage of development, a universal poverty-reduction policy is more effective in providing a threshold externality for all group members, while as group average income increases to higher level, targeted poverty-reduction policy will be more effective in developing individual capability.

Reference:

Azariadis, C., 1996, "The Economics of Poverty Traps, Part One: Complete Markets", *Journal of Economic Growth*, Vol.1: 449-486.

Azariadis, C. and J. Stachurski, 2006, Poverty Traps, in *Handbook of Economic Growth*, Vol.1.eds. P. Aghion and S. Durlauf , Amsterdam, 295–384.

Antman, F. and D. Mckenzie, 2007, "Poverty Traps and Nonlinear Income Dynamics with Measurement Error and Individual Heterogeneity", *Journal of Development Studies*, Vol.43(6): 1057-1083.

Bates, D., and J. Pinheiro, 1998, "Computational Methods for Multilevel Modeling", mimeo, http://franz.stat.wisc.edu/pub/NLME/ or http://stat.bell-labs.com/NLME/CompMulti.pdf

Benabou, R., 1996, "Heterogeneity, Stratification, and Growth: Macroeconomic Implications of Community Structure and School Finance", *American Economic Review*, Vol.86(3): 584-609.

Brock, W. and S. Durlauf, 2001, "Interactions-Based Models", in *Handbook of Econometrics* Vol.5. eds. J. Heckman and E. Leamer, Amsterdam: North Holland, 3297-3371.

Brooks-Gunn, J., G. Duncan, and L. Aber, 1997, *Neighborhood Poverty: Context and Consequences for Children*. New York: Russell Sage Foundation.

Bruhn, John, 2009, *Group Effect: Social Cohesion and Health Outcomes*, Springer Publisher.

Corrado, L.and B. Fingleton, 2011, "Multilevel Modeling with Spatial Effects", Strathclyde discussion paper No.11-05.

Durlauf, S., 2001, "The Memberships Theory of Poverty: The Role of Group Affiliations in Determining Socioeconomic Outcomes", in *Understanding Poverty in America*, eds. S. Danziger and R. Haveman, Cambridge: Harvard University Press.

Duncan, C. and K.Jones, 2000, Using Multilevel Models to Model Heterogeneity: Potential and Pitfalls, *Geographical Analysis,* 32, 280-305.

Evans, W.M., W. Oates, and R. Schwab, 1992, "Measuring Peer Group Effects: A Study of Teenage Behavior". *Journal of Political Economy*, 100, 966-991.

Galor, O. and D. Tsiddon, 1997, "The Distribution of Human Capital and Economic Growth", *Journal of Economic Growth*, Vol.2(1):93-124.

Garner, C.L., and S.W. Raudenbush, 1991, "Neighborhood Effects on Educational Attainment: A Multilevel Analysis". *Sociology of Education,* 64, 251-262.

Goldstein, Harvey, 1987. *Multilevel Models in Educational and Social Research*. London: Griffin.

Grilli, L. and C. Rampichini, 2006, " Model Building Issues in Multilevel Linear Models with Endogenous Covariate", Working paper, Dipartimeto di Statistica, Universita di Firenze,Florence.

Hoff , K. and A. Sen, 2006, "The Kin System as a Poverty Trap", in *Poverty Traps*, eds. Bowles S., S. Durlauf and K. Hoff.

Jalan J. and M.Ravallion, 2002, "Geographic Poverty Traps? A Micro Model of Consumption Growth in Rural China", *Journal of Applied Econometrics*.2002(17):329-346.

Jalan J. and M.Ravallion, 2004, "Household Income Dynamics in Rural China", in *Insurance Against Poverty*, ed. S.Dercon, Oxford University Press.

Johnson, R., 2009, "Health Dynamics and the Evolution of Health Inequality over the Life Course: The Importance of Neighborhood and Family Background", Working paper: http://ist-socrates.berkeley.edu/~ruckerj/johnson_HlthnHood_6-09.pdf

Knight, J., Li Shi, and Deng Quheng, 2010, "Education and the Poverty Trap in Rural China: Closing the Trap", *Oxford Development Studies*. No.4, 1-24.

Manski, C., 1993, "Identification of Endogenous Social Effects: The Reflection Problem", *Review of Economic Studies*. Vol. 60: 531-542.

Mckenzie, D. and H. Rapoport, 2007, "Network Effects and the Dynamics of Migration and Inequality: Theory and Evidence from Mexico", *Journal of Development Economics*. No.1: 1-24.

National Bureau of Statistics (NBS), 2009, *Report on Poverty Measurement in Rural China*, China Statistics Publisher.

Nguyen P., D. Haughton, I. Hudson and J. Boland, 2010, "Multilevel Models and Small Area Estimation in the Context of Vietnam Living Standards Surveys", *42èmes Journées de Statistique*.

Sampson, R.J. and W.B. Groves. 1989. Community Structure and Crime: Testing Social-Disorganization Theory. *American Journal of Sociology*, 94, 774-802.

Sharkey, Patrick and Felix Elwert, 2011, "The Legacy of Disadvantage: Multigenerational Neighborhood Effects on Cognitive Ability", *American Journal of Sociology,* Vol. 116(6) : 1934-81

Shen, Kunrong, and Ma Jun, 2002, "Club convergence in Chinese Economic Growth: Characteristics and Causation", *Journal of Economic Research*, No.1, 33-39.

