CSAE Working Paper WPS/2014-36

Multi-dimensional Intertemporal Poverty in Rural China*

Jing You,[1, 2] Sangui Wang,[1, †] Laurence Roope[3]

Abstract

We analyse intertemporal poverty in two important dimensions – income and nutrition – in less developed northwest China during 2000-2004. A generalised recursive selection model is proposed which enables simultaneous estimation of the causes of intertemporal poverty within and between dimensions. Improvement in agricultural production is crucial for reducing both dimensions of intertemporal poverty. We find evidence suggestive of intertemporal income-nutrition poverty traps. Higher labour productivity, especially in agriculture rather than local off-farm activities or out-migration, holds much potential for breaking the vicious circle. Agricultural innovation and mechanisation, regarded by the government as indispensable, yield mixed outcomes for intertemporal multi-dimensional poverty reduction.

Key words: intertemporal poverty, multi-dimensional poverty, rural China
JEL codes: D63, I3, O52

1. School of Agricultural Economics and Rural Development, Renmin University of China; 2. Department of Land Economy, University of Cambridge; 3. Health Economics Research Centre, University of Oxford.

* You and Wang: School of Agricultural Economics and Rural Development, Renmin University of China, 59 Zhongguancun Street, Beijing 100872, China. (e-mail: jing.you@ruc.edu.cn and wangsg@ruc.edu.cn); Roope: Health Economics Research Centre, Nuffield Department of Population Health, University of Oxford, Old Road Campus, Oxford, OX3 7LF, UK (e-mail: laurence.roope@dph.ox.ac.uk). The authors are extremely grateful to Stephan Klasen and Christophe Muller, for helpful comments on an earlier draft. The paper has also benefitted from helpful discussions with a number of participants at the International Conference “Poverty, Equity, and Growth in Developing and Transition Countries”, held jointly by the Courant Research Center and the Ibero-America Institute of Economic Research, at the University of Göttingen during 2-4 July 2014, and the Annual Conference of the Chinese Economic Association (Europe) held during 1-2 September 2014 at the University of Göthenburg. The usual caveats, of course, apply. Finally, we wish to gratefully acknowledge generous financial support by the National Natural Science Foundation of China (Grant No.: 71403282) and the Humanity and Social Science Foundation of the Ministry of Education of China (Grant No. 13YJCZH231).

† Corresponding author.

1. Introduction

Over the last few years, two major developments in the way poverty is conceptualised and measured stand out. These regard, respectively, poverty's multi-dimensionality and its dynamic nature over time. Developing measurement techniques which appropriately capture these important aspects of poverty has been a very active area of research lately. The vast majority of contributions though have focused on capturing either the multi-dimensional aspect, or the temporal aspect, and have not attempted to deal with both simultaneously.

With regard to multidimensionality, notable contributions have been made by many authors including, among others, Tsui (2002), Bourguignon and Chakravarty (2003), Atkinson (2003) and Alkire and Foster (2011a).[1] Despite the advances, there remains quite a fundamental point of difference in the literature. In one camp are those, such as Alkire and Foster (2011b), who argue for the value of identifying the poor by considering the joint distribution of deprivations, and of using a methodology which can indicate changes over time in a unified and internally consistent framework. In the other camp are those such as Ravallion (2011), who, citing difficulties in choosing which dimensions to include, and how they should be weighted, argues that we should "…aim for a credible set of "multiple indices" rather than a single "multidimensional index."" (p. 247).

As well as the importance of multidimensionality, it is also increasingly recognised that measuring a "snapshot" of poverty, at a single point in time, or even consecutive "snapshots", is inadequate for capturing poverty as people experience it.[2] It seems clear that the way in which poor spells are interspersed with non-poor spells, and the overall proportion of poor spells and their intensity must play an important role. Yet there is scope for a variety of views on how best to aggregate such information and there are a fast growing number of methodologies. These include Foster (2009), who accounts for the detrimental impact of spending a high proportion of time in poverty on the overall level of chronic poverty; Hoy and Zheng (2011), who account, among other things, for the particularly damaging impact of poverty early in life on capability or

[1] The latter has been especially influential in empirical work and provides a suite of indices that have been adopted to monitor multi-dimensional poverty by a number of national governments. Since 2010, a special case of these indices (Alkire and Santos, 2011) has been reported in the UNDP's Human Development Report.

[2] It also tends to underestimate the number of people affected by poverty; a much greater proportion of people may experience poverty when observed over a longer time frame (Baulch and Hoddinott, 2000).

human capital formation, resulting in low long-term wellbeing, in the context of lifetime poverty; Bossert *et al.* (2012), who attach importance to the debilitating impact of prolonged periods spent in poverty, and Dutta *et al.* (2013), who incorporate also the mitigating impact that affluent spells might have on subsequent periods of poverty.[3]

While much progress has been made in measuring poverty both across dimensions, and over time, attempts to simultaneously account for multi-dimensional and intertemporal aspects of poverty in its measurement are in their infancy. The few such studies include Alkire *et al.* (2013), who combine the counting approach of Foster (2009) over time, with the counting approach across dimensions of Alkire and Foster (2011a), and D'Ambrosio (2013). The approach taken in the latter study begins by calculating intertemporal poverty in each dimension of interest separately and identifying individuals as multi-dimensionally poor if they experience functioning failure in at least one dimension, as in Atkinson (2003). Then, in the spirit of Alkire and Foster (2011a), a weighted average of all dimensions is used as an aggregate index for multi-dimensional intertemporal poverty.[4]

The contributions of this study are both empirical and methodological. Empirically, our interest is in shedding light on poverty, and its possible determinants, in two poor regions of rural northwest China – Gansu and Inner Mongolia. Using the measures of Dutta *et al.* (2013), we capture poverty as a multi-dimensional intertemporal phenomenon, across two important aspects of wellbeing – income and nutrition.

There have been relatively few studies of income poverty in rural China which explicitly account for its temporal aspect. The studies that have been conducted have been largely concerned with decomposing total poverty into chronic and transient components. Jalan and Ravallion (1998) and McCulloch and Calandrino (2003), estimated overall poverty, at a household level, for rural Sichuan province, in southwest China, in the second half of the 1980s and the first half of the 1990s, respectively, and decomposed it into chronic and transient components. In these studies, total household intertemporal poverty is given by the mean per period poverty gap, raised to some power. The chronic poverty component is obtained by comparing the mean income over

[3] This list is far from exhaustive. Other notable studies include, among others, Calvo and Dercon (2009), Zheng (2011) and Mendola and Busetta (2012, 2013).
[4] The weights are determined according to European respondents' perceptions of the relative importance of each welfare dimension.

time with the poverty lines, so that a household is chronically poor only if their mean income lies below this. More recently, Duclos *et al.* (2010) built on these approaches to develop a framework in which total societal intertemporal poverty depends not only on mean poverty gaps, over time and across individuals, but is exacerbated by variability in poverty over time, both at an individual level, and with regard to inequality across individuals. Their approach was then applied to 82 villages in nine Chinese provinces (Anhui, Gansu, Guangdong, Henan, Hunan, Jiangsu, Jilin, Shanxi, and Sichuan).

The theoretical literature on measuring intertemporal poverty has recently reached quite a high level of sophistication, accounting, as described above, for individual poverty trajectories; the effect of the sequencing of poor and non-poor periods on an individual's overall intertemporal poverty. We apply poverty indices proposed by Dutta *et al.* (2013) to a sample of Chinese rural households. These measures have a number of appealing features. They are sensitive to (i) orders of poverty transitions; (ii) the length of poor and non-poor spells; as well as more standard concerns such as the depth of poverty when poor.[5] These measures have been applied empirically to data for Great Britain (Roope and Peters, 2013) and for a number of countries in the European Union (D'Ambrosio, 2013). To the best of our knowledge, this is the first study which applies these recent techniques in a developing country context; indeed most, if not all, existing applications of recent intertemporal poverty measures are for developed countries (e.g., *ibid*; Gradín *et al.*, 2012). For rural China, there has been no assessment of households' intertemporal poverty profiles which takes into account dynamic factors such as those outlined above.

It is widely recognised that the poor in the developing world not only suffer from income or consumption shortfalls, but also face a many-faceted deprivation space encompassing nutrition, health, education and various poor living conditions. Recent examples in a Chinese context include Labar and Bresson (2011), who study multi-dimensional poverty in rural China from 1991 to 2006, and Ray and Mishra (2012), who make comparisons between China, India and Vietnam. This study adds to this literature on multi-dimensionality of deprivations too, by exploiting a balanced household panel with annual waves from 2000 to 2004, which contains data on income and nutrition. We use this data to provide the first empirical estimates of household

[5] A special case of the measures also attaches some importance to the extent of affluence when not poor.

intertemporal poverty in rural China, across these important dimensions. In so doing, we unearth evidence consistent with a possible intertemporal nutrition-income poverty trap. The conventional nutrition-income trap has been well-established according to the nutrition-based efficient wage hypothesis: higher wages allow households to invest more income in health and nutrition (e.g., Leibenstein, 1957; Bliss and Stern, 1978; Dasgupta and Ray, 1986, 1987; Strauss and Thomas, 1998). Evaluating income and nutrition poverty over a longer term sheds greater light on who are truly the poorest in these dimensions. This, in turn, enables better estimates of the correlation between deprivations in the two dimensions.

Having estimated the extent of multi-dimensional intertemporal poverty, we also investigate its determinants. We contribute to the literature by proposing a methodological framework, of general applicability, that takes into account the household unobservables which jointly determine various dimensions of wellbeing over time, and possible interdependence between observed poverty outcomes in different dimensions. Our approach goes some way towards reconciling the strands of literature on multi-dimensional and intertemporal poverty, in the sense that determinants of poverty, both over time and across dimensions, are estimated jointly and recursively, in a unified framework.[6] Our methodology builds on Roope and Peters (2013), who employ a Heckman selection model to measure the extent of intertemporal income poverty in the UK, conditional upon being short of income. Here, we propose a generalised selection model, and estimate the determinants of intertemporal poverty, in each dimension, conditional upon being poor in at least one dimension at one time. Our approach allows for the realistic possibility that the factors which allow us to "observe" poverty, in the sense that a household is below the poverty line in at least one time period and one dimension, may differ from the factors that, conditional upon this, determine the overall severity of poverty in one or more dimensions, over the full period of analysis. Our method also allows for the (also realistic) possibility that the unobserved household-specific determinants of poverty in each dimension are correlated. Our model can easily be applied to other developing countries where panel data are available.

[6] We do not, however, endeavour to develop an overall index of multi-dimensional intertemporal poverty and, in this sense, our approach might be interpreted as being in the spirit of Ravallion (2011).

We find that the correlation between income and nutrition deprivations is high, consistent with a poverty trap hypothesis in an intertemporal context. Our results also suggest that those residing in Gansu, relying on circular migration as their main livelihood and not having any family members belonging to ethnic minorities, are poorer intertemporally in both dimensions than their counterparts in Inner Mongolia, who make a living by agriculture or local non-agricultural production and have at least one family member from an ethnic minority.[7] In the early stages of development, when agricultural production is the major component of household livelihood, agricultural development, in terms of increased labour productivity, bigger farm sizes and investment in productive assets, appears to hold much potential for alleviating both intertemporal income and nutritional deprivation. However, China's long exercised poverty alleviation policy in terms of investment in village infrastructures appears not to contribute to intertemporal poverty reduction, at least in the short-term.

This paper proceeds as follows. A theoretical framework for measuring intertemporal poverty, and our multi-dimensional generalised selection model, are described in Section 2. The dataset is discussed in Section 3. Results are presented in Section 4, while Section 5 concludes with possible suggestions to inform current policy.

2. Theoretical Framework and Empirical Methodology

2.1. Measuring intertemporal poverty

Following Dutta *et al.* (2013), an intertemporal poverty measure is a function which assigns to an individual's (or household's) poverty profile a non-negative number, i.e. $P : \cup_{T\in\mathbb{N}}[0,1]^T \longrightarrow \mathbb{R}_+$. A particular time period is denoted by $t \in \{1,\cdots,T\}$. Households are indexed by $i \in \{1,\cdots,N\}$, but the index is suppressed in the remainder of this subsection for notional simplicity. A household has a poverty profile, in a given dimension of attainment (here, income or calorific intake) given by $\mathbf{p} = (p_1,\cdots,p_T) \in [0,1]^T$, where p_t indicates the household's "snapshot" poverty level

[7] This finding is context specific for Inner Mongolia where ethnic minorities are richer compared with those in other parts of China, as their livelihood arrangement is a mixture of both agriculture and husbandry and the region is resource-rich. Nevertheless, ethnic minorities in China are, on average, poorer than the ethnic majority *Han* people. Section 3 gives detailed statistics for the two sample provinces.

at time t as indicated by a normalized poverty gap from a poverty line z.[8] As usual, therefore, $p_t = 1$ indicates the maximum possible level of poverty in period t (no income, or no nutrition), while $p_t = 0$ indicates that the household is non-poor.

For a given profile $\mathbf{p}$, n_t denotes the number of consecutive non-poor periods immediately prior to a poor period t. We use k_t to denote the number of preceding periods of uninterrupted poverty, up to and including the poor period t. Formally,

$$n_t = \begin{cases} 0, \quad if\ t = 1\ or\ p_{t-1} > 0 \\ t - \min\{s: s < t\ and\ p_s = \cdots = p_{t-1} = 0\}, otherwise \end{cases}$$

and

$$k_t = \begin{cases} 1, \quad if\ t = 1\ or\ p_{t-1} = 0 \\ t - \min\{s - 1: s < t\ and\ p_{t'} > 0, \forall\ t' \in \{s, \cdots, t\}\}, otherwise \end{cases}$$

We will use Dutta *et al.* (2013)'s constant-relative affluence-dependent intertemporal poverty measure, which is given by:

$$P_R(\mathbf{p}) = \frac{1}{T}\sum_{t=1}^{T} \frac{k_t^{\alpha}}{(1+n_t)^{\beta}} p_t^{\varphi},\ where\ \alpha, \beta, \varphi \geq 0. \qquad (1)$$

The parameter φ captures the sensitivity of the poverty experienced in each time period to the income shortfall.[9] The damaging impact of consecutive periods of poverty is captured by k_t, while the parameter α determines the extent of this intensifying effect. Similarly, the size of β determines how much the poverty analyst believes that the impact of a poor episode is mitigated due to preceding uninterrupted spells of non-poverty. (When $\beta = 0$, there is no such mitigation and if also $\alpha = 0$, the measures collapse to the average of per-period static poverty measures.)

Implicit in (1) is quite a strict interpretation of the "focus" axiom in poverty measurement, where if income (or nutrition) in a non-poor period is increased further above the poverty line, this has no effect on overall poverty. Dutta *et al.* (2013) relax

[8] In principle, any of a wide range of static poverty indices from the literature can be used. The normalized poverty gap has some appealing properties, including sensitivity to the size of the shortfall and scale invariance. In the case of income, it also has a natural interpretation, when denormalized, as the minimum cost to society of removing a household from poverty.

[9] Using $\varphi = 1$, as we do for most of our analysis leaves the normalized poverty gap as the static measure of poverty; $\varphi = 0$ and $\varphi = 2$ would convert the static poverty measure into the headcount measure and FGT2 measure, respectively.

this property in their relative affluence-dependent intertemporal poverty measure, which we also use. This is given by:

$$\tilde{P}_R(\mathbf{p}) = \frac{1}{T}\sum_{t=1}^{T}\frac{k_t^{\alpha}}{(1+\tilde{n}_t)^{\beta}}p_t^{\varphi} \qquad (2)$$

where parameters α, β, $\varphi \geq 0$ play a similar role as in (1) and the extent of the relative affluence in preceding non-poor periods is reflected by:

$$\tilde{n}_t = \begin{cases} \sum_{t'=s}^{t-1} \lambda_{t'}, & if\ p_{t'} = 0\ for\ all\ t' \in \{s, \cdots, t-1\} \\ & 0\ otherwise \end{cases}$$

where $\lambda_{t'} = \begin{cases} \gamma\ \ if\ x_{t'} > \delta z\ ;\ for\ some\ \gamma \geq 1\ and\ \delta > 1 \\ \qquad 1\ otherwise \end{cases}$ and $x_{t'}$ denotes the household's observed income or nutrition per equivalent adult at the affluent period t'.

The measures in (1) and (2) have much in common. In particular, both account for the exacerbating effect of long periods of poverty, and both allow prolonged periods of relative affluence to have a mitigating on subsequent periods of poverty. They also have the same upper and lower bounds, and if $\alpha = \beta = 0$ both collapse to Foster (2009)'s intertemporal poverty measure.[10] The main difference between them is that in (1), the mitigating effect of non-poor periods depends only on the length of time a household has been non-poor for, while in (2), the extent of this mitigating effect can be increased if households are far above the poverty line when they are non-poor.

Dutta *et al.* (2013) justify their approach by arguing that periods of affluence allow people to accumulate valuable resources that help mitigate the deprivation experienced in subsequent poor spells. Implicit in their approach is that,

"…in the absence of income smoothing opportunities, the mitigating effect of affluent periods is transmitted through non-income dimensions such as assets, health, social networks, human capital and so on." (p. 743).

While they treat income-based poverty as their primitive, a similar justification certainly seems to hold for nutritional poverty, and indeed nutrition might be considered a dimension of poverty which Dutta *et al.* (2013)'s measures are particularly well suited to capturing. It is well known, for example, that people who have a possibility of falling into poverty often use their "body as a store of energy" during times of relative

[10] The upper and lower bounds are $\frac{1}{T}\sum_{t=1}^{T} t^{\alpha}$, and 0. It can be inferred from the dependence of the upper bound on t that the measures can only consistently compare profiles of the same length.

affluence by employing a "feast now fast later" strategy (Dercon and Hoddinott 2003, pp. 7–8). Moreover, intensification of nutritional poverty due to prolonged spells of low calorific intake is clearly a genuine phenomenon, with starvation and death a plausible outcome in extreme cases.

