Chronic and Transient Poverty: Measurement and Estimation, with evidence from China (preliminary)

Jean-Yves Duclos*, Abdelkrim Araar† and John Giles‡

October 19, 2005

Abstract

The paper contributes to the measurement of poverty and vulnerability in three ways. First, we propose a new approach to split total poverty into chronic and transient components. Second, we provide corrections for the statistical biases often introduced by the use of a relatively small number of periods in the estimation of the importance of risk in accounting for total poverty. Third, we apply these tools to the measurement of chronic and transient poverty in China using a rich panel data set that extends over approximately 17 years. We find that alternative measurement techniques can give significantly different views on the relative importance of chronic and transient poverty, and that statistical bias corrections can greatly enhance the precision of such poverty estimates.

Keywords: Poverty dynamics; Transient poverty; Chronic poverty; Permanent poverty; China.
JEL Classification: D12; D63; H53; I32; I38.
This research was partly funded by the PEP programme of the International Development Research Centre and by Canada's SSHRC and Québec's FQRSC. We are grateful to Erik Thorbecke for his guidance.

* Département d'économique and CIRPÉE, Pavillon de Sève, Université Laval, Québec, Canada, G1K 7P4; email: jyves@ecn.ulaval.ca; fax: 1-418-656-7798; phone: 1-418-656-7096

† CIRPÉE, Pavillon de Sève, Université Laval, Québec, Canada, G1K 7P4; email: aabd@ecn.ulaval.ca; fax: 1-418-656-7507; phone: 1-418-656-7096

‡ Department of Economics, Michigan State University, 101 Marshall Hall, East Lansing, MI 48823; email: gilesj@msu.edu; phone: 1-517-355-7755

1 Introduction

Most of poverty measurement takes place in an hypothesized world of certainty. Poverty measures, and the impact of policies on such measures, are indeed usually estimated after all uncertainty surrounding well-being is assumed to have been resolved.

In some limited instances, this certainty assumption might not seem too strong. It could be argued, for instance, that analysts should be able to infer the *ex post* impact of some economic policy on well-being by comparing data on before and after the introduction of the policy. But policy design is rarely done with the benefit of hindsight, and the distributive impact of policy can often vary widely within classes of *ex ante* relatively observationally homogeneous agents. Some policies also generate a greater average level of well-being but at the cost of greater social and individual risk. In such contexts, *ex post* policy analysis would seem to be at best incomplete.

This mean/risk tradeoff is important for analyzing policy impacts, but it is also more generally valid for comparing welfare across natural, social and economic environments of varying degrees of risk and ”vulnerability”. The term ”vulnerability” has been used with increased frequency recently, in particular since it was highlighted in the 2001 World Development Report (World Bank, 2001). A large number of definitions of the term exist. In our present context, we can understand it as the impact of risk on the ”threat of poverty, measured ex-ante, before the veil of uncertainty has been lifted” (Calvo and Dercon, 2005, p.2). We will see that the current paper offers useful and intuitive indicators of this impact.

This important distinction between low expected well-being and vulnerability is nicely described by Hulme and McKay (2005):

> ”Historically, the idea that some people are trapped in poverty while others have spells in poverty was a central element of analysis. For example, officials and social commentators in eighteenth century France distinguished between the *pauvre* and the *indigent*. The former experienced seasonal poverty when crops failed or demand for casual agricultural labour was low. The latter were permanently poor because of ill health (physical and mental), accident, age, alcoholism or other forms of vice. The central aim of policy was to support the *pauvre* in ways that would stop them from becoming *indigent*.” (p.3)

Thus, not only is ”chronic poverty” different from ”temporary” or ”transient” poverty, but the difference between the two is likely to call for distinct policy responses, as stressed for instance in Chronic Poverty Research Centre (2004)[1].

