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Poverty Dynamics of Households in Rural China*

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Abstract

The objective of our study is to identify patterns and causes of households' transitions into and out of poverty using the long household panel data on rural China in 1989–2009. We propose a discrete-time multi-spell duration model that not only corrects for unobserved heterogeneity, but also addresses the endogeneity due to dynamic selection associated with household's livelihood strategies. The household choosing farming or out-migration as a main livelihood strategy was more likely to escape from persistent poverty than those taking local non-agricultural employment. The present study emphasizes the central role of agriculture in helping the chronically poor escape from poverty.

I. Introduction

While rural poverty has continued to decline in China due to spectacular economic growth over the last three to four decades, much of the reduction is concentrated in two relatively brief periods: 1979–84 and 1995–97 (Ghosh, 2010). Substantial reduction in rural poverty was achieved in 1979–84 as a result of de-collectivization of agricultural production and the introduction of the Household Responsibility System which dramatically raised agricultural productivity (Lin, 1992). Reduction of rural poverty was accelerated again in 1995–97 by significant increases in procurement prices of agricultural products which pushed up income growth of rural households (Benjamin, Brandt and Giles, 2005). Since then, although the speed of poverty reduction has slowed down (Chen and Ravallion, 2010), it has been increasingly difficult for the government or international agencies to direct their poverty alleviation policies or aid programmes to those who remain poor in rural China as

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they tend to live in remote areas (World Bank, 2009). While some rural households seem to be chronically poor, considerable mobility in and out of poverty has been reported in rural China (e.g. McCulloch and Calandrino, 2003; Gustafsson and Ding, 2009) and thus 'transient poverty' is a non-negligible part of total poverty (Jalan and Ravallion, 1998; Duclos, Araar and Giles, 2010). An effort to help the poor more efficiently thus calls for understanding of the pattern and causes of households' poverty transitions as households manage their livelihoods in response to the changing environment. Incorporating a time dimension into the analysis of household poverty is crucial not only for understanding the evolution of households' poverty status and underlying causes, but also for designing and implementing effective anti-poverty programmes.

The empirical literature of 'poverty dynamics' has addressed transitions of poverty status for a household or an individual over long periods in both developed and developing countries, usually using household panel data. A typical approach to analyzing poverty dynamics is to include lagged poverty status as an additional independent variable to capture the dynamics of poverty (Cappellari and Jenkins, 2002; Antman and McKenzie, 2007). However, considering poverty status only in the previous year may oversimplify the dynamics across many years and fail to recognize the cumulative nature of household poverty.

To address this concern, the present study analyses poverty dynamics by using the duration model which takes account of how long the household has been or has not been in poverty as well as when it moved in or out of poverty. One of the significant advantages of the duration model is to track an individual's unique history and experience. That is, our model captures the story in which, for example, a farming household experienced poverty for four years due to the low productivity, but escaped from poverty as one of the household members had access to non-farm employment and stayed 'non-poor' for four years and then slipped into poverty and remained poor for the next six years due to the illness of a household head. While some studies have analyzed poverty in developed countries using the duration model (Canto, 2002; Devicienti, 2002, 2011; Maes, 2013), there have been few works on developing countries.[1] More specifically, to explore the pattern of poverty dynamics, we incorporate unobserved heterogeneity in a discrete-time duration model and apply a fully non-parametric approach to the long household panel data on rural China. This methodology aims to minimize possible misspecifications to offer better estimates. Our framework controls for (i) unobserved heterogeneity that can be correlated across multiple poverty transitions of each household and (ii) the dynamic selection underlying multi-path transitions, neither of which has been done in the context of developing countries. This enables us not only to understand trajectories of household poverty status, but also to identify the underlying socio-economic factors which influence the changes in poverty status.

It is noted that the above empirical literature on 'poverty dynamics' is closely associated with the parallel empirical literature on 'poverty traps'. For example, Carter and Barrett (2006) proposed an asset-based approach to distinguish a structural component of poverty that is systematically poor over the years from 'poverty that passes naturally with time due to systemic growth process' (p. 178). They also suggested the need for controlling

[1] Exceptions include Baulch and McCulloch (2002) for Pakistan, Bigsten and Shimeles (2008) for Ethiopia and Glauben, Herzfeld and Wang (2012) and You (2011) for China.

for unobserved household characteristics and the initial endogeneity (p. 194). This is fully taken into account by the present study. Considering the asset dynamics, Adato, Carter and May (2006) have applied both quantitative and qualitative approaches for South African panel data and have shown that a large number of households are trapped into poverty without a pathway out. Antman and McKenzie (2007) used the pseudo panel data of Mexico with nonlinear income dynamics and allowed for measurement errors and heterogeneity. They showed that there is no evidence for poverty traps. These studies point to the need for identifying the structural component of poverty by eliminating stochastic components or measurement errors. While our binary classification of poverty depends on the raw consumption data which are to some extent subject to measurement errors or stochastic fluctuations, the present study will provide explanations on why poor households are trapped into poverty by tracking the individual's unique history and experience, which has been neglected in the literature on poverty traps.

The rest of the article proceeds as follows. Section II presents our econometric models. Section III introduces the data and examines the trend of poverty in rural China. Econometric results are then discussed and explained in section IV. Section V offers concluding remarks and policy implications.

II. Methodology

Modelling poverty exit and entry

In the baseline model, households are indexed by i. In the time interval j, a standard discrete-time hazard model is defined by:

$$h_i(t_j) = \Pr(T_i = t_j \mid T_i \geqslant t_j), \tag{1}$$

where T_i is the time a (non-)poverty spell ends. Empirically, we use a complementary log–log specification to accommodate the underlying discrete time when a transition into or out of poverty occurs. As in Devicienti (2002) and You (2011), the probability that household i escapes from poverty at duration d at time t_j, given it has stayed in poverty spells up to t_j, takes the following form:

$$e_i(d, X_{ij} \mid \upsilon_i^P) = 1 - \exp[-\exp(f^P(d) + X_{ij}'\beta^P + u_i^P)], \tag{2}$$

where $f^P(d)$ is the baseline hazard which is a function of duration that i has been stuck in poverty spells; X_{ij} includes household-specific characteristics and aggregate covariates that are time-varying and supposed to affect poverty transition; $u_i^P \equiv \log(\upsilon_i^P)$ denotes the unobserved household-specific heterogeneity which is time-invariant and shared by i's all poverty spells. By analogy, the probability that household i enters poverty at duration d at time t_j, given that it has been non-poor up to t_j, is written by:

$$r_i(d, X_{ij} | \upsilon_i^N) = 1 - \exp[-\exp(f^P(d) + X_{ij}'\beta^N + u_i^N)], \tag{3}$$

where $f^P(d)$ is a function of duration that i has successfully maintained non-poverty spells; X_{ij} is defined as before; $u_i^N \equiv \log(\upsilon_i^N)$ is the unobserved heterogeneity accounting for non-poverty spells.

It is useful to elaborate on two empirical issues which may bias the estimation of equations (2) and (3). First, how to define two baseline hazards could potentially make significant differences in estimated duration dependence. We attempt a fully non-parametric form, that is, a set of dummy variables specifying duration as well as an interval at which households are at risk of shifting out of (non-)poverty spells.[2] Second, failure to consider the unobserved heterogeneity would seriously bias the estimated duration-dependence and the proportionate responses of the hazards to estimated coefficients (Jenkins, 2005). In section IV, we will take into account unobserved heterogeneity in estimating equations (2) and (3). This second step further involves two problems that deserve attention. For one thing, the estimation of hazard models with unobserved heterogeneity requires knowledge of the distribution of these unobservables in order to integrate them into the estimation. We use Heckman and Singer's (1984) non-parametric maximum likelihood (NPML) estimation where the distribution of unobserved heterogeneity is approximated by a bivariate discrete distribution with a number of latent classes – also termed mass points – which are left determined by the data. This is a more general method than the parametric approach in which, for example, normal and gamma distributions are assumed for the unobserved heterogeneity.