In our empirical analysis then, we estimate both (1) and (2) for our two dimensions of household welfare: income and nutrition, to reveal the extent of multi-dimensional intertemporal poverty. Considering the substantial income growth and monetary poverty reduction in rural China over the period of analysis, we use the measures defined by (2) to investigate the determinants of income and nutritional intertemporal poverty, while using (1) to check the robustness of results.

2.2. Determinants of intertemporal poverty in multi-dimensions

Having described our measures of household intertemporal poverty, in income and nutrition, we now describe our approach to investigating their determinants. A given household's observed income (y_1) and nutritional status (y_2) (i.e. poor or non-poor) is denoted by dichotomous outcomes $\mathbf{y}=\left(y_1, y_2\right)'$ which are determined by the underlying vector of attainments in these dimensions $\mathbf{y}^{*\prime}=\left(y_1^*, y_2^*\right)'$. Let $y_1=\mathbf{1}\left(y_1^*>0\right)$ (or $y_2=\mathbf{1}\left(y_2^*>0\right)$) if the household has suffered from income (or nutritional) poverty at least once over the period 2000-2004. Household intertemporal poverty (as captured by either of our measures), is a weighted average of per period measures and, thus, is truncated at zero, since the per period measures of poverty are also truncated at zero. Intertemporal poverty is "observed" only for those who have experienced at least one period of poverty. In each dimension, those who have never been poor do not then have any intertemporal poverty. In this sense, we encounter a selection problem when studying the determinants of a household's intertemporal poverty; only those who have ever been poor are observed to have any. As argued in Roope and Peters (2013), intertemporal poverty should, thus, be modelled conditional upon being poor in at least one time period.

We begin by making the strong assumption that income and nutritional poverty, for a given household, are independent events. Given the truncation in our intertemporal poverty measures, we construct a selection model to describe the household's observed intertemporal income poverty p_1 defined by (2) with $\alpha = \beta = \varphi = 1, \gamma = 2$ and $\delta = 3.2$ as follows:

$$\begin{aligned} p_1 &= p_1^* \cdot \mathbf{1}\left(y_1^* > 0\right) \\ p_1^* &= \mathbf{x}'\beta_1 + \overline{\mathbf{x}}'\beta_2 + \upsilon_1 \\ y_1^* &= \mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_1'\theta_3 + \varepsilon_1 \end{aligned} \tag{3}$$

Here, $\delta = 3.2$ is the average ratio, across the three waves, of the household income per adult equivalent, at the 75th percentile of the income distribution, over the income poverty line.[11] We consider those in the upper income quartile as being far above the poverty line and this status is assumed to provide a greater mitigating impact on subsequent income poverty than would a merely non-poor status; the greater mitigation is reflected by $\gamma = 2$. In (3), y_1^* is a latent variable which captures the household's intertemporal income poverty. It can take negative values, but intertemporal poverty is only observed ($p_1 > 0$) for those who have at some time fallen below the income poverty line; $\mathbf{x}' = \left(x_1, \ldots, x_k\right)'$ contains k determinants of household income poverty in the first wave; $\overline{\mathbf{x}}'$ is a vector made up, for each household, of the intertemporal means of these k variables, in order to control for at least some of the household specific unobserved time-invariant heterogeneity (Chamberlain, 1984, pp. 1250) that may underlie their intertemporal poverty; $\mathbf{z}_1'$ contains the restriction, i.e., the excluded instrument, in order to enhance identification of the model. In particular, we use households' pre-determined income poverty status in 1999 as the excluded instrument. It takes the value of one if the household's per capita equivalent net income in 1999 fell below a certain poverty line and zero otherwise. Terms ε_1 and υ_1 are the unobservables affecting the household's per-period income poverty status, and the extent of its overall intertemporal income poverty, respectively.

Analogously, we also construct a selection model to describe the household's observed intertemporal nutritional poverty p_2, also defined by (2), with the same parameter values as p_2, except for δ, which is set at 1.05, as follows:

[11] Using as high a threshold as this to define "absolute affluence" also helps mitigate the impact of measurement errors in income and nutrition on our results.

$$
\begin{aligned}
p_2 &= p_2^* \cdot \mathbf{1}\left(y_2^* > 0\right) \\
p_2^* &= \mathbf{x}'\beta_1 + \overline{\mathbf{x}}'\beta_2 + \upsilon_2 \\
y_2^* &= \mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_2'\theta_3 + \varepsilon_2
\end{aligned}
\tag{4}
$$

Here, $\delta = 1.05$ is the average ratio, across all waves, of the household nutrient intake per adult equivalent at the 75th percentile of the nutrition distribution, over the nutritional poverty line. We consider those in the upper nutrient quartile as being far above the nutrition poverty line. Analogously to above, this status is assumed to provide a greater mitigating impact on subsequent nutrition poverty than would a merely non-poor status; the enhanced mitigation is reflected by $\gamma = 2$. In (4), $\mathbf{x}_1'$ and $\overline{\mathbf{x}}'$ are defined as before; the restrictions in the selection equation ($\mathbf{z}_2'$) are various food prices in each period t, as these are closely related to households' per-period nutritional intake, but less so to Dutta *et al.* (2013)'s weighted averages of nutrition shortfall over the entire period of analysis.[12]

The unobservables in the selection and outcome equations (of both (3) and (4)) are assumed to jointly affect both household poverty status (poor or non-poor) and the overall extent of intertemporal poverty. The two error terms then follow a binormal distribution for each variety of poverty, that is $(\upsilon_j, \varepsilon_j) \sim NID(0, \Sigma_k)$ where $j = \{1,2\}$ indicates income or nutritional deprivation and the variance-covariance matrix is given by $\mathbf{\Sigma}_j = \begin{bmatrix} \sigma_{\upsilon_j}^2 & \rho_{\upsilon_j\varepsilon_j}\sigma_{\upsilon_j\varepsilon_j} \\ \rho_{\upsilon_j\varepsilon_j}\sigma_{\upsilon_j\varepsilon_j} & 1 \end{bmatrix}$, where $\rho_{\varepsilon_j\upsilon_j} \neq 0$ to reflect interrelated y_j^* and p_j^* for the same household i and $\sigma_{\varepsilon_j}^2 = 1$ to facilitate normalisation. Based on this, we use two approaches to estimate (3) and (4).

Applying the Heckman (1979) two-step procedures, to (3) and (4) separately, yields consistent parameter estimates $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\theta}}$. The first step is to insert the inverse Mills' ratios, derived from the selection equations, $\lambda_j = \dfrac{\phi\left[-\left(\mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_j'\theta_3\right)\right]}{1-\Phi\left[-\left(\mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_j'\theta_3\right)\right]}$, where $j=1$ for income and $j=2$ for nutrition, as additional regressors in the two

[12] The food items include grain, oil, vegetables, fruit, pork, beef, lamb, poultry, egg, alcohol, milk, and dairy products. They are also components in our calculations of households' nutritional intake. Their prices are calculated by the expenditure (in *yuan*) the household paid for this variety of food over the amount (in kg) it purchased. The monetary values of prices are translated into real term by dividing them by the spatial price index.

respective outcome equations. $\phi(\cdot)$ and $\Phi(\cdot)$ denote the standard and cumulative normal density functions, in turn. The augmented outcome equations are then estimated by OLS in the second step.

A conventional two-step method like Heckman (1979) relies less on the functional form, and so is more robust than other estimation strategies such as maximum likelihood (ML) estimation. Nevertheless, the two-step estimators are less efficient than the ML ones. Given this, we also implement partial ML estimation and calculate the likelihood ratio statistics for the models. The likelihood function for (3) and (4) can be written as:

$$
\begin{aligned}
L_j &= \prod_{y_j=0} \Pr\left(y_j = 0 \mid \mathbf{z}_j, \mathbf{x}, \overline{\mathbf{x}}\right) \times \prod_{\substack{p_j>0 \\ y_j=1}} \Pr\left(p_{ij} = p_{ij}^* \mid y_{ij} = 1, \mathbf{x}, \overline{\mathbf{x}}\right) \\
&= \prod_{i=1}^{N} \left\{ \begin{array}{l} \left[1-\Phi\left(\mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_j'\theta_3\right)\right]^{(1-y_{ij})} \\ \times \left[\Phi\left(\mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_j'\theta_3\right) h_j\left(p_j \mid \mathbf{z}_j, \mathbf{x}, \overline{\mathbf{x}}, \sigma_{\varepsilon_j\upsilon_j}, \rho_{\varepsilon_j\upsilon_j}\right)\right]^{y_{ij}} \end{array} \right\}
\end{aligned} \tag{5}
$$

where $j = \{1, 2\}$ indicates income or nutritional deprivation, and $h_j\left(p_j \mid \mathbf{z}_j, \mathbf{x}, \overline{\mathbf{x}}, \sigma_{\varepsilon_j\upsilon_j}, \rho_{\varepsilon_j\upsilon_j}\right)$ is the conditional normal density function for the jth outcome equation. The log-likelihood to be maximised takes the following expression under the joint bivariate normal distribution:

$$
\begin{aligned}
\ell_j &= \sum_{i=1}^{N} \left(1-y_{ij}\right) \ln\left[1-\Phi\left(\mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_j'\theta_3\right)\right] \\
&+ \sum_{i=1}^{N} y_{ij} \ln \Phi\left[\frac{\left(\mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_j'\theta_3\right) + \left(\rho_{\upsilon_j\varepsilon_j}\sigma_{\upsilon_j\varepsilon_j} / \sigma_{\upsilon_j}^2\right)\left(p_{ij} - \mathbf{x}'\beta_1 - \overline{\mathbf{x}}'\beta_2\right)}{\sqrt{1-\rho_{\upsilon_j\varepsilon_j}^2 \sigma_{\upsilon_j\varepsilon_j}^2 / \sigma_{\upsilon_j}^2}}\right] \\
&+ \sum_{i=1}^{N} y_{ij} \ln \phi\left(\frac{p_{ij} - \mathbf{x}'\beta_1 - \overline{\mathbf{x}}'\beta_2}{\sigma_{\upsilon_j}}\right) - \sum_{i=1}^{N} y_{ij} \ln \sigma_{\upsilon_j}
\end{aligned} \tag{6}
$$

So far we have treated income and nutritional poverty independently. A household could, however, be either just poor in one of these dimensions during the period of analysis, or could endure both forms of poverty sometime during the T periods. In other words, for the same household, the unobservables that determine its multi-dimensional poverty incidence, and the extent of its deprivation in different dimensions, may well be correlated. We take this into account and model households' multi-dimensional intertemporal poverty by the system containing, simultaneously, (3) and

(4), while the unobserved components for the same household i, $(\boldsymbol{\varepsilon},\boldsymbol{\upsilon})' = (\varepsilon_1, \varepsilon_2, \upsilon_1, \upsilon_2)'$, are not independent, but jointly normally distributed as $(\boldsymbol{\varepsilon},\mathbf{v})|\mathbf{x},\bar{\mathbf{x}},\mathbf{z} \sim NID(0,\boldsymbol{\Sigma})$ The variance-covariance matrix $\boldsymbol{\Sigma}$ consists of the following elements:

$$\boldsymbol{\Sigma} = \begin{bmatrix} 1 & \sigma_{\varepsilon_1\varepsilon_2} & \sigma_{\varepsilon_1\upsilon_1} & \sigma_{\varepsilon_1\upsilon_2} \\ \sigma_{\varepsilon_1\varepsilon_2} & 1 & \sigma_{\varepsilon_2\upsilon_1} & \sigma_{\varepsilon_2\upsilon_2} \\ \sigma_{\varepsilon_1\upsilon_1} & \sigma_{\varepsilon_2\upsilon_1} & 1 & \sigma_{\upsilon_1\upsilon_2} \\ \sigma_{\varepsilon_1\upsilon_2} & \sigma_{\varepsilon_2\upsilon_2} & \sigma_{\upsilon_1\upsilon_2} & 1 \end{bmatrix}$$

It has unit diagonal entries in order to normalise the scale for the equations in (3) and (4). In other words, the correlation coefficients between the unobservables reduce to, for example, $\rho_{\varepsilon_1\varepsilon_2} = \mathrm{cov}(\varepsilon_1, \varepsilon_2 \mid \mathbf{x}, \bar{\mathbf{x}}) = \sigma_{\varepsilon_1\varepsilon_2} \neq 0$.

This structure of $\boldsymbol{\Sigma}$ essentially transforms the model to a two-stage self-selection process with two selection criteria in the first stage and two outcomes in the second stage. The full sample therefore consists of four categories according to households' observed experiences in income and nutritional poverty. These, and the corresponding probabilities, are:

(i) Always non-poor in both dimensions: $\Pr(y_1 = 0, y_2 = 0 \mid \mathbf{z}_1, \mathbf{z}_2, \mathbf{x}, \bar{\mathbf{x}})$;

(ii) Poor in income at least once, while never poor in nutrition: $\Pr(p_1 = p_1^*, p_2 = 0 \mid y_1 = 1, y_2 = 0, \mathbf{x}, \bar{\mathbf{x}}) \cdot \Pr(y_1 = 1, y_2 = 0 \mid \mathbf{z}_1, \mathbf{z}_2, \mathbf{x}, \bar{\mathbf{x}})$;

(iii) Poor in nutrition at least once, while never poor in income: $\Pr(p_1 = 0, p_2 = p_2^* \mid y_1 = 0, y_2 = 1, \mathbf{x}, \bar{\mathbf{x}}) \cdot \Pr(y_1 = 0, y_2 = 1 \mid \mathbf{z}_1, \mathbf{z}_2, \mathbf{x}, \bar{\mathbf{x}})$;

(iv) Poor in both income and nutritional dimensions at least once, while poverty spells of two dimensions do not necessarily take place at the same time: $\Pr(p_1 = p_1^*, p_2 = p_2^* \mid y_1 = 1, y_2 = 1, \mathbf{x}, \bar{\mathbf{x}}) \cdot \Pr(y_1 = 1, y_2 = 1 \mid \mathbf{z}_1, \mathbf{z}_2, \mathbf{x}, \bar{\mathbf{x}})$.

The likelihood function of the system (3) and (4) is the product of the probabilities of all four cases:

$$
\begin{aligned}
L = & \prod_{y_1=0, y_2=0} \Pr\left(y_1 = 0, y_2 = 0 \mid \mathbf{z}_1, \mathbf{z}_2, \mathbf{x}, \overline{\mathbf{x}}\right) \\
& \times \prod_{\substack{p_1>0, p_2=0 \\ y_1=1, y_2=0}} \Pr\left(p_1 = p_1^*, p_2 = 0 \mid y_1 = 1, y_2 = 0, \mathbf{x}, \overline{\mathbf{x}}\right) \Pr\left(y_1 = 1, y_2 = 0 \mid \mathbf{z}_1, \mathbf{z}_2, \mathbf{x}, \overline{\mathbf{x}}\right) \\
& \times \prod_{\substack{p_1=0, p_2>0 \\ y_1=0, y_2=1}} \Pr\left(p_1 = 0, p_2 = p_2^* \mid y_1 = 0, y_2 = 1, \mathbf{x}, \overline{\mathbf{x}}\right) \Pr\left(y_1 = 0, y_2 = 1 \mid \mathbf{z}_1, \mathbf{z}_2, \mathbf{x}, \overline{\mathbf{x}}\right) \\
& \times \prod_{\substack{p_1>0, p_2>0 \\ y_1=1, y_2=1}} \Pr\left(p_1 = p_1^*, p_2 = p_2^* \mid y_1 = 1, y_2 = 1, \mathbf{x}, \overline{\mathbf{x}}\right) \Pr\left(y_1 = 1, y_2 = 1 \mid \mathbf{z}_1, \mathbf{z}_2, \mathbf{x}, \overline{\mathbf{x}}\right)
\end{aligned} \tag{7}
$$

On the assumption of multivariate normality of the error terms, (7) can be expressed as:

$$
L = \prod_{i=1}^{N} \left\{
\begin{array}{l}
\left[1 - \Phi_2\left(\mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_1'\theta_1, \mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_2'\theta_2, \rho_{\varepsilon_1\varepsilon_2}\right)\right]^{(1-y_{i1}y_{i2})} \\
\times \left[\begin{array}{l} \left(\Phi\left(\mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_1'\theta_1\right) - \Phi_2\left(\mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_1'\theta_1, \mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_2'\theta_2, \rho_{\varepsilon_1\varepsilon_2}\right)\right) \\ h\left(p_1^* \mid \mathbf{z}_1, \mathbf{z}_2, \mathbf{x}, \overline{\mathbf{x}}, \boldsymbol{\Sigma}\right) \end{array}\right]^{y_{i1}(1-y_{i2})} \\
\times \left[\begin{array}{l} \left(\Phi\left(\mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_2'\theta_1\right) - \Phi_2\left(\mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_1'\theta_1, \mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_2'\theta_2, \rho_{\varepsilon_1\varepsilon_2}\right)\right) \\ h\left(p_2^* \mid \mathbf{z}_1, \mathbf{z}_2, \mathbf{x}, \overline{\mathbf{x}}, \boldsymbol{\Sigma}\right) \end{array}\right]^{y_{i2}(1-y_{i1})} \\
\times \left[\Phi_2\left(\mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_1'\theta_1, \mathbf{x}'\theta_1 + \overline{\mathbf{x}}'\theta_2 + \mathbf{z}_2'\theta_2, \rho_{\varepsilon_1\varepsilon_2}\right) h\left(p_1^*, p_2^* \mid \mathbf{z}_1, \mathbf{z}_2, \mathbf{x}, \overline{\mathbf{x}}, \boldsymbol{\Sigma}\right)\right]^{y_{i1}y_{i2}}
\end{array}
\right\} \tag{8}
$$

where $\Phi_2(\cdot)$ is the bivariate standard normal cumulative distribution function; $h(\cdot)$ denotes the conditional multivariate normal density function. The log transformation of (8) is evaluated by the maximum simulated likelihood (MSL) method using the GHK simulator to calculate the trivariate and four-variable normal integral and Halton draws (Roodman, 2011).