This paper also suggests strategies to compute unbiased estimators of the relative importance of risk in total ill-fare. With the increased availability of longitudinal data sets, it is now well known[2] that there is a lot of movement in and out of poverty as well as within poverty itself. It is also widely recognized that these findings are very sensitive to the presence of measurement errors – see for instance Rendtel *et al.* (1998) and Breen and Moisio (2003). A similar concern arises when only a small number of time observations is available for each individual and when the estimators of interest are non-linear across time observations. Most of the literature on the measurement of poverty and vulnerability seems nevertheless to have ignored this last issue until now. Unlike corrections for measurement errors, which are typically difficult to provide, corrections for small-number-of-time-periods biases are relatively straightforward to design and to apply, as demonstrated below.

The current paper thus aims to contribute to the measurement of poverty and vulnerability in three ways. First (Section 2), we follow the recent literature and investigate how we may split the measurement of total poverty into chronic and transient components, the latter component being generated by the presence of risk. In doing this, we build on the influential work of Ravallion (1988) and Jalan and Ravallion (1998) and show how money-metric measures of low average well-being (chronic poverty) and risk (transient poverty) can jointly account for total deprivation (total poverty) in a society.

Second (Section 3), we provide methods for correcting statistical biases in the estimation of chronic and transient poverty. This is important since the number of periods over which total poverty is assessed is usually relatively small, and this can lead to distortions in one's estimate of the importance of risk in accounting for total ill-fare. Note that these corrections are derived explicitly in this paper for only two alternative measurement systems – Jalan and Ravallion's and a money-metric one. The paper's methodology can, however, be used to can extend these statistical methods to other indices such as the recent ones of and Chaudhuri *et al.* (2002), Ligon and Schechter (2003), Suryahadi and Sumarto (2003), Chris-

[1] See also the special issue on chronic poverty published in *World Development*, volume 31, issue 3, pages 399–665, March 2003.

[2] See among many others Bane and Ellwood (1986), Gaiha (1988), Gaiha (1989), Jarvis and Jenkins (1997), Baulch and Hoddinnott (2000), Atkinson *et al.* (2002), Chaudhuri *et al.* (2002), Ligon and Schechter (2003), Bourguignon *et al.* (2004), Christiaensen and Subbarao (2004), and Kamanou and Morduch (2004).

tiaensen and Subbarao (2004), and Kamanou and Morduch (2004), or to many other poverty measurement systems.

Third (Section 4), we apply these tools to the measurement of chronic and transient poverty in China using a rich panel data set that extends over approximately 17 years. We find that alternative measurement techniques can give significantly different views on the relative importance of chronic and transient poverty, and that statistical bias corrections can greatly enhance the precision of such poverty estimates.

2 Measuring chronic and transient poverty

2.1 Measuring poverty

Consider a vector $\mathbf{y} = (\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_n)$ of living standards $\mathbf{y}_i$ (incomes[3], for short) for n individuals, where $\mathbf{y}_i = (y_{i1}, y_{i2}, ..., y_{it})$ is itself a vector of individual i's incomes across t periods. For expositional simplicity, we assume that each income y_{ij} has initially been normalized by the poverty line of period j. An individual i with $y_{ij} = 1$ is thus exactly at the poverty line at time j. A useful tool in this paper will be that of (normalized) *poverty gaps*, defined for an income y_{ij} as

$$g_{ij} = (1 - y_{ij})_+ , \tag{1}$$

where $f_+ = \max(f, 0)$. The vectors $\mathbf{g} = (\mathbf{g}_1, \mathbf{g}_2, ..., \mathbf{g}_n)$ and $\mathbf{g}_i = (g_{i1}, g_{i2}, ..., g_{it})$ are then the corresponding vectors of poverty gaps. Many of the common poverty measures can be expressed in terms of such poverty gaps[4]. An important subset of these measures is the well-known class of the FGT (Foster, Greer and Thorbecke, 1984) additively decomposable indices. Over the n individuals and the t periods, and thus over the vector g, the FGT indices are defined as

$$P_\alpha(\mathbf{g}) = (nt)^{-1} \sum_{i=1}^{n} \sum_{j=1}^{t} g_{ij}^{\alpha}. \tag{2}$$

[3]Note that we do not discuss here the more general problem of the relative advantages and disadvantages of using monetary *vs* non-monetary indicators for assessing chronic and transient poverty – for a discussion of this, see *e.g.* Hulme and McKay (2005).