Specifically, suppose there are $w \in \{1,2,\ldots,W\}$ groups of households within the study population who are endowed with different but unobserved characteristics that underlie different hazards of poverty exit and entry. Falling into the group w is attached by a probability π_w with $\sum_{w=1}^{W} \pi_{\hat{w}} = 1$. For the type w, the hazard functions of poverty exit and re-entry [equations (2)–(3)] can be re-written by:

$$e_i(d, X_{ij} \mid \mu_w^P) = 1 - \exp[-\exp(f^P(d) + X'_{ij}\beta^P + \mu_w^P)] \tag{4}$$

and

$$r_i(d, X_{ij} \mid \mu_w^N) = 1 - \exp[-\exp(f^N(d) + X'_{ij}\beta^N + \mu_w^N)], \tag{5}$$

where μ_w^P and μ_w^N with $w \in \{1,2,\ldots,W\}$ are known as location parameters which are a number of discrete values capturing the effects of the latent classes on the exit and entry rates, respectively.[3]

Another issue attached to heterogeneity is that we have so far implicitly assumed that there is no correlation between u_i^P and u_i^N for parametric estimations and independent μ_w^P and μ_w^N in the non-parametric case, that is, they follow the non-parametric distributions $G(\mu_1^P, \mu_2^P, \ldots, \mu_W^P)$ and $G(\mu_1^N, \mu_2^N, \ldots, \mu_{W'}^N)$ with their own optimal numbers of latent classes W and W', respectively.[4] In other words, the unobservables pushing households up to a

[2] We have also tried (i) a parametric specification making the baseline hazard dependent on the log time spent in (non-)poverty spell and (ii) a piece-wise semi-parametric specification grouping different durations into time periods. Both specifications yielded broadly consistent results.

[3] The optimal number of the latent classes W is determined by the data itself using the Gâteaux derivative method (Lancaster, 1990). That is, we begin by assuming two mass points and estimate the equations (3)–(4). The maximum likelihood and estimators of the model are saved and passed to a new round of estimation with an additional mass point which is located by moving from the smaller mass point to the bigger one with some number of steps (grids). We check the maximum increase in likelihood by computing the Gâteaux derivatives which are directional derivatives along the location we insert new mass points. We keep adding new mass points until the maximum increase in likelihood is zero, that is, the maximum Gâteaux derivative is not positive. It is noted that W is not necessarily the same across exit and entry regressions.

[4] Here we distinguish between W and W' as distributions of heterogeneity can be different for exit and entry regressions.

poverty line are irrelevant to those pulling them back again, which is an over-simplified and strict assumption. It would be a matter of concern if the unobservables pertinent to poverty and non-poverty spells were actually correlated. Devicienti (2011) and Maes (2013) introduce a discrete-time hazard model that relaxes this assumption and allows for the initial poverty status to be determined endogenously.

To minimize misspecifications, we rely on the non-parametric setup [equations (4)–(5)] and stick to NPML. Drawing upon Devicienti's work, we assume that μ_w^P and μ_w^N are jointly distributed with the un-predetermined distribution function $G(\mu_1^P,\ldots,\mu_W^P,\mu_1^N,\ldots,\mu_{W'}^P)$ together with optimal numbers of mass points W for the exit regression and W' for the entry one. These adjusted models are estimated by ML.

The models presented in this subsection are aimed at identifying the determinants of poverty exit or entry. As the estimations are virtually based on pooled non-poverty spells across households and over time, these models can also be understood as a *static* model of poverty transition. In what follows, we proceed to investigate who moves in and out of poverty and why they do so by tracking individual household's history of multiple transitions. In this sense, we will provide a *dynamic* picture that will unveil time-varying and 'transition-destination' specific impacts of the correlates on poverty transitions.

Modelling multi-path of multiple poverty transitions

We are interested not only in the actual transition outcome which is simply labelled exit or entry, but also in the specific destinations of such a transition. For example, suppose there are two households A and B who have the same high probability (hazard rate) of shifting out of a poverty spell and they experience only this single spell of poverty. The household A has realised this probability because it has members who have migrated and have regularly sent remittances back, while B has escaped because it has succeeded in increasing the efficiency and profitability of agricultural production. A similar argument can be applied to multiple spells during which two households descend into poverty following the first exit and then escape again. The causes of the first and second shifts out of poverty are not necessarily identical for the same household, or across households. In cases of both single and multiple transitions, latent heterogeneity also plays a role in households' decision-making besides their observed characteristics. These complex and endogenous pathways under lying multiple transitions cannot be captured by the baseline model unless we track individual household's spells and transitions of non-poverty as well as associated household choices.

We give particular attention to (i) multiple spells of poverty and non-poverty, (ii) endogenous 'dynamic selection' and (iii) unobserved heterogeneity correlated across spells as well as various destinations within the spell. Figure 1 presents pathways of poverty transition according to different household livelihood strategies.[5] We classify household livelihood strategies into three categories: farming, local non-agricultural employment and out-migration. These categories are defined by the household's labour allocation. A household, for example, is regarded as a 'farming' household if the household's labour input

[5] We also examined pathways of poverty transition according to the availability of social protection. The details will be provided on request.

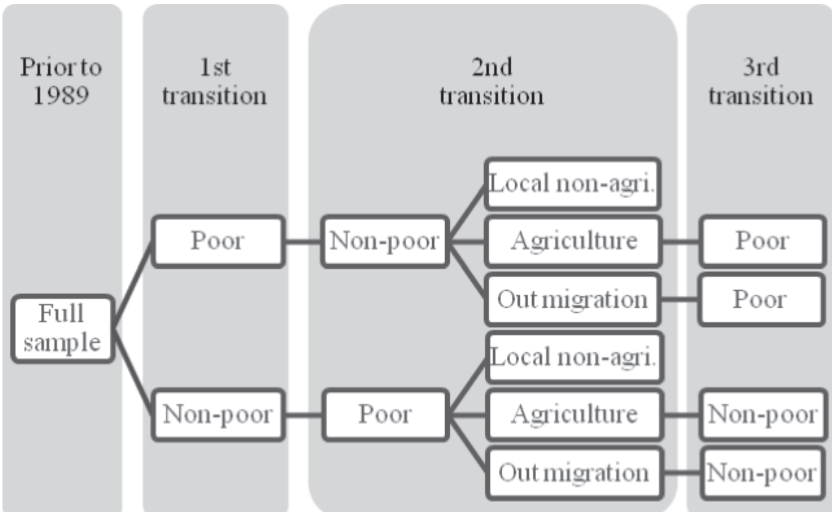

Figure 1. Pathways of poverty transition (by livelihood strategy)

in agricultural production (in terms of the number of household members who reported the main employment as ‘farming’) is the largest of the three. Defined in this way, three categories are made mutually exclusive and interdependent. That is, they are competing but correlated destinations – also known as ‘dependent competing risks’ in duration analysis – which are faced by the household when it shifts from the current spell.

As shown in Figure 1, we are supposed to have ‘a full sample’ prior to the first survey in 1989. In 1989 when we first observed households’ poverty status, some of them were poor while others were not, which could be determined by observed as well as certain unobserved characteristics, such as intrinsic capabilities, effort levels and cognitive abilities of household members. Households endogenously ‘selected’ themselves to be poor in 1989. A few of them experienced chronic poverty until 2009. In this case, these households were considered to have experienced only a single poverty spell. By contrast, some households were able to escape from poverty, that is, they faced the second transition and started the second spell of ‘non-poverty’. We stop tracking households at the third transition.