3. Data

We employ a panel dataset in two western provinces of China, Gansu and Inner Mongolia, with 5 annual waves from 2000 to 2004. This incorporates data from individuals as well as surveys for their households and villages.

Our dataset was collected by the National Bureau of Statistics (NBS) local branches, covering 1,500 households in 150 villages from 15 counties. Of these, 700 households in 7 counties are in Gansu and the remaining 800 households are from 8 counties in Inner Mongolia. Gansu is one of the poorest provinces in China with its real per capita GDP ranking in the bottom 3 out of 31 provinces for two decades (1990-2010).[13] By contrast, Inner Mongolia ranked in the middle (16-20) in the same period

[13] Authors' calculation based on data from China Statistical Yearbooks published annually by the NBS.

and was characterised by rich natural resources, typically coal mines, animal husbandry and related processing industries such as meat, dairy and cashmere. Enumerators regularly visited respondents throughout the year and income and consumption data were collected by the daily diary method. Therefore, the data should be expected to be more accurate than those relying on one-time interviews and memory and the non-response rate and attrition were negligible (Christiaensen *et al.*, 2013). We use household equivalent units in our analysis. The modified OECD equivalence scale is used to adjust for household size and produce household monetary variables per equivalent adult. All monetary values are translated into real terms by using spatial price indices to obtain compatibility over time and between the two provinces.[14]

Income poverty reduction accelerated in the sample time period as a result of large-scale government-led investment projects and loans. The proportion of poor people in rural China declined from 10.46% in 2001 to 9.47% in 2004 under the US$ 1-a-day poverty line (World Bank, 2009). Our dataset suggests a similar trend – as shown in Figure 1(a), the total poverty incidence in our two sample provinces dropped from 12.5% in 2000 to 7.3% in 2004, under the same poverty line. Temporal 3.7-7.9 percentage point increases in total poverty rates can also be observed between 2000 and 2001 under three choices of income poverty lines. All increased poverty came from Inner Mongolia as suggested by the annual provincial poverty rates in Figure 1(a). Under the updated World Bank poverty line of US$1.25/day, the poverty rate in Inner Mongolia in our data rose from 33.4% in 2000 to 43.1% in 2001, which was possibly due to a grazing ban which was enforced between 15 March and 15 June in 2000 (Christiaensen *et al.*, 2013). The poverty rate in Gansu declined consistently over the sample periods, while the magnitude was higher than that of Inner Mongolia in each wave except 2001. The slight increase in poverty rate from 2003 to 2004 in our data is consistent with the national poverty profile. According to the NBS, the first increase in the size of the poor population took place in 2003, when more than 80 million people returned to poverty due to natural disasters.[15] In our data, the increased poverty rate in 2004 was driven largely by a 5.3 percentage points increase in Inner Mongolia. From

[14] See Table A.1 in Appendix for detailed definitions and descriptive statistics for all variables.
[15] The farming areas in China destroyed by natural disasters increased by 30.3% in 2003 according to the China Statistical Yearbook published annually by the NBS.

January to June in 2004, drought swept Inner Mongolia and the rainfall dropped by 30-80% to the lowest level since 1951.[16]

[Figure 1]

As with poverty incidence, Figure 2(a) shows that there was also an overall 37.5% decrease in the average income poverty gap (from 8% in 2000 to 5% in 2004) under the US$1.25-a-day line. This is despite increases, mainly in Inner Mongolia, between 2000 and 2001, and after 2003, when poverty incidence also rose. The interesting observation from Figure 2(a) is that the higher the income poverty line, the less the decrease in the poverty gap over time. This implies that those who escaped from severe poverty (say, the US$1-a-day line) did not continue to improve their situation much further, but rather remained around the poverty line. This can be reaffirmed to some degree by the "extent of affluence" in Figure 3: for the highest the poverty line, the gap between the household's observed income or nutrition and the poverty line increases least over time.

[Figures 2-3]

As the World Bank (2009), among others, has warned, successful reduction in income and consumption poverty does not necessarily synchronise with improvement in other dimensions of human well-being. We also examine nutritional poverty to recognise probable many-faceted hardship. Figure 1(b) shows that incidence of nutritional poverty actually increased over the same period that incidence of income poverty declined. On average, 70% of sample households lived on less than 2,100 kcal per person per day. More people suffered from nutritional shortage than from income deprivation throughout the sample period, and the gap between the incidence rates of the two kinds of deprivation widened, as can be seen by comparing Figures 1(a) and 1(b). The nutritional poverty rate increased by about 8 percentage points (12% of proportional change) from 2000 to 2004, while household equivalent per capita net income grew by 31% concurrently.[17] The depth of nutritional poverty also increased. The average nutrition poverty gap, which is illustrated in Figure 2(b), increased by 14.4% during 2000 to 2004, under the 2,100 kcal threshold, from 22.3% in 2000 to 25.5% to 2004. This seems to have been driven largely by a further increase in the already

[16] Data come from the Report on the State of the Environment in China 2004 published by the Ministry of Environmental Protection.

[17] When income increases, Chinese households are inclined to consume more oil and fat rather than more grains, which have more calories. Those in Inner Mongolia eat more meat and dairy products compared to grains, which also contains lower calories than diets with grains as the staple. Higher and more volatile food prices also affect nutrient intake. See You (2014) for a recent review and You *et al.* (2014) for a comprehensive analysis of explanations for the 'higher income-lower nutrition' paradox in China.

substantial depth of nutrition poverty in Inner Mongolia. Also alarmingly, the "extent of affluence" in Figure 3 in the nutrition domain is relatively stable over time, with even a slightly decreasing trend.[18]

Divergent trends in income and nutrition have also manifested in other large panel datasets, for example, the China Health and Nutrition Surveys (CHNS). Based on its 1989-1997 waves, Du *et al.* (2004) ascribe the detrimental effects of income increases on nutrition to a shift from high-carbohydrate foods toward high-fat, high-energy density ones, as people become wealthier. Based on its 2000-2006 waves, Shimokawa (2013) finds little correlation (0.04) between households' per capita calorie intake and per capita income, and that more wealth results in worsening diet structure, in terms of higher energy intake from fats but proportionally less from fruit and vegetables. You *et al.* (2014) provide a comprehensive analysis of possible explanations for the income-nutrition paradox, in both rural and urban China.

Over time, chronic and transient poverty have co-existed in rural China with the former being slightly more dominant than the latter (e.g., Jalan and Ravallion, 1998 for the 1980s; McCulloch and Calandrino, 2003 for the first half of the 1990s; Duclos *et al.*, 2010 for the period 1986-2002; and Wan and Zhang, 2013 for two decades from 1985 to 2005). Our data are consistent with these findings. As indicated in Table 1, 14.23% of sample households had fallen below US$1.25 per day. For those who were poor in a given period, poverty would persist into the next period with a probability of 29.63%. Both chances of escape, for those who were poor, and sliding backwards for the initially non-poor are nontrivial – 70.37% and 11.26%, respectively. It can be inferred from the upper panel of Table 2 that 28.67% of the full sample has experienced at least 3 poverty transitions, and 53% of poor spells suffered by sample households stopped after one year (Figure 4). However, 28.6% of poor spells persisted for at least three years (Figure 4). There appears to be a higher incidence of both transient and persistent nutritional poverty than is the case for income poverty. Under the threshold of 2,100 kcal per person per day, 70.85% of households were deprived of nutrition at least once (lower panel of Table 1) and 38% of households have changed their poverty status at least 3 times (lower panel of Table 2). It can also be inferred from the lower panel of Table 1 that 80.65% of those without sufficient nutrition in a given period

[18] It should be borne in mind that the scope for very high levels of "affluence" in nutrition is considerably more limited than is the case for income, as there are physical limits to the number of calories people can eat.

would continue to suffer in this way in the subsequent period. Moreover, once sinking into nutritional deprivation, households were more likely to remain in nutritional deprivation – 47.8% had not taken sufficient calories for at least 3 waves (lower panel of Table 2). Moreover, consistent with Table 1, and as expected, with regard to both income and nutrition, higher poverty lines enhance the likelihood of persistent poverty, and dampen the likelihood of escape.

[Tables 1-2]

[Figure 4]

In spite of repeated poverty spells, households also spent some time in relative affluence. Table 2 shows that 52.6% (4%) of households remained successfully in non-poverty of income (nutrition) throughout the sample period; 72.87% (49.6%) of households once lived above US$1.25 per day (2,100 kcal per person per day). It can be deduced from Figure 5 that 47.8% (36.7%) of non-poor spells of income (nutrition) have lasted for at least 3 waves. The not negligible number of affluent episodes, together with frequent transitions and some persistent poverty spells, justify a household poverty measurement approach such as that of Dutta *et al.* (2013), which takes account of dynamic factors like these.

[Figure 5]

4. Estimation results and discussion

4.1. Household intertemporal poverty

The analyses henceforth, except where specified, are based on the poverty lines of US$1.25/day for income and 2,100 kcal for nutrition. The average intertemporal income poverty over the entire sample period is 0.064, without accounting either for any intensification imposed by previous poor spells, or for any mitigating effects of previous affluent spells (i.e., Foster's (2009) indicator in Column 1 of Table 3). To give an indication of the role that the actual levels of incomes during poor periods have in this estimate, Foster's (2009) measure would be 1.3 times larger (0.15) if we hypothesise the maximum poverty gap, which is one, for every poor episode, while keeping income or nutrition in non-poor periods as it is (which does not, in any case, affect Foster's (2009) measure). Nevertheless, if every household could enjoy sufficient affluence (i.e., assigning the 75th percentile observed income (nutrition) level to every household in each of their non-poor spells or, in other words, setting $x_{t'} = \delta z = 3.2z$ ($\delta z = 1.05z$) in every non-poor spell), while experiencing the actual observed depth of poverty in poor spells, their relative-constant intertemporal poverty, according to $\tilde{P}_R(\mathbf{p})$ with $\alpha = \beta = \varphi = 1, \gamma = 2$ and $\delta = 3.2$ would have dropped from 0.063 to 0.059 in the income dimension and from 0.525 to 0.520 in the nutrition dimension. The above exercise suggests that these "not-so-poor" households not only confronted the risk of returning to poverty, as they still remained close to the poverty line, but also benefitted less from non-poor periods than those who had successfully managed to escape far from the poverty line, at least according to $\tilde{P}_R(\mathbf{p})$.

[Table 3]

We also calculate each intertemporal measure for selected sub-populations.[19] Geographically, the poorer province, Gansu, experienced higher intertemporal poverty than the wealthier one, Inner Mongolia, in all measures of the income dimension. Nevertheless, intertemporal nutritional poverty is found to be much higher in Inner Mongolia than in Gansu (Columns 5-6 of Table 3), even affluent periods are allowed to have a mitigating effect. This could be driven primarily by a 19-49% larger nutritional poverty gap in Inner Mongolia than in Gansu throughout the sample period as shown in Figure 2(b), although the nutritional poverty incidence was actually lower in the former as shown in Figure 1(b).

According to the production activity to which the household allocates the most labour (days per year), we divide the full sample into agricultural, local non-agricultural and circular migrating households. Interestingly, those putting the most labour into local non-agricultural production were least poor in both income and nutrition, but relying on circular migration made households worse-off intertemporally, especially when referring to relatively low income and nutrition poverty lines (e.g., Columns 1, 2 and 5 of Table 3). We will return to this by discussing the roles of different labour productivity in Section 4.2. Ethnic identity appears to be an additional correlate of intertemporal poverty. The household was substantially less intertemporally poor if at least one family member belonged to an ethnic minority. This is consistent with the exploratory data analysis in Section 3 that the ethnically autonomous province, Inner Mongolia, was richer than Gansu in every wave. Together with higher average intertemporal nutrition poverty in Inner Mongolia than in Gansu, we conjecture that the

[19] The division of samples does not consider gender, as only 7 out of 1,500 households were headed by females.

Han people in Inner Mongolia might struggle with the toughest nutritional shortage in the study population.

All discussions so far also hold broadly for higher poverty lines (Columns 3-4 and 7-8 of Table 3). As expected, the same intertemporal poverty measure is always higher under the higher poverty line than that under the lower poverty line.

4.2. The roles of agriculture and household material well-being in determining intertemporal poverty

Table 4 summarises the two-step estimation results of Eqs. (3) and (4), which attempt to identify the determinants of household multi-dimensional intertemporal poverty. The estimated coefficient of the inverse Mills' ratio is broadly statistically significant in both income and nutrition models, implying the existence of endogeneity and lending some justification to our choice of estimation approach, as this estimator essentially captures the correlation between the probability of being poor and the extent of intertemporal poverty, i.e., $\hat{\rho}_{\upsilon_j \varepsilon_j} \hat{\sigma}^2_{\upsilon_j}$, with $j = \{1, 2\}$ denoting the income or nutritional dimension.[20] Re-estimating Columns (3) and (7) of Table 4 by ML (Eq. 5) yields broadly similar results shown in Columns (4) and (8), but with smaller standard errors – as expected since ML is more efficient than two-step estimation. The correlation coefficient between the errors in selection and outcome regressions ($\hat{\rho}_{\varepsilon_j v_j}$ with $j = \{1,2\}$) is positive in income (0.99) and negative in nutrition (-0.64) dimensions, both significantly different from zero with the *F*-statistics being 6.61 (*p*-value=0.01) for income and 24.3 (*p*-value=0.00) for nutrition. This also corroborates the existence and direction of endogeneity within each poverty dimension identified by Heckman two-step estimators. Table 5 reports estimation results of Eq. (8), further correcting for simultaneity between income and nutritional deprivation. The bottom panel of Table 5 reports cross-correlation coefficients of selection and outcome regressions within the system, indicating the existence of joint determination of income and nutritional deprivation. The hull hypothesis that these coefficients are jointly zero is firmly rejected in all specifications in Table 5 at the 1% significance level. This justifies the presumption on the structure of the variance-covariance matrix underlying the

[20] That $\hat{\lambda}$ is significantly positive in income regressions and negative in nutrition regressions means that more able households would earn more income but consume fewer calories. This is consistent with the aforementioned observations of higher income but lower nutrient intake in Section 3.

usefulness of our generalised selection model (3)-(4), with jointly distributed disturbances within and between poverty dimensions. Again similar results as the two-step estimation are obtained but with smaller standard errors.

[Tables 4 and 5]

Specifically, there were no age effects in household multi-dimensional intertemporal poverty.[21] A doubled initial proportion of children and the elderly within the household (dependency ratio variable) would add 0.155-0.223 to its intertemporal nutritional deprivation (Columns 5-8 of Table 4, Columns 5-6 of Table 5). Having at least one ethnic family member in 2000 was associated with 0.232-0.572 lower subsequent intertemporal nutritional poverty (Columns 5, 6 and 8 of Tables 4, Columns 4-6 of Table 5), as the mean household per capita nutritional intake in 2000 was 51.4% higher in ethnic minorities than in Han people.[22] The negative association with being from an ethnicity minority and intertemporal nutritional poverty also echoes the lower levels of average nutritional intertemporal poverty measures for ethnic minorities in Table 3. Neither dependency ratio nor ethnic status has a robust association with income poverty.

Human capital, as captured by the sum of household labour force weighted by their years of education, robustly dampens intertemporal income poverty with the marginal impact of 0.002-0.004 at the 1% significance level (Columns 1-4 of Table 4 and Columns 1-3 of Table 5), but tends to raise intertemporal nutritional poverty by a larger marginal amount of 0.004-0.008 at the 1% significance level (Columns 5-6 of Table 4 and Column 4 of Table 5). This may be understandable, considering that more initial human capital, especially primary education, promotes income growth for Chinese rural households in lagging regions (e.g., Sato, 2010; Song, 2012), which is in turn associated with a dietary shift towards low total calorie intake and unhealthier food consumption through a negative income effect (e.g., Du *et al.*, 2004). Moreover, insufficient diets and micronutrient supplementation, unsatisfactory or even non-existent catering infrastructure in rural schools, and misaligned supply-side incentives for health improvement programmes in rural China have been widely criticised as resulting in high prevalence of malnutrition among rural students (e.g., Kleiman-

[21] We also inserted the squared term of age and re-estimated Table 4, but neither age variable was found to be statistically significant.

[22] The ethnic minorities in study provinces are basically Mongolian. Their higher nutritional intake than that of Han people may be caused by their traditional diet preference and structure dominated by milk, other dairy-products and meat.

Weiner *et al.*, 2012; Luo *et al.*, 2011; Miller *et al.*, 2012), undermining human capital formation and resulting in undernutrition during adulthood.