[4]Note that focussing on poverty gap measures is not needed for the analysis, although it simplifies the exposition. The same is true for the use of the FGT indices in the paper: other additive indices, such as the Watts (1968) index, could equally be used.

When $\alpha = 0$, (2) gives the proportion of the t time periods over which the n individuals have been poor; when $\alpha = 1$, (2) gives the average poverty gap over the t time periods and the n individuals; and for $\alpha > 1$, (2) yields poverty indices that are sensitive to the distribution of poverty gaps and that give greater weights to greater poverty gaps.

$P_\alpha(\mathbf{g}_i)$ is analogously defined as

$$P_\alpha(\mathbf{g}_i) = t^{-1} \sum_{j=1}^{t} g_{ij}^{\alpha}. \tag{3}$$

Note that $\alpha \geq 0$ may be considered as a measure of "poverty aversion". It is also a measure of aversion to inequality and variability in the poverty gaps: a larger α gives a greater weight to a loss of income when income is already low than when it is large. P_0 gives the headcount ratio, which is well-known for being *inter alia* insensitive to falls or increases in the welfare of the poor, so long as they remain poor. It is also well-known that the headcount can increase following a mean-preserving equalizing transfer of income. The same is true for a mean-preserving decrease in the variability of income over time: this can increase $P_0(\mathbf{g})$. For these reasons — to which we will come back again later — we exclude the headcount from the analysis and also suppose that $\alpha \geq 1$.

$P_1(\mathbf{g})$ yields the average poverty gap, whose sensitivity to changes in incomes is the same regardless of the income of the poor (so long, again, as the poor remain poor). When $\alpha > 1$, a marginal equalizing transfer of income from a poor person to anyone who is poorer decreases $P_\alpha(\mathbf{g})$, thus making these indices "distribution" and "variability" sensitive.

2.2 Jalan and Ravallion's chronic and transient poverty

Jalan and Ravallion (1998) (JR, for short) use $P_\alpha(\mathbf{g})$ to propose intuitive measures of "chronic" and "transient" poverty. To see how, note first that $\widehat{\overline{y}}_i = t^{-1}\sum_{j=1}^{t} y_{ij}$ is an estimate of i's "permanent income" over the t periods. JR argue that an estimate of the "chronic" poverty of an individual i can be obtained by replacing his income y_{ij} for all periods j by this estimated permanent income. $t^{-1}\sum_{j=1}^{t}\left(1-\widehat{\overline{y}}_i\right)_+^{\alpha}$ is then an estimate of the "chronic" contribution of individual i to aggregate poverty. Summing across all individuals, aggregate chronic poverty would then be equal to[5]

[5]Note that JR's definition (and ours) differs conceptually from that of Chronic Poverty Research Centre (2004), where chronic poverty is defined as "poverty experienced by individuals

$$P^*_\alpha(\mathbf{y}) = n^{-1}\sum_{i=1}^{n}\left(1-\widehat{\overline{y}}_i\right)_+^{\alpha}. \tag{4}$$

The difference between total poverty, $P_\alpha(\mathbf{g})$, and chronic poverty, $P^*_\alpha(\mathbf{y})$, can then be interpreted as a measure of the magnitude of transient poverty and of its contribution to total poverty. Transient poverty, $P^T_\alpha(\mathbf{y})$, is then defined by JR as the residual between total poverty and chronic poverty:

$$P^T_\alpha(\mathbf{y}) = P_\alpha(\mathbf{g}) - P^*_\alpha(\mathbf{y}). \tag{5}$$

Although intuitive and simple, this formulation has a few disadvantages:

- It is well-known that an increase in α gives greater *relative* weight to the ill-fare of the poorest. An increase in α thus makes the poverty index more representative of the ill-fare of the poorest among the poor, and should thus increase measured poverty. But it is easily checked that $P_\alpha(\mathbf{g})$ *decreases* with α for some given g. This feature often causes confusion in the applied poverty literature. In the current chronic-transient setting, an increase in α will also decrease $P_\alpha(\mathbf{g})$, $P^*_\alpha(\mathbf{y})$, and $P^T_\alpha(\mathbf{y})$, leading to the additional awkward result that an increase in poverty aversion decreases the measure of both transient and chronic poverty. One way to avoid this problem is to do the chronic-transient analysis only for some fixed α (such as $\alpha = 2$). That, however, would seem to constrain unduly the ethical and normative freedom that has for a long time been deemed desirable in distributive analysis.