The transition (or the hazard rate) at the end of the first spell is associated with three correlated destinations associated with households’ different livelihood strategies. Latent heterogeneity matters along the entire chain of shifts. The unobserved heterogeneity affecting households’ initial poverty status in the first transition and the one forcing them to fulfil different routes of poverty exit and re-entry in the following transitions might be correlated. Moreover, there might be a correlation between unobservables (e.g. ability, skills or entrepreneurship) and observed variables (e.g. educational attainment) which would bias the estimates of observed covariates. This sort of endogeneity along the household’s observed sequence of transitions over time is termed ‘dynamic selection’ in Cameron and Heckman (1998).

Having laid out Figure 1, we match multiple transitions into and out of poverty with interdependent destinations at each of them. We therefore follow Jenkins’ (2005) multinomial logit framework to estimate the dependent competing risks model, while extending it to the multinomial transition model with unobserved heterogeneity (MTMU) developed by Karlson (2011) who applied it to individuals' educational choices for various stages of education. In the remainder of this section, we will first present standard multinomial models but relax the well-known assumption of independent from irrelevant alternatives (IIA) at each transition to accommodate dependent competing risks, and then link each transition as in its observed sequence with the jointly distributed unobserved heterogeneity to phase out endogeneity caused by the dynamic selection.

We assume that each household i embodies unobserved latent propensity y^*_{iak} towards choosing the alternative path $a$at transition $k \in \{1,2,3\}$. Within each transition, there are A different alternative pathways indexed by a and A could vary across transitions. y^*_{iak} can be described by a number of factors x_{ij} as follows:

$$y^*_{iak} = \sum_{j=1}^{J} b_{ajk} x_{ij} + \varepsilon_{iak}, \tag{6}$$

where b_{ajk} measures the influence of the covariate x_{ij} on i's latent propensity for choosing the alternative a at transition k; ε_{iak} denotes the transition-alternative-specific random error terms that are distributed extreme value, $\varepsilon_{iak} \sim \mathrm{EV}(0, \sigma_k^2 \pi^2/6)$.[6] Let y_{ik} denote household i's observed status at the kth transition. The household i would choose a if it suggests the largest propensity for a, that is,

$$y_{ik} = a \quad \text{if } y^*_{iak} > y^*_{ia'k} \quad \text{for all } a \neq a'. \tag{7}$$

In the standard multinomial logit framework, ε_{iak} ought to be uncorrelated across all alternative pathways within each transition, which is the IIA assumption. Let $a = 1$ be the reference alternative against which other contrast choices (or 'competing risks' in the duration analysis) are defined. The probability of choosing $a > 1$ in a standard multinomial form is:

$$\Pr(y_{ik} = a \mid x_{ij}) = \frac{\exp(\sum_{j=1}^{J} \beta_{akj} x_{ij})}{1 + \sum_{s=2}^{A} \exp(\sum_{j=1}^{J} \beta_{skj} x_{ij})} \quad \text{for } a > 1, \tag{8}$$

where $\beta_{akj} = b_{akj}/\sigma_k$ is the logit coefficient (log odds-ratio) with the scale factor σ_k; $\beta_{1kj} = 0$ for normalizing the model so that the baseline alternative is recognised by $a = 1$.

We have so far presented standard multinomial logit models at each transition k with the IIA assumption binding. Recall that we have argued that the unobservables could affect simultaneously poverty spells and non-poverty spells. Here the same argument will hold. Households' choices may be correlated through ε_{iak} because if removing one alternative, those who would have chosen this pathway are less likely to distribute their choices randomly across the remaining alternatives (Karlson, 2011). The violation of IIA could therefore be understood as 'correlated unobserved heterogeneity' across alternative choices within the transition. To see this, consider that $\varepsilon_{iak} = \upsilon_{iak} + \xi_{iak}$ where υ_{iak} denotes the household unobserved heterogeneity influencing its choice over a at the kth transition; ξ_{iak} is a random residual which is alternative-irrelevant and satisfies i.i.d. In this way, we can also refer to Heckman and Singer (1984) to relax the IIA assumption on ε_{iak} and handle the problem of omitted important unobservables. We assume that households fall into $u_{akw} \in \{u_{ak1}, u_{ak2}, \ldots, u_{akW}\}$ latent classes

[6] A standard logit model is traditionally normalized to $\pi^2/6$. See Train (2009) for detailed discussion about the normalization with i.i.d. errors and the scale parameter σ_k.

with the probability π_w being attached to each latent class w to approximate the unobserved heterogeneity (υ_{iak}) for household's choosing alternative a at the kth transition. Thus, for those falling into the class w at the kth transition, the standard multinomial logistic model (8) can be extended to the one which is conditional on the unobserved heterogeneity as:

$$\Pr(y_{ik}=a\,|\,x_{ij},\upsilon_{iak})=\frac{\exp(\sum_{j=1}^{J}\beta_{akj}x_{ij}+u_{akw})}{1+\sum_{s=2}^{A}\exp(\sum_{j=1}^{J}\beta_{skj}x_{ij}+u_{skw})}\quad \text{for } a>1, \tag{9}$$

where u_{akw} is the location parameter. The distribution function $G(u_{ak1},\ldots,u_{akW},\ldots,u_{Ak1},\ldots,u_{AkW})$ can be approximated non-parametrically by a number of latent classes for each alternative. As such, the choice of each alternative destination within the transition is made dependent on 'jointly distributed' and 'alternative-specific' unobserved heterogeneity of the household.

Now we proceed to link transitions by households' own unique routes. Suppose household i opts for the alternatives, a, a' and a'' from the first to the third transition in turn, as illustrated in Figure 1. Based on equation (9), the probability of making three consecutive transitions is defined by:

$$\Pr(y_{ik}=a\,|\,x_{ij},u_{a1w})\times\Pr(y_{ik}=a'\,|\,x_{ij},u_{a2w})\times\Pr(y_{ik}=a''\,|\,x_{ij},u_{a3w}). \tag{10}$$

Households fall into the latent class w in each transition [i.e. $(u_{a1w},u_{a2w},u_{a3w})$] with the probability π_w making them choose the route $\{a,a',a''\}$. The multivariate probability unconditional on unobserved heterogeneity is therefore expressed by a finite mixture model:

$$\begin{aligned}
&\Pr(y_{ik}=a,a',a''\,|\,x_{ij})\\
&=\sum_{w=1}^{W}\Pr(y_{i1}=a\,|\,x_{ij},u_{a1})\times\Pr(y_{i2}=a'\,|\,x_{ij},u_{a2})^{I}\times\Pr(y_{i3}=a''\,|\,x_{ij},u_{a3})^{I'}\pi_w\\
&=\sum_{w=1}^{W}\frac{\exp(\sum_{j=1}^{J}\beta_{a1j}x_{ij}+u_{a1w})}{1+\sum_{s=2}^{A}\exp(\sum_{j=1}^{J}\beta_{s1j}x_{ij}+u_{s1w})}\times\left[\frac{\exp(\sum_{j=1}^{J}\beta_{a'2j}x_{ij}+u_{a'2w})}{1+\sum_{s'=2}^{A'}\exp(\sum_{j=1}^{J}\beta_{s'2j}x_{ij}+u_{s'2w})}\right]^{I}\\
&\quad\times\left[\frac{\exp(\sum_{j=1}^{J}\beta_{a''3j}x_{ij}+u_{a''3w})}{1+\sum_{s''=2}^{A''}\exp(\sum_{j=1}^{J}\beta_{s''3j}x_{ij}+u_{s''3w})}\right]^{I'}\pi_w,
\end{aligned} \tag{11}$$

where I (I') is an indicator variable taking the value one if the household who has 'survived' to face the second (third) transition and zero otherwise. As stated earlier, we have assumed a joint unspecified distribution for the unobservables affecting households' separate choices in three transitions. The distribution function $G(u_{a1},u_{a2},u_{a3})$ is approximated non-parametrically by a number of latent classes w as in Heckman and Singer (1984). Here, unobservables are allowed not only to affect alternatives within transitions, but also to be correlated across transitions. This captures the 'dynamic selection' and hence, addresses the endogeneity associated with the initial poverty status. The finite mixture multinomial logit model (11) is what we mean by MTMU and can be estimated by NPML.