Initial physical capital, which is proxied by households' fixed productive assets, also appears to be associated positively with subsequent intertemporal nutritional poverty (Column 8 of Table 4 and Columns 5-6 of Table 5). However, its net outcome is still negative (poverty-reducing), considering the larger negative impact of households' intertemporal average asset holdings. The statistically significant and negative estimates of initial productive assets in Columns 5-6 of Table 4, when the intertemporal asset holdings are not purged, also offer support for the view of a net poverty-reducing influence of productive asset accumulation. We observed similar phenomena for the role of land in both poverty dimensions. Having more areas of cultivated land owned by the household is associated with a net benefit to reducing multi-dimensional intertemporal poverty. This stems from having more land holdings in the long term, represented by a higher intertemporal mean farm size, rather than more initial land endowments.[23]

Initial labour productivity correlates negatively with both intertemporal income and nutritional poverty at the 1% significance level (-0.117 and -0.052 in Columns 1 and 5 of Table 4, respectively). We further disaggregate this into three kinds of production arrangement commonly practised by rural households, namely (local) agriculture, local non-agriculture and circular migration.[24] A 10% increase in initial agricultural labour productivity, measured by the net agricultural income (*yuan*) per agricultural labour input (day), would suppress 0.004-0.005 of the household's subsequent intertemporal income poverty (Column 2 of Table 4 and Column 1 of Table 5), and 0.003 of its intertemporal nutritional poverty (Columns 4 of Table 5). The magnitude of the above reductions is equivalent to 6% (0.004/0.063) and 0.6% (0.003/0.521) of the average intertemporal income and nutrition poverty, respectively, across all households. Note that statistical significance of the initial agricultural labour productivity gives way to that of its intertemporal mean (Columns 3-4 and 7-8 of Table

[23] The positive correlation between intertemporal poverty and initial land and asset holdings may be caused by the temporal increase of poverty from 2000 to 2001 which was discussed in Section 3. Its explanation may also apply to the positive, but insignificant, correlation between intertemporal poverty and initial agricultural labour productivity. However, the importance of agriculture cannot be simply denied, given its significant poverty-reducing effects through rural households' capacity building in agricultural production.

[24] Circular migration in rural areas refers to working, or seeking jobs temporarily, outside of the residence village but with registration being attached to the original household.

4, Columns 2-3 and 5-6 of Table 5). The magnitude of marginal decreases in intertemporal poverty brought by a 10% increase in households' intertemporal mean agricultural productivity also rose to as much as 0.01 for income (Column 4 of Table 4), equivalent to a 16% (0.01/0.063) decrease in average intertemporal income poverty, and 0.009 for nutrition (Column 6 of Table 5), equivalent to a 2% (0.009/0.521) decrease in average intertemporal nutritional poverty. This implies that households' long-term growth in agricultural labour productivity functions as a more effective instrument to fight against intertemporal income and nutritional poverty in the course of poverty transitions than do short-term increases, or simply a higher initial endowment, of agricultural labour productivity. The long-term benefit of agricultural improvement is consistent with other empirical findings. In respect of poverty transitions over time in rural China, agriculture prevents re-entry into poverty for those who have recently escaped and engaged mainly in out-migration (Imai and You, 2014), by assuring them of some safety nets for subsistence livelihood when shocks and uncertainties hit (Wang *et al.*, 2013).

Local non-agricultural activities also appear to reduce intertemporal income as well as nutritional poverty in both Heckman (Table 4) and generalised selection models (Table 5). The impact on the former is felt through both initial and intertemporal improvement in labour productivity in local non-agricultural production, while the impact on the latter is realised only when long-term improvement is achieved. If referring to the average level of multi-dimensional intertemporal poverty as listed in Table 3, a 10% increase in initial local non-agricultural labour productivity can yield about 6% (0.004/0.063 in Column 2 of Table 5) and 0.6% (0.003/0.521 in Column 6 of Table 5) reductions in intertemporal income and nutritional poverty, respectively, both of which are the same or smaller than those brought by equivalent gains in either short- or long-term agricultural labour productivity.

In contrast, circular migration only suggests a significant income poverty-reducing effect through its initial rather than long-term level, which is indicated by statistically insignificant estimates of intertemporal mean variables in Columns 3-4 of Table 4 and Columns 2-3 of Table 5, and does not help improve nutrition. As previously shown in Table 3, households relying most on circular migration endure the severest intertemporal poverty among three different livelihood groups, especially at lower poverty lines and in the income dimension. This might be explained by the mixed role of migration in poverty dynamics. From a static point of view, migration helps households escape from monetary poverty as it brings more income and consumption particularly for the poor (de Brauw and Giles, 2012). Re-calculating Table 1 for households, respectively, ever with and always without, out-migrating family members between 2000 and 2004, we find that the average probability of escaping income poverty against US$1.25/day across two consecutive waves is 80.1% for the former group as opposed to 67.1% for the latter. Nevertheless, when accounting for dynamic aspects of poverty, such as transitions, migration may also incur the risk of repeated poverty, especially for those living without any agricultural production, possibly due to various uncertainties and economic risk in underdeveloped factor markets (Imai and You, 2014) and no investment effect of migration on households' productive activities (de Brauw and Giles, 2012). In our data, 37.6% of households with out-migrating family members, and which have ever managed to escape income poverty, remained successfully above the poverty line throughout the sample period; 25.2% managed to stay in non-poverty in just one wave. By contrast, 43.1% of those without any out-migrating family members, but having ever escaped income poverty, maintained their non-poverty status throughout the sample period and only 20.7% were non-poor in just one wave.

The insensitivity of household nutrient intake to migration could be explained by the structure of household consumption expenditure when more income is generated by circular out-migration. Although our dataset did not record how or where the households used remittances, previous studies and some cross-tabulations of our data may provide some clues. Specifically, in a household survey in six provinces in 2000, de Brauw and Rozelle (2008) find that in relatively affluent areas, where the median incomes were more than twice the poverty line, an additional migrant increased investment in housing and consumer durables by 20%, while there was no association between remittances and productive investment in remaining households in the village. The much stronger propensity to consume, in particular to construct houses, compared to saving on receipt of remittances, is reaffirmed by Zhu *et al.*'s (2012) study based on another survey in 2006. They further document even less savings for productive investment in both agriculture and household business in migrant, than in non-migrant, families. Our data from two poor provinces also lend support to these findings. The correlation coefficient between households' real food consumption per adult equivalent and out-migration (i.e., a dummy variable taking the value of 1 for migrant households) is -0.174. Conversely, a 1% increase in household incomes of migrants is associated with a 0.1% increase in the real value of the house, at the 5% significance level. Compared with non-migrant households, migrant households lived in better houses, with 3.84 more squared metres of brick areas, at the 10% significance level.[25]

Comparing the above three livelihood arrangements, the magnitude of the impact of initial agricultural labour productivity on reducing intertemporal poverty is significantly larger than that of local non-agriculture activities and circular migration: the Wald test of equal estimated coefficients for the three kinds of labour productivity in Column 2 of Table 4 and Column 1 of Table 5 is firmly rejected at 1% significance level with $\chi^2(2)$ being 15.14 and 38.23, respectively.

Our finding of the crucial role of agriculture in fighting against poverty echoes the recent resurgent discussion on agriculture in developing countries (e.g., de Janvry and Sadoulet, 2010 for summary arguments with Vietnam as an example; Ravallion, 2009 for rural China; Dethier and Effenberger, 2012 for a recent literature review), especially for the poorest of the poor (Christiaensen *et al.*, 2011). For rural China in particular, at the national and provincial levels, the agricultural sector alone contributes to 75-80% of the drop in national poverty incidence (Ravallion and Chen, 2007) as opposed to little influence from manufacturing and services industries (Montalvo and Ravallion, 2010). At the household level, as in the macro-level studies, Christiaensen *et al.* (2013) use the same dataset as ours and also find that local agricultural production *per se* provides the most effective pathway out of poverty in the early stage of development. Agricultural labour productivity is the largest of three kinds of labour input and suggests the highest elasticity of poverty (-0.53 for Inner Mongolia and -0.73 for Gansu) compared to local diversification to non-agricultural sectors (-0.07 and -0.16 for two provinces, respectively) and circular migration (-0.01 and -0.09 for two provinces, respectively).

In addition to labour productivity gains in agriculture, we are particularly interested in whether agricultural innovation and modernisation could serve as an underlying channel through which agriculture alleviates poverty. This interest is

[25] The estimates in this and previous sentences are obtained by the following household fixed-effect instrumental variable estimation. We regressed the natural logarithm of the real value of the house (the squared metres of housing areas constructed by bricks) on the natural logarithm of real household incomes from circular migration (the dummy variable taking the value of 1 for migrant households), which was instrumented by its average at the village level in each wave, and other covariates including the household size measured by the equivalent adults, the dependency ratio, ethnicity, gender, age and education of the household head, village and wave dummies, and the household fixed effects.

motivated by both the existing literature – for example, that technological changes increase simultaneously income and nutrient intake (e.g., Lakdawalla *et al.*, 2005) – as well as the nation-wide drive for agricultural modernisation and mechanisation by 2020, emphasised by the Chinese government in the 3rd Plenary Session of the 18th CPC Congress in December 2013 and put into effect by the Ministry of Agriculture. We use several indicators as proxies for agricultural innovation and mechanisation, including (1) the share of cultivated land used for planting high quality gains, (2) the shares of cultivated land under mechanised cultivation, sowing, irrigation and harvest, respectively, (3) the share of cultivated land using plastic mulches, and (4) the share of greenhouse areas in households' total cultivated land. Endogeneity in technological adoption are taken into account by re-estimating the entire income and nutrition system jointly with correlated error terms within and between multi-dimensions of poverty (i.e., the specifications of Columns 2 and 5 of Table 5). Results are, nevertheless, quite mixed, hinging on specific technologies.[26] Only mechanised harvest in the initial period reduces both intertemporal income and nutritional poverty subsequently, with estimated coefficients of 0.164 and 0.331 at 1% significance levels, respectively. There is also long-term alleviating impact on nutrition poverty with the estimated coefficient of the intertemporal mean value of mechanised harvest being -0.379, significant at the 1% level. More initial mechanised cultivation is only an effective means to alleviate intertemporal income poverty in the short-term (-0.035 at the 10% significance level). By contrast, higher initial degrees of mechanised irrigation only alleviate subsequent deprivation of nutrition (-0.199 at the 1% significance level) but raises income poverty (0.074, significant at the 5% level), both of which are in the short-term. Both initially and intertemporally more mechanised sowing even significantly push up intertemporal poverty, in both dimensions, in the subsequent time period. Adoption of high quality grain seeds does not affect income deprivation but exhibits a distinct impact in the nutritional dimension: a short-term (initial) adoption would increase intertemporal nutrition poverty (by 0.131, significant at the 10% level), while the long-term (intertemporal) more high quality grain seeds reduce substantially the intertemporal nutrition poverty (by -0.27, significant at the 5% level. Plastic mulches and greenhouses seem to be irrelevant to either dimension of intertemporal poverty.

[26] Full estimation results are available from the authors upon request.

The overall sluggish and sometimes diversified short- and long-term responses of intertemporal poverty reduction to agricultural technological innovations and mechanisation seem to be inconsistent with conventional wisdom, and suggest that the government's pledges of agricultural innovation and mechanisation may be misguided in certain circumstances. This result could be driven by the way the policy was implemented, according to the authors' fieldwork in another three-wave panel dataset in all "national clustered poor areas" designated by the State Council in five provinces from costal to inland China (including the two sample provinces in the present study) over the period 2010-2014. For example, seeds and agricultural devices have been allocated by the upper-level governments without considering local conditions, including affordability, and different options for rural households – they can only accept what have been allocated or assigned. Some are useful in the short-term, but it is usually the case that households do not use them after three years. Similar short-term utilisation behaviour, with the same reasons, has also been found by Liu *et al.* (2013) in adoption of biogas stoves in rural China. Similarly, Hanna *et al.*'s (2012) randomised control trials for clean energy consumption behaviour in rural India demonstrate that households with revealed low valuation of stoves were more likely to adopt improved cooking stoves, which reduced indoor air pollution and fuel consumption more in the first year than in the following four years.

Other aspects of household well-being also matter. Better off households, in the sense of having better living conditions, are not necessarily less prone to intertemporal poverty. Having sanitation facilities at home reduces intertemporal income and nutrition poverty as a result of its long-term benefit to alleviating deprivation of both dimensions (-0.161 and -0.153 for income in Columns 2-3 of Table 5 and -0.17 for nutrition in Column 6 of Table 5), but its short-term effect is nutritional poverty-increasing by 0.073-0.234 (Column 8 of Table 4 and Columns 4-6 of Table 5). We can see from Columns 4-6 of Table 5 that access to tap water and installing heating facilities also aggravate intertemporal nutritional poverty, mainly through their long-term influence, while the short-term impact of the latter limits intertemporal nutritional poverty. Although using firewood as the main fuels relates to 0.046-0.051 higher subsequent intertemporal income poverty (Columns 1-2 of Table 5), it helps suppress nutritional deprivation in the long-term by 0.05 (Column 5 of Table 5). The above unfavourable wealth effects on intertemporal nutritional poverty might be explained through the detrimental impact of wealth on nutritional intake in China, as reviewed in

Section 3, as those living conditions may be indicative of household wealth status.[27] Another channel could be physical activity. Using the CHNS (1991-2006), Ng *et al.* (2009) find that urbanisation, in terms of improved sanitation and housing infrastructure, causes physical activity to decline, which, together with dietary changes, is conducive to worsened nutritional status (Ng *et al.*, 2011).

At the village level, the long-term higher average village income is associated strongly with lower intertemporal income poverty, but higher nutritional deprivation (Columns 4 and 8 of Table 4 and Columns 2-3 and 5-6 of Table 5), which again could be on account of the negative income effect on household nutrition. The longer the distance to education and health services, the lower the intertemporal income and nutritional poverty, either in the short- or long-term or the net of the two effects. We suspect that this may be because schools and hospitals at greater distance are of better quality, as the Chinese government launched a campaign in rural areas from 2001 which dismantled village schools in remote areas and combined them with those in towns or counties, in order to provide better quality educational services for rural students.[28] Hospitals in towns and counties are also generally equipped with more qualified doctors and better facilities than village clinics.

In addition, we re-estimated Tables 4 and 5 with more kinds of infrastructures, including the proportion of villages in the county with access to electricity, roads and TV signals. However, none of them were statistically significant. This is worrying, as village-targeted investment projects, and aid which goes mainly to infrastructure, have long been a major theme of policy intervention in rural China. At least in the intertemporal respect, many village-level infrastructure investments appear not to be an effective instrument for alleviating poverty.

4.3. Robustness checks

We check the robustness of our findings to alternative poverty lines, normative assumptions of influence of poor and affluent spells during transitions, and

[27] The correlation coefficients between household per capita net income and those three variables range between 0.15 and 0.32.

[28] It is notable that although nutritional poverty-reducing in the long-term, longer distance to the primary school is likely to raise intertemporal nutritional poverty in the short-term, reflected by significantly positive estimates of initial distance to primary schools in Columns 6-8 of Table 4 and 4-6 of Table 5. This may be ascribable to low quality of school meals and misaligned incentives of school heads to supply nutrition-rich and healthy diets in rural China, as cited before in Kleiman-Weiner *et al.* (2012), Luo *et al.* (2011) and Miller *et al.* (2012).

intertemporal poverty measures. Specifically, we re-estimated simultaneously all equations within the system with inter-dependent random errors (i.e., Columns 1-2 and 4-5 of Table 5) under higher poverty lines of US$2/day and 2,400 kcal for income and nutritional dimensions, respectively. Results are reported in Columns (1)-(2) and (5)-(6) of Table 6. We also replaced linear intensification and mitigation effects ($\alpha=\beta=\varphi=1$) with an increased influence of both households' past poor and past affluent experiences ($\alpha=\beta=2;\varphi=1$). These results are reported in Columns (3)-(4) and (7)-(8) of Table 6.[29]

[Table 6]

Many of the aforementioned effects still hold, while some are either reinforced or diminished. For example, labour productivity gains in local non-agricultural and circular migration become a significant driving force in suppressing not only intertemporal income poverty, but also in the nutritional dimension (Columns 5-8 of Table 6). More land cultivated by the household in the long-term is also strongly and negatively associated with both income and nutritional poverty, and the magnitude dominates the short-term poverty-increasing effects stemming from an initially larger farm size (Columns 2, 4, 6 and 8 of Table 6). The dependency ratio, in general, loses statistical significance, while the magnitude of ethnic distinction becomes more salient in both income and nutritional dimensions, with ethnic minorities being less poor intertemporally.

We were also concerned with the impact of the normative assumptions of our intertemporal poverty measures, that is, how our findings might differ when considering simply incidence of non-poverty (i.e. assigning the same mitigating value to all non-poverty spells regardless of the extent of affluence), versus allowing an enhanced mitigating effect of non-poor spells which are far above the poverty line. We re-estimated Table 5 under "standard" poverty lines of US$1.25/day and 2,100 kcal/day for income and nutritional dimensions, respectively, but replaced the dependent variables with the constant-relative affluence-dependent intertemporal poverty measure, i.e., Eq. (1) with $\alpha=\beta=\varphi=1$. Table 7 reports new estimates. By comparing Columns

[29] We also checked the sensitivity of results by assigning higher values to δ (i.e., defining "absolute affluence" as those in at least the 80th or 85th income or nutrition percentile) while keeping other parameters the same as before in Eq. (2). Compared with Table 3, the new multi-dimensional intertemporal poverty measures only differ from the 2nd decimal places. As such, re-estimating Table 5 with these new measures does not yield significant changes in results.

(1)-(2) and (4)-(5) between Tables 5 and 7, it can be seen that our previous findings hold broadly under the constant-relative measures.

[Table 7]

4.4. Interlocked poverty and nutritional intertemporal poverty

In addition to common unobserved factors and shocks affecting jointly household income and nutritional intake (i.e., simultaneity), we also consider the possible two-way effects between the two kinds of poverty (i.e., recursion). It has been well-established in theory that malnutrition can undermine individuals' income generating capability by deterring human capital accumulation, and that low income can, in turn, worsen nutritional status (Dasgupta and Ray, 1986). The two-way effects constitute nutritional poverty traps. Empirical evidence has been found in India (Jha *et al.*, 2009), but remains scarce for rural China (even taking a static approach to poverty measurement, let alone in an intertemporal perspective).