- The $P_\alpha(\mathbf{g})$ indices have no obvious cardinal interpretation when α differs from 0 or 1. The basic reason is that their measurement units are in dollars to the power α. This makes it difficult to compare values of and changes in $P_\alpha(\mathbf{g})$ with the money-metric indicators used commonly in efficiency and cost-benefit analysis.

- A more minor point concerns the construction of the $P^*_\alpha(\mathbf{y})$ chronic poverty index. As shown in (4), this is assessed using average income over t periods of time. Hence, someone in severe poverty over $t-1$ periods may still be

and households for extended periods of time or throughout their entire lives" (p. 131) and where transitory poverty is defined as "poverty experienced as the result of a temporary fall in income or expenditure although over a longer period the household resources are on average sufficient to keep the household above the poverty line" (p. 132).

deemed to have zero chronic poverty if his income during the t^{th} period is large enough to make average income over the t periods be above 1. Some analysts will feel uneasy with this. One alternative is to use the average of incomes censored at the poverty line — an idea we explore below in the illustrative section. Another alternative is consider instead chronic poverty to be a measure of "average" poverty — measured as an average of the poverty status experienced over the t periods. This is *inter alia* what we propose to do in the following sections.

2.3 EDE poverty gaps

A simple monotonic transformation of P_α leads to a useful money-metric measure of poverty. In the manner of Kolm (1969) and Atkinson (1970) for the measurement of social welfare and inequality, let $\Gamma_\alpha(\mathbf{g})$ be the "equally-distributed equivalent" (EDE) poverty gap, *viz*, that poverty gap which, if assigned equally to all individuals and in all periods, would produce the same poverty measure as that generated by the distribution g of poverty gaps. Using (2), $\Gamma_\alpha(\mathbf{g})$ is given implicitly as

$$\Gamma_\alpha(\mathbf{g})^\alpha \equiv P_\alpha(\mathbf{g}), \tag{6}$$

and thus we have that

$$\Gamma_\alpha(\mathbf{g}) \quad = \quad P_\alpha(\mathbf{g})^{\frac{1}{\alpha}}. \tag{7}$$

Note that $\Gamma_1(\mathbf{g})$ is the average poverty gap. As mentioned above, using $\Gamma_1(\mathbf{g})$ as a measure of poverty fails to capture the distribution of poverty (as distinct from its average depth). Inequality in poverty presumably raises the social cost of poverty above the average poverty gap. This argues that an inequality-corrected measure of poverty should in general be no less than $\Gamma_1(\mathbf{g})$ in order for poverty to be sensitive to the presence of inequality among the poor. Such a property holds for $\Gamma_\alpha(\mathbf{g})$ whenever α is greater than or equal to 1.

Whenever all have the same poverty gap, we have that $\Gamma_\alpha(\mathbf{g}) = \Gamma_1(\mathbf{g})$. A mean-preserving increase in the income spread between two individuals (with at least one of them being poor) increases strictly $\Gamma_\alpha(\mathbf{g})$ whenever $\alpha > 1$. Thus, for a given α, the more important the difference between $\Gamma_\alpha(\mathbf{g})$ and $\Gamma_1(\mathbf{g})$, the more unequal we can think the distribution of poverty gaps to be. An obvious measure of the cost of inequality in the distribution of poverty gaps is then given by:

$$C_\alpha(\mathbf{g}) \quad = \quad \Gamma_\alpha(\mathbf{g}) - \Gamma_1(\mathbf{g}). \tag{8}$$

Note that $C_\alpha(\mathbf{g})$ is given in *per capita* money-metric terms, which makes it directly comparable to $\Gamma_1(\mathbf{g})$. $C_\alpha(\mathbf{g})$ is the cost in average poverty gap that a Social Decision Maker (SDM) would be willing to pay to remove all inequality in the distribution of poverty gaps, without an increase in total poverty – recall Atkinson (1970) for a similar interpretation in terms of social welfare. $C_\alpha(\mathbf{g})$ is always non-negative. Rewriting (8), total poverty can be expressed as

$$\Gamma_\alpha(\mathbf{g}) = \Gamma_1(\mathbf{g}) + C_\alpha(\mathbf{g}). \tag{9}$$