III. Data

We employ a balanced panel tracking the same rural households over time. The panel is extracted from China Health and Nutrition Surveys (CHNS) in 1989, 1991, 1993, 1997, 2000, 2004, 2006 and 2009 covering seven provinces. The provinces included are Jiangsu and Shandong, the coastal provinces with a higher level of economic and human development in terms of the provincial Human Development Index (HDI) (UNDP, 2005), Henan, Hubei and Hunan, the central provinces with their GDP per capita and HDI ranked in the middle and Guizhou and Guangxi, south-western provinces with the high population share of ethnic minority groups and with the lowest levels of GDP per capita and human development. The population in these provinces covers 35.57% of the total population and 37.84% of the rural population at the end of 2006. While no household in the north east or in the municipalities are included, the data capture well the diversity in rural China. The survey used a multistage, random cluster process to select individuals. Counties in every province were stratified based on the gross value of agricultural and industrial output, and one county is selected from each quintile. The same criteria were applied to select villages in each county, and finally households were randomly chosen in each village.

We begin by selecting 'rural' households as those with rural registration (*Hukou*) and living in villages in 1989. From this pool, we picked up those who have been re-interviewed in the seven follow-up rounds and kept living in villages full-time. There are 1,304 rural households in our balanced panel data.[7,8,9] The sample households are equally spread across provinces and income quintiles.[10]

[7] Households were tracked using the 'dwelling' rule. Those who migrated entirely from one sample community to a new one out of sample areas were not followed. However, when only some family members migrated and the original family still lived in the sample areas, this family would still be included and the family members not living in the family at the time of interview would be tracked as long as they could be contacted.

[8] An important question is whether a household is an appropriate unit of analysis and is comparable over such a long period. First, it is difficult to estimate individual income or consumption not only because a significant part of income or consumption is shared among household members but also because reliable individual income or consumption data are unavailable in China. Second, while the problem of attrition is inevitable for such a long panel in which '(o)ver time, households form, grow, shrink and spilt apart' (Jenkins, 2011, p. 36), it would not be totally unreasonable to assume that we can track the same household and compare its consumptions consistently over time despite the limitations. This is because (i) non-random attrition was observed, but it was not as serious as expected for such a long panel in which the annual equivalent attrition rate of households was 3.5% and much lower than 7% for Brazil, 6% for South Africa or 9.5%–12.5% for developing countries (Barrientos and Mase, 2012): on average only 24.5% of households in the panel reported 'excluded' family members in one of the eight survey years due to events like marriage, migration and death, and in these households the average number of 'excluded' family members was only 1.5; from 1993, only 4 to 14 out of 1,304 households reported new family members in various survey years; (ii) all the household members who lived elsewhere (i.e. 'excluded') at the time of interview were included if they maintained economic connections with the household, for eample, sending remittances; and (iii) the same questionnaire has been used over the years. However, our results will have to be interpreted with caution because of these structural changes in household composition over time. It is also noted that re-estimating the same models using an unbalanced panel has given broadly similar results (Table 1). The initial sample size for the unbalanced panel was 2,537.

[9] We have tested whether attrition stems from some observed characteristics like demographic changes or asset accumulation, and unobserved characteristics and whether it affects household consumption by the added regressor test (Giesbert and Schindler, 2012) and a Heckman-type selection method proposed by Wooldridge (2002). We found that attrition appears to be irrelevant to households' both unobserved and most observed characteristics (except migration) and its effects on household per capita consumption are not statistically significant. Migration increased the likelihood of household attrition with marginal statistical significance at 10% level in 2000 and 2009. In order to check further the sensitivity of our results to this non-negligible attrition caused by migration, we adopted Fitzgerald, Gottschalk and Moffitt's (1998) procedure to weight observations by inverse probabilities, that is, by giving excluded households relatively more weight. Re-estimating columns (1) and (4) of Table 1 with the weighted balanced panel yielded similar results, which will be furnished on request. However, these are only statistical validations and do not imply that the structural changes in household composition are unimportant.

[10] See Appendix for the list of variables.

It is worth noting that the choice of poverty indicator could affect seriously the picture we can draw from the data about sample households' welfare. Income has been widely used to study poverty in China, while this indicator has been criticized as underestimating China's poverty headcounts by about 10% as average income is 10%–20% higher than expenditure (Park and Wang, 2001). It may also overstate income mobility (Naschold and Barrett, 2011) and inflate the dynamics of poverty (Baulch and Hoddinott, 2000) due to greater volatility coming from measurement errors and/or households' consumption-smoothing behaviour.[11] In the context of developing countries where individual or household income is measured with considerable errors due to over- or under-reporting problems or other factors, per capita household consumption is the best available indicator for measuring poverty over time (Deaton, 1997; World Bank, 2009).[12] Jenkins (2011) rightly argues that individual income, despite its limitations, should be ideally used as an indicator to analyze poverty dynamics because of the difficulty of tracking the household income or consumption consistently over time, but this option is usually difficult in developing countries and the World Bank has thus proposed a use of per capita household consumption as a benchmark of international poverty using the US$1.25 or US$2 a day cut-off (Ravallion, Chen and Sangraula, 2009). The present study will follow the World Bank approach while remaining aware of its limitations.

Taking these empirical issues into account, we use consumption as the welfare indicator and study household poverty measured by per capita consumption against a set of monetary poverty lines. Specifically, we first recalculate the international poverty lines of US$1.25/day and US$2/day to accommodate different cost-of-living for the poor in rural and urban areas (37% higher for the urban poor in 2005 as suggested by Chen and Ravallion, 2010). Then, to better insulate consumption from the influence of measurement errors, we follow Devicienti (2002) and define the poor as those whose per capita household consumption falls below 90% (or 110%) of the poverty line of US$1.25/day or US$2/day. This is what we call 'adjusted' poverty lines in contrast to the 'unadjusted' ones which are simply the 1.25 dollar-a-day and 2 dollar-a-day lines. At the same time, we use a food poverty line of 620 yuan in 2002 prices based on 2,100 calories intake per person per day as a robustness check.[13]

[11] Naschold and Barrett (2011) argued that estimated income mobility is greater as it is magnified by the stochastic factors and that degree of income mobility is likely to be sensitive to the duration chosen. First, the use of consumption, not income, would greatly mitigate these problems. Second, we have used different poverty thresholds/durations as sensitivity tests for measurement errors with broadly similar results.

[12] Closely following the definition taken by Benjamin, Brandt and Giles (2005), who constructed consumption data with a national representative survey conducted annually by the Research Center for the Rural Economy (RCRE) at the Ministry of Agricultural of China, we calculated our household consumption as the sum of household food expenditure (including the own consumption of self-produced crop) as well as non-food expenditure on consumer durables, medical and health insurance, services and other items available in CHNS data. For food consumption, we used the imputed price based on the Rural Household Survey conducted annually by the National Bureau of Statistics (NBS) times the quantity recorded in the CHNS. For other kinds of expenditure, CHNS directly recorded the monetary values. All monetary variables have been translated into real terms by using the spatial price index for rural areas which was constructed by the CHNS team and comparable across sample provinces and over time. We compared constructed average household per capita consumption in CHNS with relevant indicators in Rural Household Survey which is conducted annually by the NBS and is the most representative survey for rural China. They appear to be very close to each other.

[13] This is an average food poverty line for rural China (Ravallion and Chen, 2007).