We revise the system (Eqs. 3-4) with inter-dependent random errors to reflect possibly mutually determined income and nutritional poverty. The selection equations in the system are replaced by recursive ones, as follows:

$$y_1^* = \mathbf{x}'\theta_1 + \bar{\mathbf{x}}'\theta_2 + \mathbf{z}_1'\theta_3 + \gamma_2 p_2 + \varepsilon_1 \tag{9}$$

$$y_2^* = \mathbf{x}'\theta_1 + \bar{\mathbf{x}}'\theta_2 + \mathbf{z}_2'\theta_3 + \gamma_1 p_1 + \varepsilon_2 \tag{10}$$

As such, the latent variable y_1^*, which determines a household's observed income poverty incidence, is affected by its intertemporal nutritional deprivation p_2, and vice versa. At the same time, the error terms within the whole system are still jointly distributed, $(\boldsymbol{\varepsilon}, \mathbf{v})|\mathbf{x}, \bar{\mathbf{x}}, \mathbf{z} \sim NID(0, \boldsymbol{\Sigma})$. This recursive system can be estimated consistently by MSL (Roodman, 2011).

There appears to be an intertemporally inter-locked vicious circle between income and nutrition. Columns (3) and (6) of Table 5 report the estimation results. The estimates are broadly the same as in our previous findings. It is noticeable that $\hat{\gamma}_2$ in Eq. (9) is positive at the 1% significance level, and implies that a unit increase in the magnitude of intertemporal nutritional poverty can make households 28.9 percentage points more likely to fall below the US$1.25-a-day poverty line in at least one year. The probability of falling below the nutritional poverty line of 2,100 kcal per person per day is nearly quadrupled (2.935) under an additional unit of intertemporal income poverty, though the effect lacks statistical significance. Intertemporally higher labour productivities in agriculture or local non-agricultural production exhibit poverty-reducing effects in both dimensions (as shown by Columns 3 and 6 of Table 5) even in the presence of intertemporal income-nutrition poverty traps, while out-migration only suggests short-term income-poverty alleviating effect through households' higher initial labour productivity in out-migration (Column 3 of Table 5).

This intertemporal relationship between income and nutrition poverty also exists under the constant-relative intertemporal poverty measures, as shown in Columns (3) and (6) of Table 7. Moreover, the impact of intertemporal nutritional poverty on intertemporal income poverty becomes larger (from 28.9 to 42.9 percentage points) as the absolute affluence in non-poverty spells mitigates deprivation less under the constant-relative intertemporal poverty measure ($\gamma = 1$ in Eq. 1) than under the relative measure ($\gamma = 2$ in Eq. 2). Nevertheless, it is worth noting that the short-term intertemporal poverty-reducing effect of initial labour productivity gains in out-migration disappears (Column 3 of Table 5 vs. Column 3 of Table 7), while the initial labour productivity gains in local non-agriculture mitigate intertemporal income deprivation in all specifications (Columns 1-3 of Table 7). Out-migration realises its substantial poverty-reducing effect only in the long-term (-0.178 at the 5% significance level in Column 3 of Table 7), and is nearly four times as large as that of the gains in agriculture (-0.045 at the 1% significance level in Column 3 of Table 7). This contrasts with the insignificant long-term effect of out-migration on the relative measure (Eq. 2) in Column 3 of Table 5. This sharp difference reaffirms our previous argument that out-migration could be a quicker means to lifting income above the poverty line than agriculture. However, when taking the extent of affluence as a long-term consequence of different livelihood arrangements, the average household net income per adult equivalent was 12-16% lower in those having ever engaged in out-migration than in those still implementing agricultural production in different waves. As noted above, this is possibly due to various risks and uncertainties in urban labour markets.

5. Conclusion

By exploiting a household panel dataset in poor rural areas in China over the period 2000-2004, we estimate household intertemporal poverty in both income and nutritional dimensions and identify various social and economic factors which appear to help shape household intertemporal poverty profiles.

Methodologically, we apply Dutta *et al.*'s (2013) affluence-dependent intertemporal poverty measures and propose a generalised selection system, together with an extension that helps to identify multi-dimensional intertemporal poverty traps. While the focus in this paper is on just two dimensions, our generalised and recursive selection approach can readily be extended to more dimensions. Strictly exogenous instrumental variables are not a necessity. The model can yield consistent estimates under correlated and jointly distributed disturbances, although weakly exogenous instrumental variables for each dimension would help improve identification. Another appealing extension of our model is that the dependent variables need not necessarily be binary, but could be continuous or categorical variables, to capture deprivations with different properties. In this case, one would only need to change the variance-covariance matrix of the disturbances in accordance with the new dependent variables to obtain consistent estimation.

To the extent that intertemporal poverty is the focus of policy makers our evidence suggests that household-focused interventions generally outperform village-level instruments. In the early stages of development, and when agriculture is a dominant element of individuals' livelihood, improvement in agricultural production, both in terms of increased agricultural labour productivity and of larger farm size and investment in productive assets, still holds the key to reducing both intertemporal income and nutritional poverty. This is true whether focusing on the poorest of the poor, or when the richer poor are also included, by adopting higher poverty lines. The finding is also robust across different normative assumptions underlying intertemporal poverty aggregation over time. Furthermore, when there is evidence suggestive of intertemporal poverty-nutrition traps, higher labour productivity in agriculture in the long-term holds more potential for breaking the vicious circle, in both income and nutritional dimensions, than does local non-agricultural production or out-migration. However, long-term labour productivity gains in out-migration dominate agriculture in reducing intertemporal income poverty if only incidence, rather than the extent, of affluence prior to poverty spells, is embedded in the intertemporal measure.

Our results suggest that the purported positive roles of local non-agricultural production and out-migration in reducing monetary poverty might be overblown, at least as an intertemporal phenomenon. They are not magic bullets. Rather, whatever effect they have on both income and nutritional dimensions is likely to be highly context specific and dependent on other factors.

Dissemination of agricultural technologies and better living conditions also help reduce intertemporal poverty to some extent, but only in the short-term. Moreover, their influence on intertemporal poverty is highly sensitive to which particular dimension of deprivation policymakers aim to tackle, and which specific technology or mechanisation households adopt. Such instruments need to be implemented with caution and awareness of contextual specifics, as our analysis suggests that they can have unintended negative consequences, both for household income and nutrition.

References

Alkire, S. and Foster, J. (2011a). Counting and multidimensional poverty measure. *Journal of Public Economics* 95(7-8), 476-487.

Alkire, S. and Foster, J. (2011b). Understandings and misunderstandings of multidimensional poverty measurement. *Journal of Economic Inequality* 9, 289-314.

Alkire, S. and Santos, M.E. (2010). Acute multidimensional poverty: a new index for developing countries. OPHI working paper series, 38.

Alkire, S., Apablaza, M., Chakravarty, S. and Yalonetzky, G. (2013). Measuring chronic multidimensional poverty: A counting approach. Paper presented at the IARIW-IBGE Conference on Income, Wealth and Well-Being in Latin America, Rio de Janeiro, Brazil, September 11-14, 2013.

Atkinson, A. Multidimensional deprivation. Contrasting social welfare and counting approaches. *Journal of Economic Inequality* 1, 51-65.

Baulch, B. and Hoddinott, J. (2000). Economic mobility and poverty dynamics in developing countries. *Journal of Development Studies* 36(6), 1-24.

Bliss, C. J. and Stern, N. H. (1978). Productivity, wages and nutrition: Theory and observations. *Journal of Development Economics* 5, 331-398.

Bossert, W., Chakravarty, S. and D'Ambrosio, C. (2012). Poverty and time. *Journal of Economic Inequality* 10(2), 145-162.

Bourguignon, F. and Chakravarty, S. (2003). The measurement of multidimensional poverty. *Journal of Economic Inequality* 1, 25-49.

Brandt, L. and Holz, C. A. (2006). Spatial price differences in China: Estimates and implications. *Economic Development and Cultural Change* 55(1), 43-86.

Bresson, F. and Duclos, J. (2012). Intertemporal poverty comparisons. CIRPÉE Working Paper, No. 12-40.

Chamberlain, G. (1984). Panel data. In Griliches Z., and Intrilligator M. D., (eds.). *Handbook of Econometrics* 2, Amsterdam: Elsevier Science Publishers B.V., pp. 1248-1318.

Christiaensen, L., Demery, L. and Kuhl, J. (2011). The (evolving) role of agriculture in poverty reduction – an empirical perspective. *Journal of Development Economics* 96(2), 239-254.

Christiaensen, L., Pan, L. and Wang, S. (2013). Pathways out of poverty in lagging regions: Evidence from rural western China. *Agricultural Economics* 44(1), 25-44.

D'Ambrosio, C. (2013). The indicators of intertemporal material deprivation: A proposal and an application to EU countries. ImPRovE Discussion Paper No. 13/08. Antwerp.

Dasgupta, P. and Ray, D. (1986). Inequality as a determinant of malnutrition and unemployment: Theory. *The Economic Journal* 96(384), 1011-1034.

Dasgupta, P. and Ray, D. (1987). Inequality as a determinant of malnutrition and unemployment: Policy. *Economic Journal* 97, 177-188.

Duclos, J., Araar, A. and Giles, J. (2010). Chronic and transient poverty: Measurement and estimation, with evidence from China. *Journal of Development Economics* 91(2), 266-277.

de Brauw, A. and Giles, J. (2012). Migrant labor markets and the welfare of rural households in the developing world: Evidence from China. IZA Discussion Paper No. 6765.

de Brauw, A. and Rozelle, S. (2008). Migration and household investment in rural China. *China Economic Review* 19(2), 320-335.

de Janvry, A. and Sadoulet, E. (2010). Agricultural growth and poverty reduction: Additional evidence. *World Bank Research Observer* 25(1), 1-20.

Calvo, C. and Dercon, S. (2009). Chronic poverty and all that: The measurement of poverty over time. In: T. Addison, D. Hulme and R. Kanbur (eds), *Poverty dynamics: interdisciplinary perspectives*. Oxford University Press, Oxford, pp. 29-58.

Dercon S., and Hoddinott, J. (2003). Health, shocks and poverty persistence. Discussion Paper No. 2003/08, WIDER, Helsinki.

Dethier, J. and Effenberger, A. (2012). Agriculture and development: A brief review of the literature. *Economic Systems* 36(2), 175-205.

Duclos, J., Araar, A. and Giles, J. (2010). Chronic and transient poverty: measurement and estimation, with evidence from China. *Journal of Development Economics* 91(2), 266–277.

Du, S., Mroz, T. A., Zhai, F. and Popkin, B. M. (2004). Rapid income growth adversely affects diet quality in China – particularly for the poor! *Social Science & Medicine* 59(7), 1505-1515.

Dutta, I., Roope, L. and Zank, H. (2013). On intertemporal poverty measures: The role of affluence and want. *Social Choice and Welfare* 41(4), 741-762.

Foster, J. (2009). A class of chronic poverty measures. In: Addison T., Hulme D., Kanbur R. (eds) *Poverty dynamics: interdisciplinary perspectives*. Oxford University Press, Oxford, pp. 59–76.

Gradín, C., Río, C. D. and Cantó, O. (2012). Measuring poverty accounting for time. *Review of Income and Wealth* 58(2), 330-354.

Hanna, R., Duflo, E. and Greenstone, M. (2012). Up in smoke: The influence of household behavior in the long-run impact of improved cooking stoves. NBER Working Paper 18033.

Heckman, J. (1979). Sample selection bias as a specification error. *Econometrica* 47(1), 153-161.

Hoy, M., Thompson, B. C. and Zheng, B. (2012). Empirical issues in lifetime poverty measurement. *Journal of Economic Inequality* 10(2), 163-189.

Hoy, M. and Zheng, B. (2011). Measuring lifetime poverty. *Journal of Economic Theory* 146(6), 2544-2562.

Imai, K. and You, J. (2014). Poverty dynamics of households in rural China. *Oxford Bulletin of Economics and Statistics* 76(6), 898-923.

Jalan, J. and Ravallion, M. (1998). Transient poverty in postreform rural China. *Journal of Comparative Economics* 26(2), 338-357.

Jha, R., Gaiha, R. and Sharma, A. (2009). Calorie and micronutrient deprivation and poverty nutrition traps in rural India. *World Development* 37(5), 982-991.

Kleiman-Weiner, M., Luo, R., Zhang, L., Shi, Y., Martorell, R., Rozelle, S. and Medina, A. (2013). Multiple micronutrient supplementation reduces anemia anxiety in rural China's elementary school children. *Journal of Nutrition*, 143(5), 640-647.

Labar, K. and Bresson, F. (2011). A multidimensional analysis of poverty in China from 1991 to 2006. *China Economic Review* 22(4), 646-668.

Lakdawalla, D., Philipson, T. and Bhattacharya, J. (2005). Welfare-enhancing technological change and the growth of obesity. *American Economic Review* 95 (2), 253-257.

Leibenstein, H. (1957). *Economic Backwardness of Economic Growth*, Wiley, New York.

Liu, W., Spaargaren, G., Heerink, N., Mol, A. P. J. and Wang, C. (2013). Energy consumption practices of rural households in north China: Basic characteristics and potential for low carbon development. *Energy Policy*, 55, 128-138.

Luo, R., Zhang, L., Liu, C., Zhao, Q., Shi, Y., Miller, G., Yu, E., Sharbono, B., Medina, A., Rozelle, S. and Martorell, R. (2011). Anaemia among students of rural China's elementary schools: Prevalence and correlates in Ningxia and Qinghai's poor counties. *Journal of Health, Population and Nutrition*, 29(5), 471-485.

McCulloch, N. and Calandrino, M. (2003). Vulnerability and chronic poverty in rural Sichuan. *World Development* 31(3), 611-628.

Mendola, D. and Busetta, A. (2012). The importance of consecutive spells of poverty: A path-dependent index of longitudinal poverty. *Review of Income and Wealth* 58(2), 355-374.

Mendola, D. and Busetta, A. (2013). Chronic Poverty in European Mediterranean Countries. In: *Advances in Theoretical and Applied Statistics*, Springer Berlin Heidelberg, pp. 339-350.

Miller, G., Luo, R., Zhang, L., Sylvia, S., Shi, Y., Foo, P., Zhao, Q., Martorell, R., Medina, A. and Rozelle, S. (2012). Effectiveness of provider incentives for anemia reduction in rural China: a cluster randomised trial. *BMJ*, 345(e4809), doi: 10.1136/bmj.e4809.

Montalvo, J. and Ravallion, M. (2010). The pattern of growth and poverty reduction in China. *Journal of Comparative Economics* 38(1), 2-16.

Ng, S.W., Norton, E.C. and Popkin, B.M. (2009). Why have physical activity levels declined among Chinese adults? Findings from the 1991-2006 China Health and Nutrition Surveys. *Social Science & Medicine* 68(7), 1305-1314.

Ng, S.W., Norton, E.C., Guilkey, D.K. and Popkin, B. M. (2011). Estimation of a dynamic model of weight. *Empirical Economics* 42 (2), 413-443.

Park, A., Wang, S. and Wu, G. (2002). Regional poverty targeting in China. *Journal of Public Economics* 86(1), 123-153.

Park, A. and Wang, S. (2010) Community-based development and poverty alleviation: An evaluation of China's poor village investment program. *Journal of Public Economics* 94(9-10), 790-799.

Ravallion, M. (2005). Externalities in rural development: evidence for China. In: Kanbur, Ravi, Venables, Tony (eds.), *Spatial Inequality and Development*. Oxford University Press: Oxford, UK.

Ravallion, M. (2009). Are there lessons for Africa from China's success against poverty? *World Development* 37(2), 303-313.

Ravallion, M. (2011). On multidimensional indices of poverty. *Journal of Economic Inequality* 9(2), 235-248.

Ray, R. and Mishra, A. (2012). Multi-dimensional deprivation in the awakening giants: A comparison of China and India on micro data. *Journal of Asian Economics* 23(4), 454-465.

Roodman, D. (2011). Estimating fully observed recursive mixed-process models with cmp. *Stata Journal* 11(2), 159-206.

Roope, L. and Peters, S. (2013). Intertemporal poverty in Great Britain. Economics Discussion Paper Series 1327, University of Manchester.

Sato, H. (2010). Growth of villages in China, 1990-2002. *Frontiers of Economics in China* 5(1), 135-149.

Shimokawa, S. (2013). When does dietary knowledge matter to obesity and overweight prevention? *Food Policy* 38, 35-46.

Song, Y. (2012). Poverty reduction in China: The contribution of popularizing primary education. *China & World Economy* 20(1), 105-122.

Strauss, J. and Thomas, D. (1998). Health, nutrition, and economic development. *Journal of Economic Literature* 36, 766-817.

Thorbecke, E. (2011). A comment on multidimensional poverty indices. *Journal of Economic Inequality* 9(3), 485-487.

Tsui, K. (2002). Multidimensional poverty indices. *Social Choice and Welfare* 19(1), 69-93.

Wan, G. and Zhang, Y. (2013). Chronic and transient poverty in rural China. *Economics Letters* 119(3), 284-286.

Wang, C., Rada, N., Qin, L. and Pan, S. (2014). Impacts of migration on household production choices: Evidence from China. *Journal of Development Studies*, forthcoming, doi: 10.1080/00220388.2013.866221.

Wang, X., Weaver, N. and You, J. (2013). The social security function of agriculture in China. *Journal of International Development* 25(1), 1-10.

World Bank (2009). From poor areas to poor people: China's evolving poverty reduction agenda.

You, J. (2014). Dietary change, nutrient transition and food security in fast growing China. In: Raghav Gaiha, Raghbendra Jha and Anil B. Deolalikar (eds.), *Handbook on Food: Demand, Supply, Sustainability and Security*. Edward Elgar Publishing: Cheltenham, UK.

You, J., Imai, K. and Gaiha, R. (2014). Decoding the growth-nutrition nexus in China: Inequality, uncertainty and food insecurity. Economics Discussion Paper Series, No. EDP-1413, University of Manchester.