This is illustrated in Figure 6. Figure 6 shows a distribution of 2 poverty gaps, g_1 and g_2 (measured along the horizontal scale), the poverty index $P_\alpha(\mathbf{g})$ for that distribution, the average poverty gap $\Gamma_1(\mathbf{g})$, and the EDE poverty gap $\Gamma_\alpha(\mathbf{g})$. Note that $\Gamma_1(\mathbf{g})$ is the average of g_1 and g_2, and that $\Gamma_\alpha(\mathbf{g})^\alpha = P_\alpha(\mathbf{g})$ is the average of g_1^α and g_2^α. The cost of inequality in poverty gaps is the horizontal distance $C_\alpha(\mathbf{g})$ between $\Gamma_1(\mathbf{g})$ and $\Gamma_\alpha(\mathbf{g})$.

2.4 Transient and chronic poverty with the EDE poverty gap approach

Transient poverty generates variability and thus inequality in the poverty status of individuals. It is thus natural to use the framework described above to capture its importance. Let $\gamma_\alpha(\mathbf{g}_i)$ be the EDE poverty gap for individual i, namely,

$$\gamma_\alpha(\mathbf{g}_i) = \left(t^{-1} \sum_{j=1} g_{ij}^\alpha \right)^{1/\alpha}. \tag{10}$$

Using the cost-of-inequality approach introduced above, a natural measure of the cost of transiency in i's poverty status is then given by

$$\theta_\alpha(\mathbf{g}_i) = \gamma_\alpha(\mathbf{g}_i) - \gamma_1(\mathbf{g}_i), \tag{11}$$

which is again non-negative for any $\alpha \geq 1$. The EDE gap $\gamma_\alpha(\mathbf{g}_i)$ can be interpreted as the variability-adjusted poverty status. $\gamma_1(\mathbf{g}_i)$ is i's average poverty gap, and — in the same spirit as in the permanent income literature — can be interpreted as i's "permanent" poverty status. In a context of risk aversion in which an individual i would augment his expected poverty gap by a risk premium, this risk premium would be given by $\theta_\alpha(\mathbf{g}_i)$, and his variability-adjusted poverty status would thus be given by $\gamma_\alpha(\mathbf{g}_i)$. Analogously to the SDM above, individual

i would be willing to pay $\theta_\alpha(\mathbf{g}_i)$ in units of his average poverty gap to remove variability in his poverty gap status.

A natural next step is to aggregate the transiency cost $\theta_\alpha(\mathbf{g}_i)$ across the n individuals such as to give the aggregate magnitude of transiency, denoted as $\Gamma_\alpha^T(\mathbf{g})$. This is given simply by:

$$\Gamma_\alpha^T(\mathbf{g}) = n^{-1} \sum_{i=1}^{n} \theta_\alpha(\mathbf{g}_i). \tag{12}$$

Let us now focus on the distribution of the individual EDE poverty gaps $\gamma_\alpha(\mathbf{g}_i)$. This distribution is the distribution of individual ill-fare in the presence of both chronic and transient poverty. Denote this distribution as $\gamma_\alpha = (\gamma_\alpha(\mathbf{g}_1), ..., \gamma_\alpha(\mathbf{g}_n))$. Aggregate poverty with γ_α is then given by

$$\Gamma_\alpha(\gamma_\alpha) = \left(n^{-1} \sum_{i=1}^{n} \gamma_\alpha(\mathbf{g}_i)^\alpha \right)^{1/\alpha}. \tag{13}$$

The cost of inequality in the EDE poverty gaps γ_α then equals

$$C_\alpha(\gamma_\alpha) = \Gamma_\alpha(\gamma_\alpha) - \Gamma_1(\gamma_\alpha). \tag{14}$$

This leads to the following result.