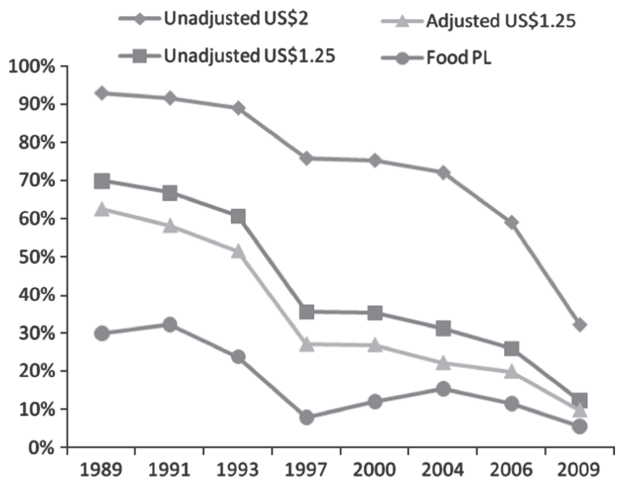

Figure 2. Profile of poverty rates
Source: Authors' calculation based on CHNS data.

Figure 2 depicts the changes of poverty rates measured by household per capita consumption against various poverty lines. Whichever poverty line is used, there is an overall decreasing trend of poverty over time. On a slowdown of poverty reduction we discussed in Section I, the poverty rate decreased by only 0.15–0.53 in percentage points under the three World Bank poverty lines and increased by 4.2 in percentage points under the food poverty line in 1997–2000. Poverty reduction has accelerated again since 2004. However, the lower the poverty line applied, the slower the pace of reduction. This signals that the poorest households tend to remain poor and that inequality has increased over time.

IV. Results and discussion

Correlates of transitions into or out of poverty

Following the discussions in section II, we have estimated single competing risk models without controlling for heterogeneity[14] [for equations (2)–(3)] and the model controlling for heterogeneity and allowing for interdependent unobservables across spells of poverty and non-poverty [for equations (4)–(5)] – the latter of which has been estimated with and without additional covariates. To save space, we present only the latter with additional covariates in Table 1. Columns (1)–(3) report the results for exit from poverty and columns (4)–(6) show those for entry into poverty. Columns (1)′ and (4)′ present the results based on the unbalanced panel.[15]

[14] We have applied a fully parametric baseline hazard function, the piece-wise semi-parametric specification and the fully non-parametric specification and obtained broadly consistent results.

[15] It is noted that the use of the unbalanced panel may significantly bias the observed number and length of poverty/non-poverty spells and the time when exit or entry happens. This is particularly problematic in the MTMU model which relies on the sequence of transition. The results of unbalanced panel should be thus interpreted with caution and our analysis primarily uses the balanced panel data.

TABLE 1

Correlates of poverty transition (by disaggregated measures)

Independent variable	*Exit (balanced panel)*			*Exit (unbalanced panel)*	*Entry (balanced panel)*			*Entry (unbalanced panel)*
	(1)	(2)	(3)	(1)′	(4)	(5)	(6)	(4)′
Duration dependence								
D1	−0.154	−0.112	−0.142	−0.113	−0.391	−0.404	−0.381	−0.362
	(0.073)**	(0.073)	(0.074)*	(0.080)	(0.116)***	(0.116)***	(0.115)***	(0.119)***
D2	−0.320	−0.357	−0.285	−0.278	−0.945	0.961	−0.926	−0.918
	(0.090)***	(0.089)***	(0.091)***	(0.094)***	(0.171)***	(0.171)***	(0.172)***	(0.174)***
D3	−0.367	−0.358	−0.352	−0.329	−2.831	−2.830	−2.830	−2.802
	(0.110)***	(0.110)***	(0.110)***	(0.114)***	(0.453)***	(0.454)***	(0.454)***	(0.454)***
D4	−0.033	−0.038	−0.018	−0.001	−3.568	−3.576	−3.563	−3.552
	(0.115)	(0.114)	(0.115)	(0.118)	(0.712)***	(0.717)***	(0.712)***	(0.712)***
D5	−0.108	−0.096	−0.093	−0.069	−2.581	−2.566	−2.568	−2.570
	(0.160)	(0.160)	(0.160)	(0.162)	(0.508)***	(0.508)***	(0.508)***	(0.509)***
D6	0.839	0.834	0.848	0.864	−3.418	−3.394	−3.433	−3.406
	(0.204)***	(0.203)***	(0.204)***	(0.205)***	(1.007)***	(1.008)***	(1.008)***	(1.008)***
Household characteristics								
hh size	−0.043	−0.043	−0.047	−0.046	0.030	0.041	0.030	0.034
	(0.024)*	(0.024)*	(0.024)*	(0.025)*	(0.040)	(0.039)	(0.040)	(0.040)
Age of hh head	0.021	0.020	0.021	0.021	0.001	0.0002	0.002	−0.018
	(0.003)***	(0.003)***	(0.003)***	(0.003)***	(0.004)	(0.004)	(0.004)	(0.029)
% primary edu.	0.442	0.426	0.461	0.428	0.171	0.142	0.192	0.204
	(0.145)***	(0.143)***	(0.145)***	(0.146)***	(0.261)	(0.260)	(0.262)	(0.266)
% secondary edu.	0.588	0.631	0.618	0.578	0.256	0.195	0.276	0.221
	(0.146)***	(0.145)***	(0.146)***	(0.148)***	(0.272)	(0.270)	(0.272)	(0.280)
% tertiary edu.	0.180	0.237	0.262	0.203	1.996	1.836	2.035	2.037
	(0.183)	(0.185)	(0.184)	(0.187)	(0.311)***	(0.302)***	(0.314)***	(0.319)***

(continued)

TABLE 1

(*Continued*)

Independent variable	*Exit (balanced panel)*			*Exit (unbalanced panel)*	*Entry (balanced panel)*			*Entry (unbalanced panel)*
	(1)	(2)	(3)	(1)′	(4)	(5)	(6)	(4)′
No. of adults	0.047	0.085	0.053	0.048	−0.018	−0.026	−0.021	−0.036
	(0.031)	(0.031)***	(0.031)*	(0.032)	(0.049)	(0.049)	(0.049)	(0.050)
Wealth								
ln(cultivated land)	0.065	0.022	0.049	0.072	−0.013	0.001	−0.017	−0.007
	(0.026)**	(0.026)	(0.026)*	(0.027)***	(0.042)	(0.042)	(0.042)	(0.043)
Index of agricultural assets	0.087	0.043	0.074	0.109	−0.628	−0.617	−0.640	0.659
	(0.086)	(0.086)	(0.087)	(0.087)	(0.187)***	(0.187)***	(0.187)***	(0.197)***
hh small business	0.064	−0.008	0.063	0.059	0.003	0.014	0.004	−0.012
	(0.051)	(0.052)	(0.052)	(0.052)	(0.081)	(0.081)	(0.081)	(0.084)
Access to off–farm labour market								
% local non-agricultural employment within hh	−0.054	0.111	−0.017	−0.060	−0.285	−0.368	−0.259	−0.169
	(0.129)	(0.127)	(0.129)	(0.130)	(0.383)	(0.386)	(0.383)	(0.384)
% village out-migration	2.453	1.994	2.178	2.598	−0.091	0.145	−0.060	−0.030
	(0.305)***	(0.310)***	(0.315)***	(0.351)***	(0.566)	(0.576)	(0.609)	(0.647)
Social protection								
% hh members having health insurance	1.500		1.572	1.509	−0.451		−0.439	−0.404
	(0.075)***		(0.075)***	(0.079)***	(0.168)***		(0.168)***	(0.212)*
% hh members having commercial insur.		−0.641				−0.040		
		(0.241)***				(0.798)		

(*continued*)

TABLE 1

(*Continued*)

Independent variable	*Exit (balanced panel)*			*Exit (unbalanced panel)*	*Entry (balanced panel)*			*Entry (unbalanced panel)*
	(1)	(2)	(3)	(1)′	(4)	(5)	(6)	(4)′
% hh members having government free insur.		−0.313				0.119		
		(0.302)				(0.639)		
% hh members having NCMS		1.515				−0.542		
		(0.075)***				(0.206)***		
Local development								
Urbanization	0.800	1.427		0.008	0.009	−0.002		−0.452
	(0.210)***	(0.203)***		(0.002)***	(0.372)	(0.367)		(0.174)***
Economic activities			−0.011				−0.023	
			(0.011)				(0.023)	
Access to markets			0.026				0.001	
			(0.008)***				(0.014)	
Social services			0.054				0.019	
			(0.013)***				(0.038)	
Log-likelihood	−4,413.743	−4,435.291	−4,405.084	−4,419.693	−4,413.743	−4,435.291	−4,405.084	−4,419.693

Notes: NCMS, new cooperative medical scheme.***, ** and * denote 1%, 5% and 10% significance levels. Standard errors are in parentheses.
Source: Authors' calculation based on CHNS data.