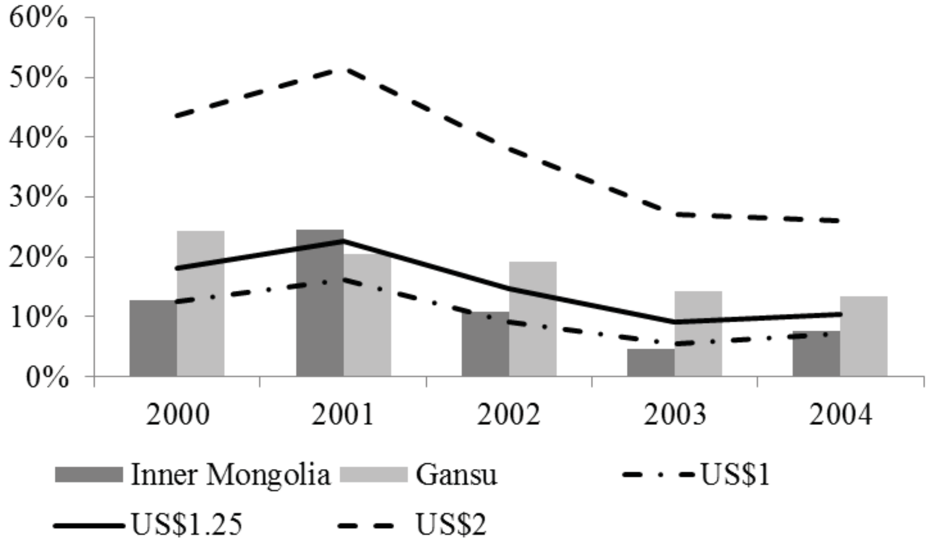
Zheng, B. (2011). Measuring chronic poverty: a gravitational approach. Department of Economics, University of Colorado, Denver.

Zhu, Y., Wu, Z., Wang, M., Du, Y. and Cai, F. (2012). Do migrants really save more? The impact of remittances on savings in rural China. *Journal of Development Studies* 48(5), 654-672

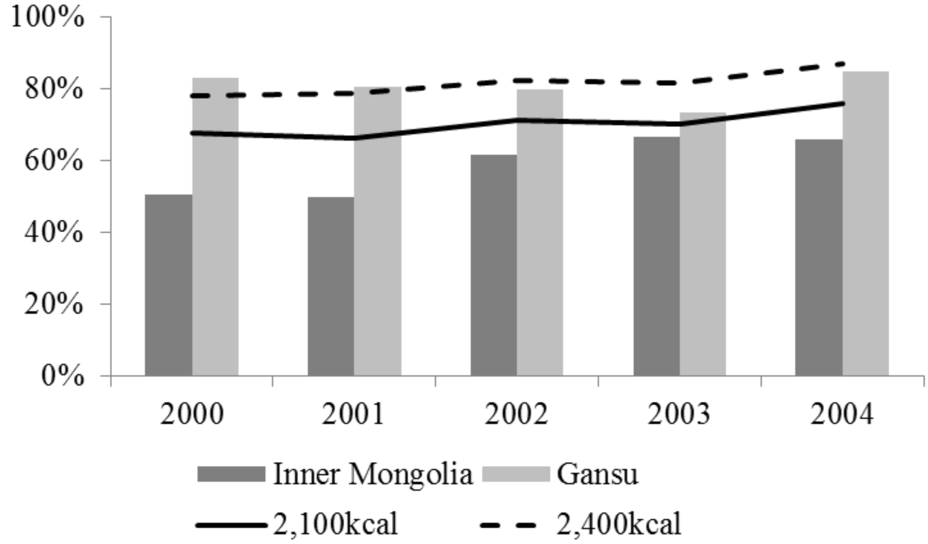
Tables and Figures

Figure 1 Static poverty statistics

(a) Income poverty rates



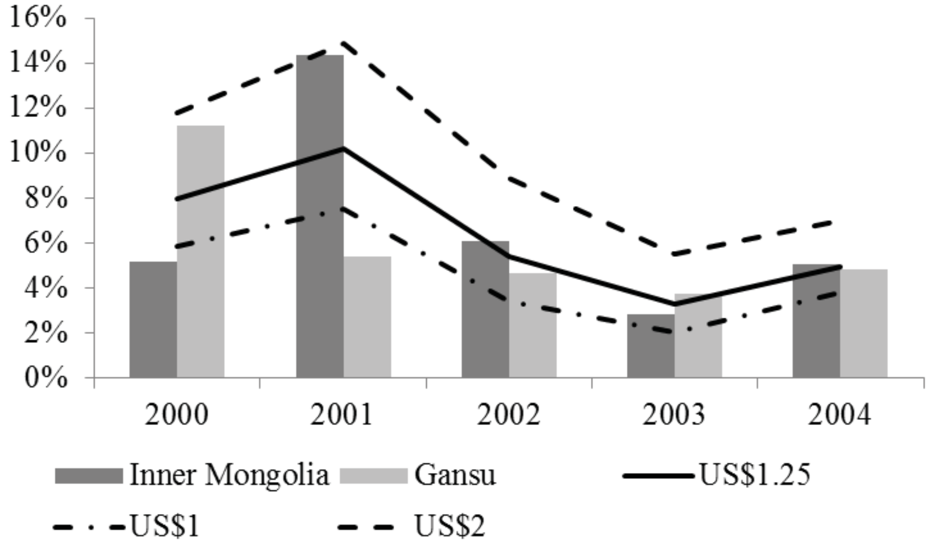
(b) Nutrition poverty rates



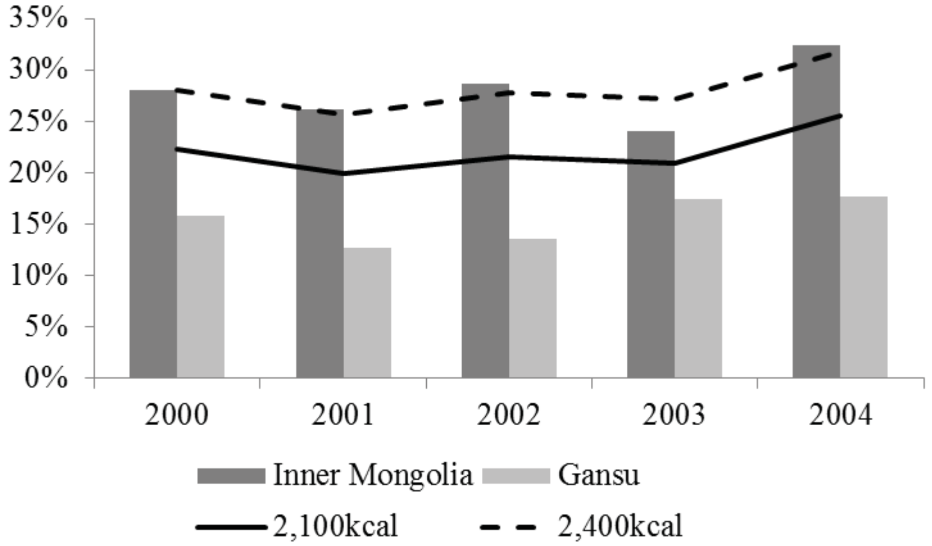
Notes: The bars represent provincial poverty rates. They are calculated against the US$1.25-a-day threshold in income dimension in Figure 1(a) and the 2,100kcal per person per day in nutrition dimension in Figure 1(b). The lines represent the average poverty rates across two provinces under different poverty thresholds. In particular, the solid lines represent poverty rates based on our preferred poverty thresholds – US$1.25/day and 2,100kcal – in estimation.
Source: Authors' calculation based on data in this paper.

Figure 2 Poverty gap

(a) Income poverty gap

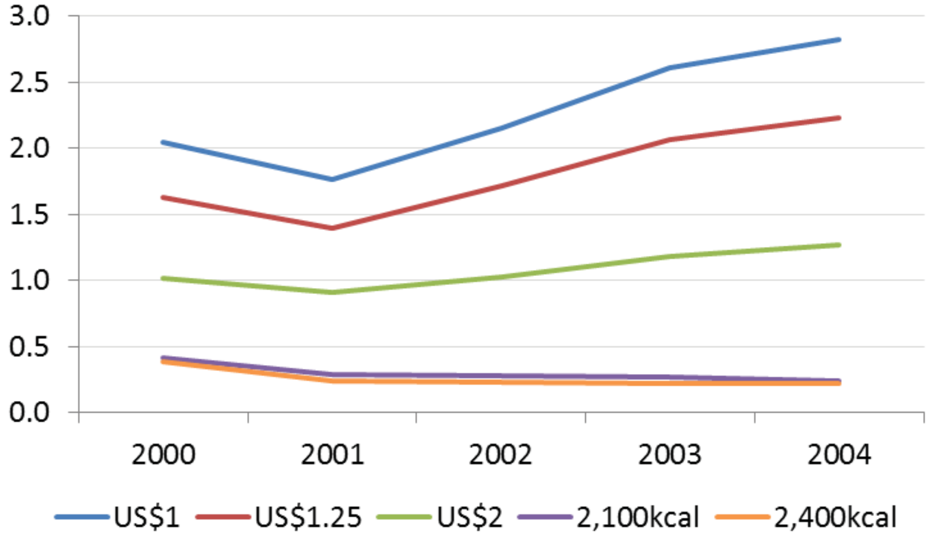


(b) Nutrition poverty gap



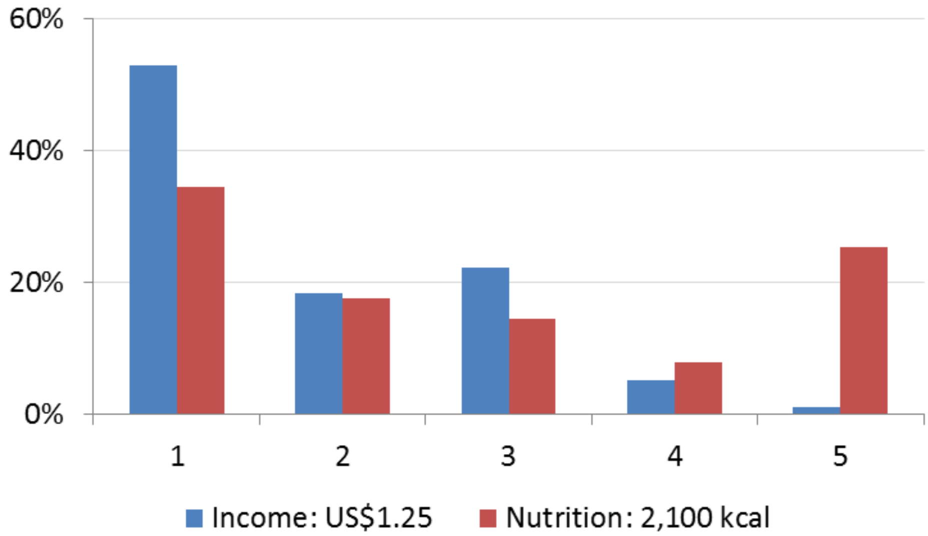
Note: The lines represent total poverty gap for two provinces under different poverty lines. The bars represent provincial poverty gap which is calculated under the US$1.25-a-day and 2,100 kcal per person per day in income and nutrition dimensions, respectively. The sample size for the total poverty gap (indicated by lines) is 1,500 in two sample provinces. The sample sizes for Gansu and Inner Mongolia (indicated by bars) are 700 and 800 households, respectively.

Figure 3 Extent of affluence



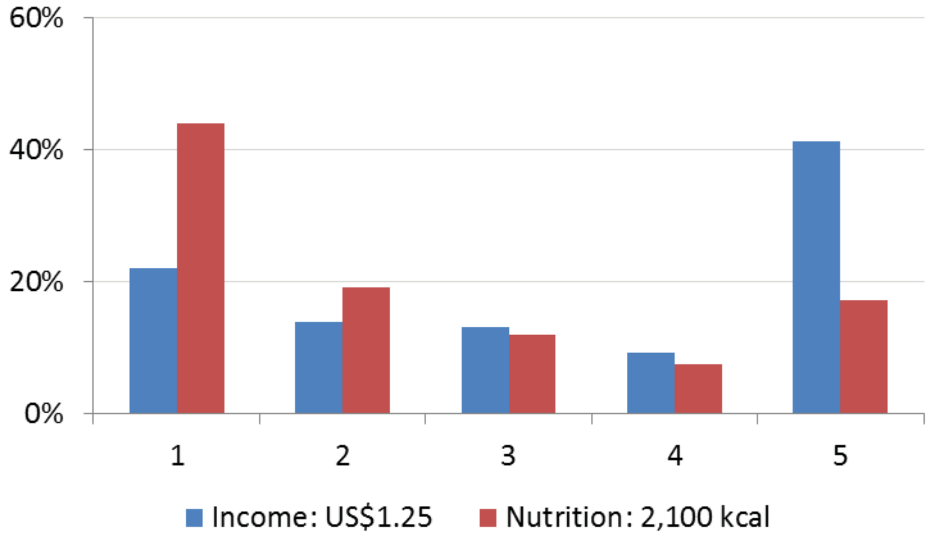
Note: The vertical axis measures the average ratio of the household's observed income (nutrient intake) per equivalent adult over different income (nutrition) poverty lines. This figure depicts the total relative affluence in these dimensions in our two sample provinces.

Figure 4 Distribution of the length of poor spells



Note: The sample size is 1,500 households in our two sample provinces.

Figure 5 Distribution of the length of non-poor spells



Note: The sample size is 1,500 households in our two sample provinces.

Table 1 Poverty transition matrix

Poverty at *t-1*	Poverty at *t*		Total
	0	1	
Income: US$ 1.25			
0	88.74	11.26	100
1	70.37	29.63	100
Income: US$ 2			
0	75.92	24.08	100
1	46.96	53.04	100
Nutrition: 2,100 kcal			
0	50.77	49.23	100
1	19.35	80.65	100
Nutrition: 2,400 kcal			
0	37.80	62.20	100
1	12.65	87.35	100

Notes: Figures are in percentages. The sample size in each transition matrix is 1,500 households. Zero and one denote non-poverty and poverty status, respectively. On average, across two consecutive periods, 14.23% and 35.68% of the sample were income poor at the US$ 1.25 and US$2 lines, respectively; 70.85% and 82.35% were nutrition poor based on the 2,100 kcal and 2,400 kcal lines, respectively.

Table 2 Dynamic poverty profile

No. of transitions	Share in total obs. (%)	No. of poor spells	Share in total obs. (%)	No. of non-poor spells	Share in total obs. (%)
Income: US$1.25					
1	52.93	0	52.60	0	0.33
2	18.40	1	39.13	1	72.87
3	22.27	2	8.00	2	25.87
4	5.20	3	0.27	3	0.93
5	1.20	4	–	4	–
Total	100	Total	100	Total	100
Nutrition: 2,100 kcal					
1	36.73	0	4.00	0	32.73
2	25.27	1	64.40	1	49.60
3	26.73	2	30.07	2	17.07
4	9.13	3	1.53	3	0.60
5	2.13	4	–	4	–
Total	100	Total	100	Total	100

Notes: The total sample size is 1,500 households. " – " means no data. We treat the data as being left-censored. In other words, households are considered to experience the first transition into their initial poverty or non-poverty status in the first wave. Thus, given that there are 5 waves in our data, the number of transitions ranges from 1 (for those who remained poor or non-poor in every wave) to 6 (for those who changed poverty status in every wave). Equivalently, the number of poor or non-poor spells for the former group (with only one transition prior to the first wave) is zero. Households with one poor (non-poor) spell are those who stayed in poverty (non-poverty) throughout the sample period and who experienced two transitions, with one transition from non-poverty (poverty) to poverty (non-poverty), and so on.

Table 3 Intertemporal poverty profile

Group	US$1.25		US$2		2,100 kcal		2,400 kcal	
	$P_R(\mathbf{p})$	$\tilde{P}_R(\mathbf{p})$	$P_R(\mathbf{p})$	$\tilde{P}_R(\mathbf{p})$	$P_R(\mathbf{p})$	$\tilde{P}_R(\mathbf{p})$	$P_R(\mathbf{p})$	$\tilde{P}_R(\mathbf{p})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\alpha = \beta = \varphi = 1$								
Full sample	0.064	0.063	0.223	0.220	0.524	0.521	0.744	0.740
Geography								
Gansu	0.068	0.067	0.314	0.313	0.322	0.318	0.513	1.658
Inner Mongolia	0.061	0.058	0.143	0.139	0.701	0.698	0.946	3.291
Labour allocation								
Agriculture	0.070	0.069	0.243	0.240	0.527	0.513	0.746	0.731
Local non-agriculture	0.023	0.040	0.120	0.158	0.506	0.544	0.743	0.772
Circular migration	0.117	0.090	0.221	0.247	0.532	0.510	0.697	0.715
Ethnicity								
Han	0.120	0.121	0.249	0.251	0.768	0.759	0.942	0.930
Minorities	0.059	0.058	0.220	0.218	0.503	0.500	0.727	0.724
$\alpha = 2, \beta = \varphi = 1$								
Full sample	0.119	0.117	0.574	0.572	1.707	1.704	2.538	2.534
Geography								
Gansu	0.129	0.129	0.876	0.876	0.974	0.970	1.669	1.664
Inner Mongolia	0.110	0.108	0.309	0.306	2.349	2.346	3.298	3.295
Labour allocation								
Agriculture	0.132	0.131	0.631	0.627	1.712	1.673	2.532	2.493
Local non-agriculture	0.038	0.069	0.295	0.399	1.664	1.796	2.591	2.666
Circular migration	0.207	0.179	0.479	0.602	1.811	1.704	2.397	2.471
Ethnicity								
Han	0.279	0.283	0.696	0.703	2.451	2.425	3.095	3.057
Minorities	0.106	0.103	0.564	0.561	1.644	1.641	2.490	2.489
$\alpha = \beta = 2, \varphi = 1$								
Full sample	0.111	0.110	0.564	0.563	1.701	1.700	2.532	2.529
Geography								
Gansu	0.124	0.124	0.868	0.868	0.967	0.964	1.661	1.658
Inner Mongolia	0.100	0.099	0.298	0.296	2.343	2.340	3.293	3.291
Labour allocation								
Agriculture	0.123	0.123	0.621	0.617	1.706	1.668	2.526	2.488
Local non-agriculture	0.034	0.064	0.288	0.391	1.657	1.791	2.585	2.662
Circular migration	0.200	0.170	0.469	0.591	1.806	1.698	2.390	2.465
Ethnicity								
Han	0.269	0.274	0.686	0.694	2.447	2.420	3.090	3.053
Minorities	0.098	0.096	0.554	0.551	1.637	1.636	2.484	2.483
$\alpha = \beta = 0, \varphi = 1$ (Foster, 2009)								
Full sample	0.064		0.137		0.221		0.288	
Geography								
Gansu	0.060		0.168		0.154		0.218	
Inner Mongolia	0.067		0.111		0.279		0.350	
Labour allocation								
Agriculture	0.070		0.148		0.222		0.290	
Local non-agriculture	0.027		0.080		0.213		0.282	
Circular migration	0.096		0.155		0.210		0.272	
Ethnicity								
Han	0.089		0.144		0.325		0.383	
Minorities	0.061		0.137		0.212		0.280	

Note: The sample size for the full sample and each category is 1,500. For the relative-affluent measures ($\tilde{P}_R(\mathbf{p})$) in Eq. (2), we set δ=3.2 for income and 1.05 for nutrition.