Theorem 1 *Total poverty is given by the sum of the average poverty gap in the population ($\Gamma_1(\mathbf{g})$), the cost of inequality in individual EDE poverty gaps ($C_\alpha(\gamma_\alpha)$), and the importance of transient poverty ($\Gamma_\alpha^T(\mathbf{g})$):*

$$\Gamma_\alpha(\mathbf{g}) = \Gamma_1(\mathbf{g}) + C_\alpha(\gamma_\alpha) + \Gamma_\alpha^T(\mathbf{g}). \tag{15}$$

See appendix. ■

Given the result of Theorem 1, it is natural to define chronic poverty as the difference between total and transient poverty, and chronic poverty is hence denoted as

$$\Gamma^*(\mathbf{g}) = \Gamma_1(\mathbf{g}) + C_\alpha(\gamma_\alpha). \tag{16}$$

Chronic poverty is then the average poverty gap plus the cost of inequality in EDE poverty gaps across individuals. Transient poverty is the cost of the variability of poverty gaps across time.

Corollary 2 *Total poverty is the sum of chronic and transient poverty:*

$$\Gamma_\alpha(\mathbf{g}) = \Gamma^*(\mathbf{g}) + \Gamma_\alpha^T(\mathbf{g}). \tag{17}$$

Note that the total cost of inequality in poverty gaps is the sum of the cost of inequality across individuals and that of variability across time:

$$C_\alpha(\mathbf{g}) = C_\alpha(\gamma_\alpha) + \Gamma_\alpha^T(\mathbf{g}). \tag{18}$$

All three expressions in (18) are increasing in α. They are also increasing in the inequality of poverty gaps: a mean-preserving inequality-increasing change in the EDE poverty gaps will increase $C_\alpha(\gamma_\alpha)$, and a mean-preserving variability-increasing change in the temporal distribution of poverty gaps will increase $\Gamma_\alpha^T(\mathbf{g})$. Both of these changes will therefore increase $C_\alpha(\mathbf{g})$ and $\Gamma_\alpha(\mathbf{g})$. All three expressions in (18) also have an interpretation in terms of average poverty gaps: $C_\alpha(\mathbf{g})$ is the cost that a SDM would be willing to incur to remove all variability in poverty status, $C_\alpha(\gamma_\alpha)$ is the cost that a SDM would be willing to incur to remove inter-individual inequality in welfare status, and $\Gamma_\alpha^T(\mathrm{g})$ is the cost that individuals would collectively be willing to incur to remove intra-individual variability in poverty status.

3 Statistical procedures

Sections 2.2 and 2.4 provide two alternative measurement systems to distinguish between total and transient poverty. JR's approach first defines an individual's chronic poverty as poverty when he is assumed to earn his permanent income, and then defines transient poverty as the difference between total and chronic poverty. Our approach in section 2.4 first defines an individual's transient poverty as the difference between his EDE and his expected poverty gap, and then measures chronic poverty as the difference between total and transient poverty.

Both approaches can in practice be easily implemented using panel data. Such panel data will, however, typically involve a relatively modest number t of time periods. As we will see, this in turn can create substantial biases between sample estimates and true (unobserved) poverty indices. With JR's approach, these biases will directly affect the estimation of chronic poverty, and for the approach of section 2.4, these biases will affect directly the estimation of transient poverty. Transient poverty (for JR) and chronic poverty (for our approach) will also be biased since they are obtained as differences between biased estimators. We thus turn to how we can can correct at least partially for these biases.

3.1 Analytical bias corrections

For each individual i, $i = 1, ..., n$, t income values are assumed to be drawn randomly from $F_i(y)$. For expositional simplicity, income is normalized by the fixed and known poverty line and its distribution $F_i(y)$ is also assumed constant across periods. This generates a sample of nt incomes denoted as $\{y_{i1}, ..., y_{it}\}_{i=1}^{n}$.