Coefficient estimates of dummy variables (D1–D6) indicate a first decreasing and then increasing duration dependence in columns (1)–(3) of Table 1. If the household experiences one or as much as three spells of poverty, the probability of escaping poverty decreases over time with coefficient estimates that are statistically significant. The more time spent in poverty, the less likely is the household to escape. However, the coefficient estimate turns to increase in absolute value from D4 to D5, which implies that the probability of exit becomes more or less stable for those who have been chronically poor for three to four consecutive periods and the probability of escaping from poverty would increase if they experienced five consecutive periods in poverty. On the other hand, consistently negative and increasing 'duration dependence' appears in the entry regressions [columns (4)–(6)]. For both exit and entry, the magnitude of coefficient estimates for D1 to D5 reveals non-linearity of negative duration dependence.

Among various demographic characteristics, a significantly negative coefficient of household size for exit indicates that a larger household is more likely to stay in chronic poverty. However, the household with more adult members is more likely to escape from poverty. Age of the household head is positive and significant for exit, implying that a household with an older head is more likely to exit from poverty.[16] Education also plays an important role. The households with more members having completed primary, secondary and tertiary education are all more likely to escape from poverty. For the entry into poverty, the coefficient estimates of primary and secondary education are statistically insignificant, but that of tertiary education is *positive* and significant. That is, households with more members who have completed tertiary education are more likely to exit from poverty but, in the meantime, they are more likely to enter into poverty. The latter result sounds counter-intuitive, while we suspect that this is due to the soaring cost of higher education in China (Gustaffson and Li, 2004; Démurger, Fournier and Yang, 2010) and/or large opportunity costs (de Brauw and Giles, 2008a).[17]

On household wealth, more cultivated land helps the poor escape from poverty [columns (1)–(3)]. Land is collectively allocated to each rural resident within the village on the basis of family size and the land rental market remains nascent. This induces land fragmentation and a mismatch between land and labour, for example, potentially idle land for some affluent families participating mainly in non-farm activities (Jin and Deininger, 2009). Endowing poor rural households who lack access to non-farm opportunities with more cultivated land can bring about substantial agricultural productivity gains (Jin and Deininger, 2009) and thus facilitate their escape from poverty. On the other hand, agricultural asset accumulation has a poverty-preventing effect [columns (4)–(6)]. The coefficient estimate for running a small business is statistically insignificant.

Recently, there has been a resurgence of interest in the role of agriculture in reducing poverty (Barrett, Carter and Timmer, 2010; de Janvry, 2010; de Janvry and Sadoulet, 2010; Christiaensen, Demery and Kuhl, 2011). Drawing upon cross-country data, Christiaensen *et al.* (2011) find that the poverty-reducing effect of agriculture is most prominent for the poor living under US$2/day. Agricultural development can also be crucial for poverty reduction for economies where there are extensive market failures in the factors market

[16] The squared term of age cannot be included as this will make impossible convergence during our maximizing the likelihood functions.

[17] Unfortunately, the expenditure on education cannot be verified by CHNS data.

(Dercon, 2009), like China. Echoing these studies, our estimation documents the paramount role of agriculture in determining rural households' poverty status. This is also consistent with the finding that productivity gains in agriculture are key to increase in rural households' income as well as poverty reduction in China (Ravallion and Chen, 2007; de Janvry and Sadoulet, 2010; Montalvo and Ravallion, 2010; Christiaensen, Pan and Wang, 2013). Overall, agricultural development is essential for healthier structural transformation, which in turn paves a sustainable pathway out of poverty (Barrett *et al.*, 2010).

Our results show that having more members engaged in local non-agricultural employment does not affect poverty exit or entry significantly. Limited local non-agricultural participation reflected by our data may explain this. In our data set, only 18%–22% of the poor had family members involved in local non-farm employment for various waves (i.e. 78%–82% of them were pure agricultural households). Among those households, the average number of family members in local non-farm employment was only 1.5–1.65 persons. Huang, Wu and Rozelle (2009) find that participation in off-farm employment is associated more with younger and well-educated households, but less with the poor.

It should be noted, however, that Knight and Song (2005) and Knight, Li and Deng (2010) found that the average and marginal returns to migrant and non-farm local employment are far higher than the returns to agricultural employment in rural China. If we take our results at face value, it is conjectured that the chronically poor did not have easy access to non-farm sector employment even though it is potentially highly productive, and they could get out of poverty only by increasing agricultural assets or land. However, it should be noted that our studies differ from Knight and Song and Knight *et al.* in a number of ways. First, we highlight consumption poverty at household levels, while Knight and Song and Knight *et al.* focus on returns to the factor of production at individual levels. Second, the data sources are different. These studies are based on much larger cross-sectional national household survey data sets in 1994 and 2002, while we use the long panel data for a smaller sample of households. In other words, the possibility that our results will hold only in the context of our data cannot be completely ruled out.

Also, village out-migration networks increase considerably the chance of escape from poverty [columns (2)–(3)], which is consistent with Du, Park and Wang (2005) and de Brauw and Giles (2008b). However, these effects of out-migration are not statistically significant for prevention of entry into poverty [columns (5)–(6)].

As revealed by Table 1, another prominent attribute to poverty transitions is health insurance. We observe that health insurance facilitates poverty exit and prevents poverty entry with large and statistically significant coefficient estimates.[18] We also added two important sources of income shocks as additional regressors and re-estimated Columns (1) and (4). A positive price shock of farm product accelerates considerably poverty exit. Weather shocks, proxied by the percentage share of cultivated land affected by various natural disasters at the provincial level, on the other hand, perpetuate chronic poverty by reducing the probability of exit. This has a significant policy implication for central and

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local governments in China particularly because rural residents in China have long been excluded from many social protection schemes that have been enjoyed mainly by urban residents. A typical example is health insurance. In 1993, only 12.8% of the rural population was covered by health insurance, such as voluntary community-based insurance, public medical care, social medical insurance and full- or semi-labour-related medical insurance. The share was smaller even after a decade of remarkable economic development (11.2% in 2003). If only the voluntary community-based insurance is accounted for, the corresponding share was only 6.6% in 1998 and 9.5% in 2003.[19] Since 2003, the government has re-launched community-based cooperative health insurance, the New Cooperative Medical Scheme (NCMS), aiming to expand social welfare for the rural population. Given the ongoing debate on whether and how far the introduction of NCMS effectively limits rural households' financial risks (Wagstaff *et al.*, 2009), we disaggregated the results into different kinds of health insurance. Columns (2) and (5) show that the positive (negative) and significant effect of health insurance on exit from or entry into poverty mainly works through the NCMS. Free insurance provided by the government, which was launched in a small range of areas and population in the early 1990s, has no statistically significant effect on exit or entry. The purchase of commercial health insurance tended to prevent a household escaping from poverty given that it involved large opportunity costs. Given the disaggregated results of health insurance, government might want to consider further extending community-based cooperative health insurance schemes in rural areas.