Table 4 Heckman two-step estimation of the determinants of intertemporal poverty

Independent variable	Income (US$1.25/day)				Nutrition (2,100 kcal/day)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Household demographics								
Ln(age of hh head)	-0.035 (0.036)	-0.025 (0.032)	-0.009 (0.070)	-0.001 (0.062)	-0.012 (0.041)	-0.051 (0.039)	-0.209 (0.081)***	-0.045 (0.108)
Dependency ratio	0.098 (0.040)**	0.082 (0.037)**	0.022 (0.060)	0.015 (0.040)	0.157 (0.046)***	0.155 (0.045)***	0.189 (0.068)***	0.213 (0.099)**
Ethnic minority	0.057 (0.107)	0.048 (0.107)	0.024 (0.176)	0.026 (0.078)	-0.232 (0.117)**	-0.241 (0.117)**	-0.113 (0.207)	-0.533 (0.287)*
Household production								
Ln(cultivated land)	0.038 (0.015)**	0.019 (0.012)	0.039 (0.022)*	0.024 (0.013)*	0.0004 (0.012)	0.011 (0.012)	0.048 (0.020)**	0.063 (0.022)***
Ln(hh per capita equivalent productive assets)	-0.001 (0.004)	-0.002 (0.004)	-0.001 (0.009)	-0.005 (0.008)	-0.016 (0.005)***	-0.017 (0.005)***	-0.002 (0.010)	-0.024 (0.013)*
Education weighted labour force	-0.004 (0.001)***	-0.002 (0.001)*	-0.004 (0.002)***	-0.003 (0.001)**	0.004 (0.001)***	0.005 (0.001)***	0.002 (0.002)	0.002 (0.002)
Labour productivity	-0.117 (0.023)***				-0.052 (0.014)***			
Agricultural labour productivity		-0.036 (0.013)***	-0.012 (0.010)	-0.002 (0.007)		-0.004 (0.009)	-0.014 (0.012)	-0.020 (0.015)
Local non-agricultural labour productivity		-0.013 (0.006)**	-0.010 (0.005)**	-0.008 (0.004)**		0.005 (0.004)	0.003 (0.005)	0.007 (0.007)
Labour productivity in circular migration		-0.013 (0.005)***	-0.013 (0.006)**	-0.007 (0.006)		-0.002 (0.005)	-0.0001 (0.007)	-0.011 (0.009)
Household living conditions								
Sanitation		-0.171 (0.118)	-0.117 (0.137)	-0.007 (0.042)		0.112 (0.090)	0.302 (0.113)***	0.203 (0.091)**
Water		0.115 (0.067)*	0.122 (0.077)	0.001 (0.026)		-0.091 (0.063)	-0.164 (0.071)**	-0.035 (0.043)
Heating		-0.010 (0.121)	-0.245 (0.242)	-0.153 (0.045)***		-0.039 (0.173)	-0.165 (0.301)	-0.453 (0.124)***
Fuel		0.006 (0.051)	0.011 (0.063)	0.049 (0.018)***		0.003 (0.062)	0.017 (0.069)	0.019 (0.034)
Village characteristics								
Ln(village per capita net income)		-0.086 (0.061)	-0.045 (0.918)	-0.001 (0.026)		0.143 (1.505)	0.606 (0.861)	0.012 (0.048)
Distance to primary school		-0.017 (0.062)	-0.273 (0.253)	-0.025 (0.013)*		0.135 (0.061)*	0.943 (0.301)***	0.046 (0.027)*
Distance to hospital		-0.015 (0.043)	-0.187 (0.842)	-0.010 (0.009)		-0.214 (0.183)	-0.120 (0.771)	-0.038 (0.016)**
Geography		-0.225 (0.152)	-0.280 (0.487)	-0.025 (0.020)		-0.108 (1.204)	-0.896 (0.395)**	-0.041 (0.031)
Unobserved heterogeneity control								
Ln(age of hh head)			-0.030 (0.077)	-0.024 (0.070)			0.279 (0.091)***	0.072 (0.118)
Dependency ratio			0.100 (0.073)	0.053 (0.046)			-0.045 (0.081)	-0.168 (0.118)
Ethnic minority			-0.080 (0.179)	-0.050 (0.079)			0.502 (0.225)**	0.268 (0.287)
Ln(cultivated land)			-0.025 (0.023)	-0.026 (0.013)**			-0.086 (0.020)***	-0.067 (0.022)***
Ln(hh per capita equivalent productive assets)			0.002 (0.010)	-0.001 (0.009)			-0.019 (0.011)*	-0.027 (0.015)*
Education weighted labour force			-0.003 (0.002)	-0.001 (0.002)			0.011 (0.002)***	0.010 (0.003)***
Agricultural labour productivity			-0.097 (0.018)***	-0.125 (0.009)***			-0.036 (0.015)**	-0.088 (0.020)***
Local non-agricultural labour productivity			-0.026 (0.011)**	-0.043 (0.006)***			-0.026 (0.009)***	-0.030 (0.011)***
Labour productivity in circular migration			-0.001 (0.019)	-0.021 (0.016)			0.016 (0.019)	0.041 (0.026)
Sanitation			-0.098 (0.210)	-0.178 (0.044)***			-0.722 (0.226)***	-0.125 (0.096)
Water			0.126 (0.153)	0.009 (0.032)			0.190 (0.160)	0.121 (0.059)**
Heating			0.568 (0.441)	0.065 (0.049)			0.172 (0.524)	0.600 (0.131)***
Fuel			0.142 (0.105)	0.002 (0.017)			-0.044 (0.085)	-0.054 (0.029)*
Ln(village per capita net income)			-0.187 (0.467)	-0.110 (0.031)***			0.366 (0.529)	0.178 (0.061)***
Distance to primary school			0.344 (0.266)	0.008 (0.017)			-1.099 (0.294)***	-0.097 (0.031)***
Distance to hospital			0.125 (0.921)	0.015 (0.012)			0.173 (0.827)	0.022 (0.020)
λ	0.155 (0.062)**	0.077 (0.074)	0.133 (0.053)**	–	-0.008 (0.133)	-0.755 (0.225)***	-0.717 (0.206)***	–
$\rho_{\varepsilon_i \mu_j}, j=\{1,2\}$	–	–	–	0.999	–	–	–	-0.640
No. of obs.	1,431	1,500	1,500	1,500	1,431	1,500	1,500	1,500

Note: Columns (1)-(4) and (5)-(8) study income and nutrition poverty, respectively. The first step probit estimation and village dummies in each column are not reported. The dependent variables in all outcome regressions, i.e., the intertemporal income and nutritional poverty, are defined by Eq. (2) with $\alpha = \beta = \varphi = 1$ and δ=3.2 for income and 1.05 for nutrition. ***, ** and * denote 1%, 5% and 10% significance levels in turn. Columns (1)-(3) and (5)-(7) are Heckman two-step estimators. Columns (4) and (8) are ML estimators where "–" means not applicable.

Table 5 Simulated maximum likelihood estimation of the determinants of intertemporal poverty

Independent variable	Income (US$1.25/day)			Nutrition (2,100 kcal/day)		
	(1)	(2)	(3)	(4)	(5)	(6)
Household demographics						
Ln(age of hh head)	-0.020 (0.031)	-0.009 (0.078)	-0.016 (0.066)	-0.064 (0.053)	-0.040 (0.107)	-0.025 (0.106)
Dependency ratio	0.042 (0.038)	0.026 (0.065)	0.018 (0.060)	0.055 (0.062)	0.223 (0.099)**	0.214 (0.098)**
Ethnic minority	-0.094 (0.036)***	-0.042 (0.183)	-0.085 (0.160)	-0.229 (0.056)***	-0.551 (0.285)*	-0.572 (0.282)**
Household production						
Ln(cultivated land)	0.008 (0.009)	0.030 (0.017)*	0.019 (0.015)	0.013 (0.013)	0.064 (0.022)***	0.066 (0.022)***
Ln(hh per capita equivalent productive assets)	0.005 (0.003)	0.005 (0.009)	-0.002 (0.008)	0.001 (0.005)	0.025 (0.013)*	0.025 (0.013)*
Education weighted labour force	-0.003 (0.001)***	-0.003 (0.002)*	-0.003 (0.001)**	0.008 (0.001)***	0.002 (0.002)	0.002 (0.002)
Agricultural labour productivity	-0.051 (0.006)***	-0.001 (0.009)	-0.006 (0.009)	-0.025 (0.010)**	-0.021 (0.015)	-0.020 (0.015)
Local non-ag. labour productivity	-0.014 (0.004)***	-0.009 (0.005)*	-0.004 (0.005)	0.0001 (0.006)	0.007 (0.007)	0.007 (0.007)
Labour productivity in circular migration	-0.013 (0.005)***	-0.010 (0.007)	-0.012 (0.006)**	-0.006 (0.007)	-0.011 (0.009)	-0.010 (0.009)
Household living conditions						
Sanitation	-0.142 (0.025)***	-0.016 (0.060)	-0.015 (0.066)	0.073 (0.039)*	0.223 (0.090)**	0.234 (0.089)**
Water	-0.028 (0.021)	-0.002 (0.031)	-0.017 (0.030)	0.070 (0.030)**	0.036 (0.043)	0.010 (0.043)
Heating	-0.127 (0.035)***	-0.136 (0.090)	-0.135 (0.080)*	-0.051 (0.061)	-0.468 (0.123)***	-0.488 (0.122)***
Fuel	0.051 (0.019)***	0.046 (0.023)*	0.026 (0.022)	0.009 (0.029)	0.014 (0.034)	0.006 (0.033)
Village characteristics						
Ln(village per capita net income)	-0.008 (0.019)	-0.009 (0.041)	-0.034 (0.031)	0.134 (0.030)***	0.009 (0.048)	0.005 (0.047)
Distance to primary school	-0.011 (0.012)	-0.024 (0.018)	-0.007 (0.019)	0.030 (0.018)*	0.048 (0.027)*	0.044 (0.026)*
Distance to hospital	-0.010 (0.006)	-0.005 (0.012)	-0.001 (0.011)	-0.026 (0.010)***	-0.036 (0.016)**	-0.037 (0.016)**
Geography	-0.022 (0.020)	-0.003 (0.031)	-0.045 (0.021)**	-0.086 (0.028)***	-0.053 (0.031)*	-0.069 (0.030)**
Unobserved heterogeneity control						
Ln(age of hh head)		-0.013 (0.087)	-0.054 (0.073)		0.069 (0.118)	0.055 (0.116)
Dependency ratio		0.049 (0.079)	0.071 (0.071)		-0.183 (0.117)	-0.170 (0.116)
Ethnic minorities		-0.048 (0.178)	-0.025 (0.158)		0.289 (0.285)	0.328 (0.282)
Ln(cultivated land)		-0.027 (0.015)*	-0.035 (0.014)**		-0.069 (0.021)***	-0.070 (0.021)***
Ln(hh per capita equivalent productive assets)		-0.001 (0.010)	0.009 (0.009)		-0.028 (0.015)*	-0.030 (0.015)**
Education weighted labour force		0.001 (0.002)	0.002 (0.002)		0.010 (0.003)***	0.011 (0.003)***
Agricultural labour productivity		-0.111 (0.013)***	-0.084 (0.012)***		-0.087 (0.020)***	-0.089 (0.020)***
Local non-agricultural labour productivity		-0.040 (0.008)***	-0.016 (0.008)**		-0.029 (0.011)***	-0.032 (0.011)***
Labour productivity in circular migration		-0.011 (0.019)	-0.012 (0.017)		0.043 (0.026)*	0.040 (0.026)
Sanitation		-0.161 (0.064)**	-0.153 (0.070)**		-0.142 (0.096)	-0.170 (0.094)*
Water		0.012 (0.040)	0.026 (0.036)		0.120 (0.059)**	0.094 (0.058)
Heating		0.047 (0.090)	0.021 (0.084)		0.607 (0.131)***	0.611 (0.130)***
Fuel		0.002 (0.020)	0.025 (0.020)		-0.050 (0.029)*	-0.046 (0.029)
Ln(village per capita net income)		-0.090 (0.046)*	-0.089 (0.037)**		0.178 (0.061)***	0.179 (0.060)***
Distance to primary school		0.007 (0.021)	0.002 (0.020)		-0.100 (0.031)***	-0.090 (0.030)***
Distance to hospital		0.008 (0.014)	0.0001 (0.013)		0.020 (0.020)	0.024 (0.020)
Selection equations						
p_2			0.289 (0.087)***			
p_1						2.935 (5.056)
Correlation coefficients						
$\rho_{\varepsilon_1 \upsilon_1}$	0.486	0.998	0.177	0.486	0.998	0.177
$\rho_{\varepsilon_2 \upsilon_2}$	-0.526	-0.593	-0.043	-0.526	-0.593	-0.043
$\rho_{\upsilon_1 \upsilon_2}$	0.120	0.082	0.081	0.120	0.082	0.081
$\rho_{\varepsilon_1 \varepsilon_2}$	0.119	0.100	0.752	0.119	0.100	0.752
Log-likelihood	-1,842.60	-1,354.51	-1,491.68	-1,842.60	-1,354.51	-1,491.68
LR test	684.55 (0.000)	991.15 (0.000)	1120.08 (0.000)	684.55 (0.000)	991.15 (0.000)	1120.08 (0.000)
No. of obs.	1,500	1,500	1,463	1,500	1,500	1,463

Note: Columns (1)-(3) and (4)-(6) study income and nutrition poverty, respectively. ***, ** and * denote 1%, 5% and 10% significance levels in turn. The dependent variables in all columns, i.e., the intertemporal income and nutritional poverty, are defined by Eq. (2) with $\alpha = \beta = \varphi = 1$ and δ=3.2 for income and 1.05 for nutrition.