3.1.1 Jalan and Ravallion's chronic-transient poverty

Let $\overline{y}_i$ then be the expected income of individual i at a given income — his permanent income. This is defined as $\overline{y}_i = \int y dF_i(y)$. An individual i's true (as opposed to estimated) chronic poverty is then given by

$$\overline{P*}_{\alpha,i} = (1 - \overline{y}_i)_+^{\alpha} \,. \tag{19}$$

We estimate $\overline{y}_i$ with panel data by $\widehat{\overline{y}}_i = t^{-1} \sum_{j=1}^{t} y_{ij}$, where y_{ij} is the observed sample income of individual i at time j. An obvious estimator for $\overline{P*}_{\alpha,i}$ is simply $\left(1 - \widehat{\overline{y}}_i\right)_+^{\alpha}$. This, however, is biased upwards for finite values of t, since

$$\begin{aligned} E\left[\left(1 - \widehat{\overline{y}}_i\right)_+^{\alpha}\right] &= \overline{P*}_{\alpha,i} + \frac{\alpha(\alpha-1)}{2t}(1-\overline{y}_i)_+^{\alpha-2}\,\mathrm{var}(y_{ij}) + O(t^{-2}) && (20)\\ &\geq \overline{P*}_{\alpha,i}, && (21) \end{aligned}$$

where $\mathrm{var}(y_{ij}) = \int (y - \overline{y}_i)^2 dF_i(y)$. Hence, an estimator that includes a first-order correction for the bias of $\left(1 - \widehat{\overline{y}}_i\right)_+^{\alpha}$ is given by $\widehat{\overline{P*}}_{\alpha,i}$ and defined[6] as

$$\widehat{\overline{P*}}_{\alpha,i} = \left(1 - \widehat{\overline{y}}_i\right)_+^{\alpha} + \frac{\alpha(1-\alpha)}{2t}(1-\overline{y}_i)^{\alpha-2}\,\mathrm{var}(y_{ij}). \tag{22}$$

Note that all of the elements in (22) can be estimated consistently, *inter alia* by substituting $\widehat{\overline{y}}_i$ for $\overline{y}_i$ and $(t-1)^{-1}\sum_{j=1}^{t}\left(y_{ij} - \widehat{\overline{y}}_i\right)^2$ for $\mathrm{var}(y_{ij})$. (22) thus provides a first-order correction for JR's index of chronic poverty.

[6]Recall that we assume here that the y_{ij} are distributed independently across the time periods j. If this were not the case, the bias correction in (22) would be insufficient and would need to be of larger order than $O(t^{-1})$. The usually small value of t can make it relatively difficult, however, to test whether this independence assumption is valid.

3.1.2 EDE Chronic-transient poverty

We now turn to a first-order bias correction for the estimation of this paper's measure of transient poverty. Let $\overline{\gamma}_{\alpha,i}$ be the true (as opposed to the estimated) EDE poverty gap of individual i. This is defined as $\overline{\gamma}_{\alpha,i} = \left(\int (1-y)_+^\alpha \, dF_i(y)\right)^{1/\alpha}$. A natural estimator of $\overline{\gamma}_{\alpha,i}$ is given by $\gamma_\alpha(\mathbf{g}_i)$. But this estimator is again biased for small values of t because $\gamma_\alpha(\mathbf{g}_i)$ is non linear in g_{ij}. Defining $\overline{P}_{\alpha,i} = \int (1-y)_+^\alpha \, dF_i(y)$, this bias is shown by the fact that

$$\begin{aligned}
&E\left[\gamma_\alpha(\mathbf{g}_i)\right] \\
&= E\Big[\overline{\gamma}_{\alpha,i} + \alpha^{-1}\overline{\gamma}_{\alpha,i}^{(1-\alpha)}\left[P_\alpha(\mathbf{g}_i) - \overline{P}_{\alpha,i}\right] \\
&-0.5\alpha^{-2}(\alpha-1)\overline{\gamma}_{\alpha,i}^{(1-2\alpha)}\left[P_\alpha(\mathbf{g}_i) - \overline{P}_{\alpha,i}\right]^2\Big] + O(t^{-2}).
\end{aligned} \quad (23)$$