Urbanization helps rural households end poverty, but is not significant for preventing entry. Here urbanization is measured by 'the urbanization index', a proxy for comprehensive development changing the rural–urban environment gradually over time, such as population structure, economic (typically non-agricultural) activities, marketization, infrastructure, communication and delivery of education, health and other social services. The urbanization index at the village level which was constructed by Jones-Smith and Popkin (2010) has been incorporated into the CHNS by the survey team. Columns (1)–(3) point to a significant poverty-reducing effect of urbanization. However, it does not prevent households from entering into poverty [columns (4)–(6)].[20]

We have also disaggregated the urbanization index into three sub-components: economic activities, access to markets and social services. More economic activities in terms of higher wages for males and the per cent of population in non-agricultural work are statistically insignificant in both exit and entry regressions. On the other hand, easier access to markets and more social services (i.e. provision of preschool for children under three years old) significantly facilitate exit from poverty, but neither of them prevents entry into poverty. The exact mechanism whereby urbanization helps poverty reduction is not made clear by these results. However, it is conjectured that (i) urbanization would guarantee

[19] Authors' calculations based on Liu and Rao (2006) and China Health Statistical Yearbook 2008 published by the Ministry of Health.

[20] Columns (1)′ and (4)′ report the results based on unbalanced panel data. The results are similar to those in columns (1) and (4), but urbanization significantly reduces the probability of entering into poverty only in the case of the unbalanced panel. This may imply the greater importance of urbanization in poverty prevention for households that cannot be tracked for all years, for example, due to their migration to urban areas involving all family members in later rounds.

easier access to markets and facilitate everyday sales and purchases of agricultural and non-agricultural commodities – which would have positive effects on both household income and consumption of the poor; (ii) provision of preschool for children under three years would make easier women's participation in the labour market; and (iii) insurance benefit would help the poor cope with temporary shocks.

Multiple pathways underlying poverty transition

From the preceding analyses, household livelihood strategies stand out as important determinants of poverty transitions over time. This subsection presents our findings on which route steadily lifts households out of poverty by the MTMU model outlined in section II. In Table 2, the baseline alternative at the first transition is 'non-poor'. The first column reports coefficient estimates and standard errors for the probability being under 'initially poor' after taking account of the endogeneity of initial poverty status. The second transition corresponds to (the transition from poverty to) 'non-poverty' for each livelihood strategy. The results for 'agriculture' and 'out-migration' are presented in the second and the third columns. The last two columns are the results for the third transition, 'poverty' (from 'non-poverty') for 'agriculture' and 'out-migration'.[21] We have found that the initial poverty status is endogenous and dynamic selection exists,[22] which justifies our use of the MTMU model specification.

Taking non-poverty as the baseline alternative at the first transition, we find strongly negative duration-dependence in Table 2 because the positive estimate of the logarithm of years in poverty [ln(d)] implies that the longer a household experiences poverty, the more likely is it to be observed as being poor. That is, there appears to be strong persistence of poverty for some households. However, duration-dependence in poverty disappears during the second transition for those choosing agriculture and out-migration, compared to those who embark on local non-agricultural employment as a route to escape from poverty. It is striking to find that the duration dependence becomes *positive* [or the coefficient of ln(d) is negative] for both agricultural and out-migration pathways during the third transition, indicating a good chance to escape at longer duration. That is, a household, while staying longer in 'poverty' during the third transition, is *more* likely to escape from poverty should its household members be engaged in agriculture or out-migration. Comparing these two routes, the likelihood of escaping from poverty was higher for the households having chosen 'out-migration', as reflected in the larger absolute value of coefficient estimate of ln(d).

[21] The results for the case where the first transition is 'initially non-poor' and those with focus on social protection will be furnished on request.

[22] Employing Gâteaux derivatives, we have detected two latent groups under each destination-specific transition. The distinction between these two groups is determined by the likelihood of a household following a specific transition by taking into account both household observable and unobservable characteristics. In our case, there is a probability of 44.8% for households to be endowed with one group that predisposes them toward poverty at the first transition, while 55.2% of them fall in another group which makes them intrinsically less likely to be initially poor. On dynamic selection, for example, households under the initially 'non-poor' group consistently have lower likelihood of choosing agriculture or out-migration as a means to escape than local non-agricultural employment in subsequent transitions. Another clue is 'correlated heterogeneity' that is indicated by non-zero elements in covariance matrices of latent heterogeneity across destination-specific transitions.

TABLE 2

Multinomial transition model with unobserved heterogeneity (by livelihood strategies)

Independent variables	*1st transition*	*2nd transition*		*3rd transition*	
	Initial state: poverty	*Non-poverty*		*Poverty*	
Livelihood strategy		*Agriculture*	*Out-migration*	*Agriculture*	*Out-migration*
Baseline alternative at the 1st transition is 'non-poor'					
ln(d)	0.399 (0.141)***	−0.107 (0.259)	0.047 (0.283)	−1.349 (0.325)***	−2.378 (0.432)***
hh size	−0.065 (0.030)**	−0.133 (0.107)	−0.152 (0.118)	−0.189 (0.100)*	−0.243 (0.128)*
Age of hh head	−0.022 (0.003)***	0.026 (0.014)*	0.019 (0.015)	−0.006 (0.009)	−0.025 (0.012)**
% primary edu.	−0.570 (0.184)***	1.333 (1.292)	1.613 (1.331)	−0.166 (0.618)	−1.121 (0.838)
% secondary edu.	−0.494 (0.199)**	0.711 (1.186)	1.033 (1.227)	0.052 (0.575)	−0.883 (0.782)
% tertiary edu.	0.481 (0.268)*	3.804 (1.532)**	3.935 (1.596)**	6.216 (1.536)***	6.227 (1.582)***
ln(cultivated land)	0.179 (0.042)***	−0.414 (0.188)**	−0.438 (0.200)**	−0.026 (0.140)	−0.764 (0.186)***
Index of agricultural assets	−0.397 (0.136)***	0.648 (0.447)	0.547 (0.487)	0.114 (0.467)	−0.738 (0.696)
% local non-agricultural employment in hh	1.063 (0.334)***	−0.234 (0.688)	1.011 (0.774)	−1.721 (0.714)**	−0.616 (0.827)
% village out-migration	−2.157 (0.770)***	2.562 (1.913)	0.042 (2.079)	−2.931 (2.052)	−0.521 (2.273)
% hh members having health insurance	−0.122 (0.145)	−0.279 (0.442)	−0.377 (0.482)	−0.249 (0.359)	0.008 (0.479)
Urbanization	0.724 (0.354)**	4.022 (1.255)***	3.102 (1.331)**	−2.506 (1.329)*	−2.171 (1.405)
Log-likelihood	−5,285.704				

Notes: ***, ** and * denote 1%, 5% and 10% significance levels. Standard errors are in parentheses.
Source: Authors' calculation based on CHNS data.

Among households' demographic characteristics, a larger family size and the age of head are correlated with a lower likelihood of being 'initially poor'. Particularly during the third transition, both tend to reduce the possibility of re-entry into poverty. More members having primary and secondary education can help households reduce the possibilities of 'being poor' at the first transition with 11% and 9.5% respectively – which are calculated as the average partial effects (APE).[23] However, these variables do not affect significantly either exit or re-entry in the following transitions, that is, primary and secondary education reduces initial poverty only. More members receiving tertiary education can increase the chance of initial poverty by 9.3% during the first transition and double the re-entry rate during the third transition for farming households and APE for those following the route of out-migration is 24.6%. Higher education carries a threat of re-entry into poverty during the third transition.