Table 6 Sensitivity of the determinants of intertemporal poverty to alternative poverty lines and normative presumptions

Independent variable	Income (US$2/day)		Income (US$1.25/day)		Nutrition (2,400 kcal/day)		Nutrition (2,100 kcal/day)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Household demographics								
Ln(age of hh head)	0.074 (0.041)*	0.032 (0.081)	-0.065 (0.040)	-0.025 (0.205)	0.215 (0.210)	0.044 (0.114)	-0.216 (0.214)	-0.137 (0.419)
Dependency ratio	0.016 (0.049)	-0.009 (0.076)	-0.023 (0.103)	-0.042 (0.168)	0.211 (0.247)	0.154 (0.106)	0.193 (0.249)	0.766 (0.387)**
Ethnic minority	-0.104 (0.047)**	-0.035 (0.218)	-0.155 (0.111)	-0.090 (0.491)	-0.676 (0.224)***	-0.575 (0.308)*	-0.841 (0.226)***	-2.275 (1.117)**
Household production								
Ln(cultivated land)	-0.027 (0.011)**	-0.029 (0.018)	-0.020 (0.027)	-0.035 (0.038)	0.024 (0.052)	0.066 (0.024)***	0.001 (0.052)	0.247 (0.086)***
Ln(hh per capita equivalent productive assets)	-0.010 (0.004)**	-0.011 (0.010)	0.001 (0.010)	-0.003 (0.022)	0.009 (0.002)	0.035 (0.014)**	0.003 (0.022)	0.084 (0.052)
Education weighted labour force	-0.003 (0.001)**	-0.003 (0.002)**	-0.010 (0.002)***	-0.007 (0.004)**	0.031 (0.006)***	0.0003 (0.002)	0.033 (0.006)***	0.008 (0.009)
Agricultural labour productivity	-0.038 (0.009)***	0.033 (0.011)***	-0.171 (0.018)***	0.020 (0.023)	-0.100 (0.039)**	0.032 (0.016)**	-0.102 (0.039)***	0.062 (0.058)
Local non-agricultural labour productivity	-0.009 (0.005)*	0.006 (0.005)	-0.063 (0.009)***	-0.021 (0.012)*	0.002 (0.022)	0.004 (0.008)	0.001 (0.023)	0.026 (0.028)
Labour productivity in circular migration	-0.015 (0.006)***	-0.003 (0.007)	-0.030 (0.012)**	-0.009 (0.015)	-0.014 (0.027)	-0.002 (0.010)	-0.007 (0.027)	-0.052 (0.037)
Household living conditions								
Sanitation	-0.224 (0.033)***	-0.080 (0.071)	-0.458 (0.068)***	-0.102 (0.151)	0.219 (0.154)	0.199 (0.097)**	0.249 (0.155)	0.720 (0.353)**
Water	-0.027 (0.025)	-0.049 (0.034)	-0.073 (0.060)	-0.035 (0.076)	0.236 (0.119)**	0.029 (0.046)	0.232 (0.120)*	0.105 (0.168)
Heating	-0.283 (0.046)***	-0.156 (0.086)*	-0.279 (0.100)***	-0.307 (0.206)	-0.166 (0.241)	-0.632 (0.131)***	-0.267 (0.244)	-1.915 (0.481)***
Fuel	0.135 (0.024)***	0.119 (0.025)***	0.199 (0.050)***	0.181 (0.055)***	0.059 (0.116)	0.013 (0.036)	0.062 (0.117)	0.067 (0.132)
Village characteristics								
Ln(village per capita net income)	-0.078 (0.024)***	0.032 (0.035)	-0.084 (0.086)	-0.072 (0.086)	0.558 (0.120)***	0.008 (0.050)	0.565 (0.120)***	0.114 (0.187)
Distance to primary school	-0.040 (0.015)**	-0.019 (0.022)	-0.065 (0.032)**	-0.077 (0.051)	0.127 (0.071)*	0.037 (0.029)	0.138 (0.072)*	0.219 (0.105)**
Distance to hospital	0.003 (0.008)	0.010 (0.012)	-0.014 (0.017)	-0.020 (0.026)	-0.087 (0.040)**	-0.032 (0.017)*	-0.102 (0.040)**	-0.139 (0.062)**
Geography	0.032 (0.024)	-0.002 (0.025)	0.013 (0.054)	-0.061 (0.057)	-0.312 (0.111)***	-0.114 (0.033)***	-0.254 (0.113)**	-0.245 (0.120)**
Unobserved heterogeneity control								
Ln(age of hh head)		0.010 (0.089)		-0.126 (0.248)		-0.029 (0.125)		0.252 (0.462)
Dependency ratio		0.036 (0.090)		0.187 (0.194)		-0.149 (0.125)		-0.554 (0.459)
Ethnic minorities		-0.108 (0.216)		-0.080 (0.482)		0.441 (0.308)		1.401 (1.117)
Ln(cultivated land)		-0.064 (0.018)***		-0.071 (0.035)**		-0.068 (0.023)***		-0.297 (0.084)***
Ln(hh per capita equivalent productive assets)		0.008 (0.011)		0.015 (0.025)		-0.043 (0.016)***		-0.097 (0.058)*
Education weighted labour force		0.0001 (0.002)		-0.002 (0.005)		0.014 (0.003)***		0.036 (0.011)***
Agricultural labour productivity		-0.127 (0.015)***		-0.268 (0.031)***		-0.099 (0.021)***		-0.325 (0.077)***
Local non-agricultural labour productivity		-0.040 (0.009)***		-0.113 (0.019)***		-0.030 (0.012)**		-0.110 (0.043)**
Labour productivity in circular migration		-0.050 (0.020)**		-0.071 (0.044)		0.033 (0.028)		0.165 (0.101)
Sanitation		-0.161 (0.076)**		-0.409 (0.162)**		-0.203 (0.103)**		-0.471 (0.374)
Water		0.108 (0.044)**		-0.092 (0.100)		0.076 (0.062)		0.373 (0.229)
Heating		-0.119 (0.092)		0.087 (0.215)		0.704 (0.139)***		2.423 (0.512)***
Fuel		-0.023 (0.023)		-0.015 (0.049)		-0.060 (0.031)*		-0.218 (0.114)*
Ln(village per capita net income)		-0.239 (0.046)***		-0.283 (0.102)***		0.145 (0.065)**		0.605 (0.238)**
Distance to primary school		-0.025 (0.025)		0.029 (0.053)		-0.070 (0.033)**		-0.448 (0.120)***
Distance to hospital		-0.001 (0.015)		0.026 (0.033)		0.031 (0.021)		0.080 (0.078)
Correlation coefficients								
$\rho_{\varepsilon_1 \upsilon_1}$	-0.338	-0.498	0.999	0.996	-0.338	-0.498	0.999	0.996
$\rho_{\varepsilon_2 \upsilon_2}$	-0.845	-0.751	-0.554	-0.547	-0.845	-0.751	-0.554	-0.547
$\rho_{\upsilon_1 \upsilon_2}$	0.120	0.110	0.126	0.082	0.120	0.110	0.126	0.082
$\rho_{\varepsilon_1 \varepsilon_2}$	0.289	0.517	0.211	0.069	0.289	0.517	0.211	0.069
Log-likelihood	-2,094.03	-1,846.41	-4,200.86	-4,066.32	-2,094.03	-1,846.41	-4,200.86	-4,066.32
LR test	964.47 (0.000)	1,455.54 (0.000)	1,362.27 (0.000)	1,631.35 (0.000)	964.47 (0.000)	1,455.54 (0.000)	1,362.27 (0.000)	1,631.35 (0.000)

Note: ***, ** and * denote 1%, 5% and 10% significance levels in turn. Columns (1)-(2) and (5)-(6) are based on higher poverty lines of US$2 and 2,400kcal, respectively. Columns (3)-(4) and (7)-(8) are based on the initial poverty lines of US$1.25 and 2,100kcal, respectively, while $\alpha = \beta = 2$ and $\varphi = 1$. The dependent variables in all columns, i.e., the intertemporal income and nutrition poverty, are defined by Eq. (2) with $\alpha = \beta = \varphi = 1$ and δ=3.2 in the case of income and 1.05 in the case of nutrition.

Table 7 The determinants of constant-relative affluence-dependent intertemporal poverty

Independent variable	Income (US$1.25/day)			Nutrition (2,100 kcal/day)		
	(1)	(2)	(3)	(4)	(5)	(6)
Household demographics						
Ln(age of hh head)	-0.001 (0.030)	-0.016 (0.069)	0.006 (0.064)	0.061 (0.055)	-0.037 (0.107)	-0.025 (0.106)
Dependency ratio	0.003 (0.036)	0.042 (0.067)	-0.012 (0.060)	0.050 (0.064)	0.218 (0.099)**	0.222 (0.097)**
Ethnic minority	-0.007 (0.035)	0.044 (0.185)	-0.077 (0.176)	-0.238 (0.058)***	-0.555 (0.285)*	-0.577 (0.281)**
Household production						
Ln(cultivated land)	0.004 (0.008)	0.028 (0.017)*	0.019 (0.014)	0.012 (0.013)	0.064 (0.022)***	0.064 (0.022)***
Ln(hh per capita equivalent productive assets)	0.001 (0.003)	0.005 (0.008)	-0.002 (0.008)	0.002 (0.006)	0.025 (0.013)*	0.025 (0.013)*
Education weighted labour force	-0.004 (0.001)***	-0.003 (0.002)	-0.003 (0.001)**	0.008 (0.001)***	0.002 (0.002)	0.002 (0.002)
Agricultural labour productivity	-0.070 (0.006)***	0.002 (0.010)	-0.010 (0.008)	-0.024 (0.010)**	0.021 (0.015)	0.021 (0.015)
Local non-ag. labour productivity	-0.026 (0.003)***	-0.009 (0.005)*	-0.009 (0.004)**	0.0005 (0.006)	0.007 (0.007)	0.007 (0.007)
Labour productivity in circular migration	-0.014 (0.004)***	-0.010 (0.007)	-0.009 (0.006)	0.006 (0.007)	-0.011 (0.009)	-0.011 (0.009)
Household living conditions						
Sanitation	-0.160 (0.023)***	-0.012 (0.064)	-0.003 (0.057)	0.074 (0.040)*	0.221 (0.090)**	0.235 (0.090)***
Water	-0.009 (0.016)	-0.010 (0.030)	0.012 (0.027)	0.068 (0.031)**	-0.032 (0.043)	0.034 (0.043)
Heating	-0.087 (0.033)***	-0.149 (0.088)*	-0.141 (0.073)*	0.054 (0.062)	-0.464 (0.123)***	-0.479 (0.122)***
Fuel	0.057 (0.017)***	0.048 (0.023)**	0.054 (0.020)***	0.013 (0.030)	0.014 (0.034)	0.005 (0.034)
Village characteristics						
Ln(village per capita net income)	-0.055 (0.018)***	-0.012 (0.031)	0.031 (0.029)	0.138 (0.031)***	0.009 (0.048)	0.005 (0.047)
Distance to primary school	-0.031 (0.011)***	-0.021 (0.019)	-0.029 (0.018)	-0.033 (0.018)*	0.049 (0.027)*	0.052 (0.026)**
Distance to hospital	-0.005 (0.006)	-0.008 (0.012)	-0.009 (0.010)	-0.025 (0.010)**	-0.037 (0.016)**	-0.035 (0.016)**
Geography	0.018 (0.018)	-0.009 (0.022)	-0.036 (0.020)*	-0.083 (0.029)***	-0.052 (0.031)*	-0.067 (0.033)**
Unobserved heterogeneity control			-0.041 (0.071)			
Ln(age of hh head)		-0.005 (0.078)	0.083 (0.071)		0.065 (0.118)	0.053 (0.116)
Dependency ratio		0.032 (0.078)	0.038 (0.174)		-0.175 (0.117)	-0.188 (0.116)
Ethnic minorities		-0.052 (0.182)	-0.028 (0.013)**		0.292 (0.285)	0.322 (0.282)
Ln(cultivated land)		-0.024 (0.016)	0.007 (0.011)		-0.069 (0.021)***	-0.072 (0.021)***
Ln(hh per capita equivalent productive assets)		-0.001 (0.009)	0.0004 (0.002)		-0.028 (0.015)*	-0.029 (0.015)**
Education weighted labour force		-0.001 (0.002)	-0.114 (0.012)***		0.010 (0.003)***	0.011 (0.003)***
Agricultural labour productivity		-0.119 (0.013)***	-0.045 (0.007)***		-0.088 (0.020)***	-0.086 (0.019)***
Local non-agricultural labour productivity		-0.042 (0.008)***	-0.022 (0.016)		-0.029 (0.011)***	-0.031 (0.011)***
Labour productivity in circular migration		-0.014 (0.018)	-0.178 (0.061)**		0.042 (0.026)	0.041 (0.026)
Sanitation		-0.172 (0.067)**	-0.034 (0.035)		-0.143 (0.096)	-0.156 (0.096)
Water		0.019 (0.039)	0.042 (0.077)		0.114 (0.059)*	0.120 (0.058)**
Heating		0.062 (0.092)	0.009 (0.018)		0.604 (0.131)***	0.609 (0.129)***
Fuel		-0.001 (0.022)	-0.088 (0.036)**		-0.051 (0.029)*	-0.042 (0.029)
Ln(village per capita net income)		-0.087 (0.040)**	0.014 (0.020)		0.179 (0.061)***	0.181 (0.060)***
Distance to primary school		0.005 (0.022)	0.016 (0.012)		-0.099 (0.031)***	-0.098 (0.030)***
Distance to hospital		0.011 (0.014)	0.008 (0.012)		0.021 (0.020)	0.020 (0.020)
Selection equations						
p_2			0.429 (0.054)***			
p_1						1.867 (1.715)
Correlation coefficients						
$\rho_{\varepsilon_1 \upsilon_1}$	0.993	0.999	0.984	0.993	0.999	0.984
$\rho_{\varepsilon_2 \upsilon_2}$	-0.458	-0.590	-0.391	-0.458	-0.590	-0.391
$\rho_{\upsilon_1 \upsilon_2}$	0.098	0.085	0.106	0.098	0.085	0.106
$\rho_{\varepsilon_1 \varepsilon_2}$	0.470	0.072	0.061	0.470	0.072	0.061
Log-likelihood	-1,608.47	-1,365.85	-1,420.64	-1,608.47	-1,365.85	-1,420.64
LR test	1,241.08 (0.000)	1,726.30 (0.000)	1,616.74 (0.000)	1,241.08 (0.000)	1,726.30 (0.000)	1,616.74 (0.000)
No. of obs.	1,500	1,500	1,500	1,500	1,500	1,500

Note: Columns (1)-(3) and (4)-(6) study income and nutrition poverty, respectively. ***, ** and * denote 1%, 5% and 10% significance levels in turn. The dependent variables in all columns, i.e., the intertemporal income and nutritional poverty, are defined by Eq. (1) with $\alpha = \beta = \varphi = 1$.

Appendix: Table A.1 Construction of variables and descriptive statistics

Variable	Definition	2000		2004	
		Mean	S.D.	Mean	S.D.
Modified OECD equivalent household size	Weighted sum of household members. The first adult in the household has a weight of 1. Each additional adult aged 14 and over has a weight of 0.5. Each child aged under 14 has a weight of 0.3. This definition can be found at Eurostat: http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Glossary:Equivalised_disposable_income [accessed Dec. 5, 2013]	3.699	0.242	3.783	0.225
Spatial rural price index	First, provincial rural CPI (previous year=1) is collected from China Statistical Yearbooks in relevant years. We set the rural CPI in 1999 in two provinces at 1 and compared rural CPI other years to 1, in order to construct a province-specific real price index. Second, we refer to the spatial price index from Table 2 in Brandt and Holz (2006) – in 2000 Gansu is 1.19 and IM is 0.97. We set the price level in Gansu as 1 and compare that in Inner Mongolia to it, i.e., Gansu=1 and IM=0.97/1.19=0.815. Third, we multiply 0.815 to the province-specific real price index obtained in the first step.	0.907	0.088	1.027	0.093
Household equivalent per capita net income	Household net income divided by equivalent household size. Household net income is total income (including agricultural and family business income, wages, transfer income and asset income) minus related costs, taxes and fees. All monetary values are transformed into real terms by dividing them by spatial CPI.	2,379	1,833	3,117	2,461
Household equivalent per capita daily nutrition	Household daily total nutrition intake divided by equivalent household size. The daily intake is the household annual total nutrition intake divided by 365 days. The household annual total nutrition intake is the sum of nutrition intake from food purchased by the household (in kg) multiplied by their energy intake (kcal/kg). Food includes grain (wheat, rice, and corn), potato, beans (soybeans and all other kinds of beans), vegetable and relevant products (root and tuber, melons, aubergine fruits, cabbage, green leafy vegetables, other fresh vegetables, dry vegetables, and salt vegetables), meat (pork, beef, mutton, poultry, and meat products), egg and relevant products, milk and dairy products, aquatic products (fish, shrimp, shellfish, crab, algae and others), sugar, liquor and beverage (spirit, beer, fruit wine, and beverage), fruit, and nuts and their relevant products. The energy intake for each food item comes from the Chinese Food Composition Table (FCT) 2002/2004 combined edition published by the National Institute of Nutrition and Food Safety at the Chinese Center for Disease Control and Prevention.	1,913	109.1	1,686	686.0
Dependency ratio	Proportion of children (<18 years old) and the elderly (>60 years old) in all household members.	0.334	0.213	0.295	0.220
Ethnic minority	Dummy taking the value of 1 if any one of the household members has non-Han nationality and 0 otherwise.	0.921	0.269	0.921	0.269
Ln(land)	Natural logarithm of land (in *mu*) owned by the household, including cultivated land, slope land, mulberry field and orchard, grassland and water area for fishery (1 mu≈666.7m^2).	7.707	1.373	7.553	1.579
Ln(hh per capita equivalent productive assets)	Natural logarithm of the value of productive assets owned by the household divided by the modified OECD equivalent household size.	7.524	2.350	7.916	1.812
Education weighted labour force	The weighted sum of labour force in the household. The weights are the number of years of education completed by the individual labourers.	17.012	9.653	17.452	10.03
Ln(labour productivity)	The annual total net income divided by the labour allocated to local agricultural production (days per year). The total net income is the total income from all sources, including local agriculture, local non-agriculture and circular migration, net of relevant production costs, taxes and fees.	2.722	0.856	4.262	0.872
Ln(agricultural labour productivity)	Natural logarithm of annual net income from local agricultural production divided by the labour allocated to local agricultural production (days per year). The net agricultural income is the total income from local agriculture net of relevant production costs, taxes and fees.	2.742	1.340	5.121	1.348
Ln(local non-agricultural labour productivity)	Natural logarithm of annual net income from local non-agricultural production divided by the labour allocated to local non-agricultural production (days per year). The net local non-agricultural income is the total income from local non-agriculture net of relevant production costs, taxes and fees.	0.623	2.209	0.659	1.953
Ln(labour productivity in circular migration)	Natural logarithm of annual income from circular migration divided by the labour allocated to circular migration (days per year). Note that the dataset does not have information on costs relating to migration.	-0.650	1.822	-0.633	1.516
Sanitation	Dummy taking the value of 1 if the household has sanitation and 0 otherwise.	0.785	0.411	0.800	0.400
Water	Dummy taking the value of 1 if the household has safe drinking water (including tap water and well water) and 0 otherwise.	0.444	0.497	0.773	0.419
Heating	Dummy taking the value of 1 if the household has heating system (including air-conditioners, heaters, heated beds, and other heating facilities) and 0 otherwise.	0.951	0.217	0.929	0.257
Fuel	Dummy taking the value of 1 if the household uses firewood and 0 otherwise (including gas and coal).	0.662	0.473	1.167	1.203
Ln(village per capita net income)	Natural logarithm of average household per capita net income in the sample village.	7.054	0.526	7.397	0.565
Distance to primary school	Distance from the sample household to the nearest primary school (km).	0.383	0.736	0.500	0.908
Distance to hospital	Distance from the sample household to the nearest hospital (km).	2.400	1.332	2.200	1.265
Geography	Categories including 1 (plain), 2 (hilly) and 3 (mountainous).	2.440	0.572	2.440	0.572

Note: All monetary values are translated into real term at 1999 price level by using the spatial rural consumer price index.