Wen, Fuxing, 2009, *Principle and Applications of Multilevel Linear Models* (in Chinese), China Light-Industrial Publisher.

Wilson, William J., 1987. *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy*. Chicago: University of Chicago Press.

Yao, Xianguo and Zhang Haifeng, 2008, "Human Capital and Regional Economic Divergence", *Journal of Economic Research* (in Chinese), No.5, 47-57.

Zou , Wei & Fang Yingfeng, 2011, "On Dynamic Multiple-dimension Measurement of Poverty in Rural China", Chinese Journal of Population Science, No.6: 49-59.

Zou, Wei and Zhou Hao, 2007a, "Measurement and Analyses of Provincial Growth Divergence in China (1978-2002)", *Journal of Management World* (in Chinese), No.7, 37-46.

Zou ,Wei and Zhou Hao, 2007b, "The Classification of Growth Clubs and Convergence—Evidence from Panel Data in China (1981-2004)", *China and World Economy*, Vol.15(5): 91-106.

Zou ,Wei and Zhou Hao, 2008, "Measuring Divergence in Provincial Growth in China: 1981-2004", *Journal of Economic Policy Reform*, Vol. 11(3): 215-227.

Zou, Wei and Liu Yong, 2010, "Skilled Labor, Economic Transition and Income Differences: A Dynamic Approach", *Annals of Economics and Finance*, Vol.11(2): 246-267.

Appendix A: Estimation method

In estimating (4), we use the general assumption that u_{1ij} and u_{0ij} , v_{10j} and v_{00j} are assumed to be correlated, i.e. their variances have the following structure:

$$_1 \quad \mathrm{var}(u) \quad \mathrm{var} \begin{matrix} u_{0ij} & {}^{2}_{u_{0ij}} & (u)_{01} \\ u_{1ij} & (u)_{10} & {}^{2}_{u_{1ij}} \end{matrix} ; \tag{A1}$$

$$_2 \quad \mathrm{var}(v) \quad \mathrm{var} \begin{matrix} v_{00j} & {}^{2}_{v_{00j}} & (v)_{01} \\ v_{10j} & (v)_{10} & {}^{2}_{v_{10j}} \end{matrix} \tag{A2}$$

where $(u)_{01} \quad Cov(u_{1ij}, u_{0ij})$, and $(v)_{01} \quad Cov(v_{10j}, v_{00j})$ respectively. However, the residuals at different levels are not correlated. The random part of (4) ahs the following variance structure:

$$\mathrm{var} \begin{matrix} u \\ v \\ e_{tij} \end{matrix} \begin{matrix} {}_1 & 0 & 0 \\ 0 & {}_2 & 0 \\ 0 & 0 & {}^2 I_n \end{matrix} \tag{A3}$$

We use Maximum Likelihood (ML) to estimate (4). The estimation equation can be reduced to:

$$y \quad X \;.\; Z(u \quad v) \quad e \tag{A4}$$

Where y is a vector of results, X is vector matrix of fixed effect , Z is vector matrix of random effect, then y is subject to normal distribution with mean of X , and variance of V . The variance V can be calculated as:

$$V \quad Z(\ _1 \quad _2)Z.' \quad ^2 I \tag{A5}$$

Define as a vector of all elements in $_1$ and $_2$, then ML estimation problem is:

$$\max_{(\ ,\ ,\ ^2)} L(\ ,\ ,\ ^2) \sim \frac{1}{2}\{n\log(2\ ) \quad \log|V| \quad (\tilde{y} \quad X\ )'V^{-1}(\tilde{y} \quad X\ )\} \tag{A6}$$

When we estimate parameters , , ^{2}, we will not solve (A6) directly, instead, we will reduce the form and resort to multilevel ML calculation (Bates & Pinheiro, 1998).

Appendix B: The statistical description of variables

	sample number	mean	standard error	minimum	maximum
Individual-level variables					
age	19856	46.445	14.13	16.04	92.71
individual income	19856	8764.319	13363.45	29.133	361458.7
phone possession	19856	0.697	0.460	0	1
TV possession	19856	0.818	0.386	0	1
the highest education level acquired	19856	1.60	1.222	0	6
automobile possession	19856	0.043	0.202	0	1
motorcycle possession	19856	0.343	0.475	0	1
employed or not	19856	0.810	0.392	0	1
family size	19856	3.912	1.578	1	13
region	19856	1-east(23.05%); 2-northeast(21.92%); 3-middle(29.75%); 4-west（25.28%)			
marriage status	19856	1-single(7.83%); 2-marriged(86.10%); 3-divorce,widowed and separated(6.07%)			
Group (community or village)-level variables					
proportion of population engaging in farming	576	0.456	0.337	0	1
Group mean income	576	9021	6170.265	668.717	60874.57
owning rate of phone	576	0.721	0.288	0	1
owning rate of automobile	576	0.0431	0.071	0	0.481
owning rate of motorcycle	576	0.335	0.236	0	1
owning rate of TV	576	0.834	0.214	0	1
Group average education	576	1.641	0.638	0.425	3.933

Notes: (1) Possession of telephone means possession of at least one of the following: fixed phone, personal handy phone or mobile phone. (2) Possession of TV means possession of one black-white or colored TV. (3) Possession of motorcycle means possession of one of the following: two-wheeled or three-wheeled motor, pedal or electric bicycle. (4) Possession of automobile means possession of one of the following: wagon tricycle, small truck, agriculture vehicle, car, sedan, or van etc.