We find a positive and selective role played by agricultural asset accumulation: it reduces the probability of being initially poor during the first transition. However, its selectivity dissipates in subsequent transitions. Surprisingly, more cultivated land appears to be correlated with initial poverty, which might be ascribable to inefficient land allocation policy in rural China (Brandt *et al.*, 2002), and less likelihood of exit during the second transition. This seems inconsistent with the results in Table 1 which shows that more cultivated land is an impetus to exit.[24] It is noted, however, that maintaining a larger area of cultivated land reduces the chance of re-entry into poverty for those who were initially poor and chose the route of out-migration during the third transition. In sum, land holdings and agricultural production appear to serve as safety nets, especially for those who migrated into cities. A larger share of household members in local non-agricultural employment seems to be associated with a higher probability of initial poverty. Nevertheless, non-agricultural employment serves as a valuable complement to the initially poor who select the agricultural route, as it reduces their likelihood of re-entry into poverty by 31.8% (APE) during the third transition. Village out-migration networks suggest strong negative correlation with initial poverty. However, this relationship disappears in the following transitions for the initially poor.

V. Conclusion

The objective of the present study is to identify the pattern and causes of households' transitions into and out of poverty using the long panel household data on rural China in the period 1989–2009, which were constructed from China Health and Nutrition Survey. We have proposed a discrete-time multi-spell duration model that not only corrects for correlated unobserved heterogeneity across transitions and various destinations within the transition, but also addresses the endogeneity due to 'dynamic selection' (Cameron and Heckman, 1998) associated with household livelihood strategies. The model identifies multiple pathways of poverty transitions through the household's endogenous choice on livelihood strategies. Our main empirical findings are summarized below.

[23] Computational details of APE as well as the estimates of APEs for all the variables will be furnished on request.

[24] In the MTMU model, we have controlled for households' history of transitions, which might have led to different results.

First, we have found (i) 'first decreasing and then increasing hazard rates' of exit as households spend more time in poverty and (ii) overall negative duration dependence between the entry rates and households' experience of non-poverty. Persistent poverty would arise from negative duration dependence as well as some latent heterogeneity predisposing households to poverty. However, households would still have a good chance to exit even though they have been subject to destitution for a long period, were they engaged more in agricultural production or out-migration. Second, primary and secondary education appears to greatly facilitate poverty exit. Although higher education tends to increase the probability of entry into poverty possibly due to the expensive tuition fees and/or large opportunity costs, it significantly increases the chance of exiting from poverty if household members chose to be engaged in agricultural employment or out-migration. Third, cultivated land is highly selective for households' initial poverty status, though it reduces the probability of falling into poverty again as a safety net if the household opted for agricultural employment or out-migration. Agricultural asset accumulation emerges to be an effective means as it reduces the probability of being poor at the initial transition. By contrast, out-migration is less likely to assist the exit from poverty for those who are initially poor. Overall, our study finds the primary role of agriculture in alleviating rural poverty given the limited roles of local non-agricultural sector and recurrent hardship accompanied by out-migration rife with various uncertainties associated with unstable jobs in cities. However, these conclusions should be interpreted cautiously as they are contradictory to Knight and Song (2005) or Knight *et al.* (2010) who found that the returns to local non-farm employment are higher than the returns to agricultural employment. We argued that many of the poor households may not have easy access to local non-farm employment.

Deriving any policy implication from the present study needs considerable caution given the rapid transformation rural areas of China are now experiencing. However, it would probably be safe to derive the following implications for policy from our empirical findings. First, poverty is a dynamic phenomenon as a majority of rural households have experienced multiple transitions between poverty and non-poverty. Policies to target the poor based on the single-year data would therefore be misleading. Public policies which would promote urbanization during rural transformations should be carefully phased and implemented, as they can have a differential effect on poverty-reduction depending on the stage of transformations. Second, although the total number of the poor has declined, there are a substantial number of households which have been chronically poor and need to be supported by public interventions. We have seen that poverty tends to be perpetuated particularly if we adopt the lower poverty lines. Third, agriculture holds great potential to address rural poverty. The policy of promoting the agricultural sector, in particular providing poor households with cultivated land and agricultural assets would be crucial to help them escape from the chronic poverty in the middle or long run. However, our results are likely to be context-specific and they will never undermine the importance of the non-farm sector in poverty alleviation in rural China. There is also room for agriculture to serve as a safety net in terms of preventing recurrent poverty, especially for those relying on out-migration to escape from poverty, because the migrants are exposed to many uncertainties without being covered by social protections. Finally, while health insurance was not universally effective as an instrument for alleviating poverty, our disaggregated analysis has shown that only the NCMS – a community-based cooperative health insurance scheme – was effective in helping the poor escape from poverty and prevent the non-poor from backsliding again. This implies that the type of insurance is crucial and government might want to consider further extending the NCMS in rural areas. In sum, supporting the agricultural sector with a particular focus on the poorest households and providing appropriate measures for insurance for them would be an optimal policy focus for the alleviation of poverty in rural China.

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V. Appendix 1

TABLE A1
List of variables

Variable	*Definition*	*Mean*	*SD*
hh per capita consumption	Household total consumption including remittances in 2009 prices divided by household size	1,839.50	1,767.81
hh size	No. of household members interviewed, including those living in the household full-time and currently living elsewhere (due to studying, migration, etc.) but still registering with the household	4.11	1.51
Age of hh head	Age (in years) of household head	49.45	12.54
% primary edu.	% of household members having primary education	0.33	0.27
% secondary edu.	% of household members having secondary education	0.33	0.27
% tertiary edu.	% of household members having tertiary education	0.16	0.22
no. of adults	No. of household members aged between 18 and 60	2.24	1.19
ln(cultivated land)	Log *mu* of cultivated land owned by the household (1 *mu* $\approx$ 667 m^2)	0.20	1.26
Index of agricultural assets	The index of agricultural assets owned by the household, which is constructed by principle component analysis	0.17	0.33
Small hh business	Categorical variables indicating the types of small business run by the household: 0 as no small business; 1 as commerce, service and peddler; 2 as manufacturing and construction	0.17	0.53
% local non-agricultural employment in hh	% household members doing local non-agricultural jobs and currently living in the household	0.08	0.18
% village out-migration	% of sample villagers currently working and living outside of the village but still registering with their families in the village	0.08	0.10
% hh members having health insur.	% household members having any form of health insurance	0.26	0.37
% hh members having commercial insur.	% household members having commercial health insurance	0.01	0.09
% hh members having gov. free insur.	% household members having government free health insurance	0.02	0.09
% hh members having cooperative insur.	% household members participating in NCMS**	0.15	0.31
Urbanization*	Index indicating the degree of urbanization of the village where the household locates	0.45	0.16
Economic activity*	Index reflecting typical daily wage for ordinary male worker (reported by community official) and per cent of the population engaged in non-agricultural work	3.28	2.61

Table A1

(*continued*)

Variable	*Definition*	*Mean*	*SD*
Access to markets*	Index reflecting the distance to the market and number of days of operation for eight different types of market	3.76	3.46
Social service*	Index reflecting provision of preschool for children under 3 years old, availability of (offered in community) commercial medical insurance, free medical insurance, and/or insurance for women and children	1.10	1.76
Purchasing price change of farm product†	% change (at the provincial level) of price at which farm households selling their agricultural product	0.04	0.11
Prov. % cultivated land in natural disasters‡	% cultivated land affected by natural disasters within the sample province	0.17	0.07

Notes: **NCMS, New Cooperative Medical Scheme. *The index is constructed by Jones-Smith and Popkin (2010) and complied into the CHNS data by the CHNS team. †Authors' calculations based on the data from China Data Centre at the University of Michigan. ‡Authors' calculations based on the data of natural disasters from Sixty Years of New China Agricultural Statistics (published by the Ministry of Agriculture in 2009) and the data of provincial cultivated land from various issues of China Statistical Yearbooks (published annually by the National Bureau of Statistics of China).