Since $E\left[P_\alpha(\mathbf{g}_i) - \overline{P}_{\alpha,i}\right] = 0$ and $E\left[\left(P_\alpha(\mathbf{g}_i) - \overline{P}_{\alpha,i}\right)^2\right] = t^{-1}\text{var}(g_{ij}^\alpha)$, we have (to leading order) that

$$\begin{aligned}
E\left[\gamma_\alpha(\mathbf{g}_i)\right] &\cong \overline{\gamma}_{\alpha,i} - 0.5\alpha^{-2}(\alpha-1)\overline{\gamma}_{\alpha,i}^{(1-2\alpha)}t^{-1}\text{var}(g_{ij}^\alpha) &(24)\\
&\leq \overline{\gamma}_{\alpha,i}. &(25)
\end{aligned}$$

This shows that $\gamma_\alpha(\mathbf{g}_i)$ is biased downwards. A first-order correction for $\overline{\gamma}_{\alpha,i}$ is given by

$$\widehat{\overline{\gamma}}_{\alpha,i} = \gamma_\alpha(\mathbf{g}_i) + 0.5\alpha^{-2}(\alpha-1)\overline{\gamma}_{\alpha,i}^{(1-2\alpha)}t^{-1}\text{var}(g_{ij}^\alpha). \quad (26)$$

Again, all of the elements in (26) can be estimated consistently. $\overline{\gamma}_{\alpha,i}^{(1-2\alpha)}$ can be estimated as $P_\alpha(\mathbf{g}_i)^{(1-2\alpha)/\alpha}$ and $\text{var}(g_{ij}^\alpha)$ can be estimated as $(t-1)^{-1}\sum_{j=1}^t \left(g_{ij}^\alpha - P_\alpha(\mathbf{g}_i)\right)^2$.

3.2 Bootstrap bias corrections

An alternative approach to correcting for the biases found in (21) and (25) is by estimating the biases that arise in numerical simulations of the longitudinal distributions of incomes. One way to proceed is by bootstrapping the empirical distribution of each subsample of t periods' incomes. This can be done as follows:

1. For each individual i, we wish to compute an estimator η_i of chronic poverty $\left(1-\widehat{\overline{y}}_i\right)_+^\alpha$ or of transient poverty $\gamma_\alpha(\mathbf{g}_i)$.

2. For each individual i, we first compute a "plug-in" estimator using i's original sub-sample of t incomes, $\{y_{i1}, ..., y_{it}\}$, and which we denote by η_i^{pin}.

3. For each individual i and for each of $k = 1, ..., K$, we generate a sample of t incomes drawn randomly (and with replacement) from the original sub-sample of t incomes for individual i, $\{y_{i1}, ..., y_{it}\}$. We compute a new estimator η_i^h for each such simulated sample k. We should choose to be K as large as is numerically and computationally reasonable.

4. η_i^B is given by the mean of these K estimators η_i^k, that is, we have $\eta_i^B = K^{-1}\sum_{k=1}^{K}\eta_i^k$. The bootstrap estimate of the bias is then given by $\eta_i^B - \eta_i^{pin}$.

Each of $\left(1-\widehat{\overline{y}}_i\right)_+^\alpha$ and $\gamma_\alpha(\mathbf{g}_i)$ can then be corrected for the bootstrap-estimated bias $\eta_i^B - \eta_i^{pin}$. The corrected estimator of JR's index of chronic poverty is given by

$$\widetilde{\widetilde{P^*}}_{\alpha,i} = \left(1-\widehat{\overline{y}}_i\right)_+^\alpha - \left(\eta_i^B - \eta_i^{pin}\right) \tag{27}$$

when η_i is set to $\left(1-\widehat{\overline{y}}_i\right)_+^\alpha$, and a bootstrap-corrected estimator of Section 2.4's index of transient poverty is given by

$$\widetilde{\widetilde{\gamma}}_{\alpha,i} = \gamma_\alpha(\mathbf{g}_i) - \left(\eta_i^B - \eta_i^{pin}\right). \tag{28}$$

when η_i is chosen to be $\gamma_\alpha(\mathbf{g}_i)$.

3.3 Bias corrections: Monte Carlo evidence

To explore the performance of the above bias-correction methods, we use Monte Carlo simulations to estimate the statistics of interest (total, chronic, and transient poverty) with and without bias corrections. To do this:

1. We assume a log-normal longitudinal distribution of incomes with mean and standard deviation both set to 1 (recall that incomes are normalized by the poverty line). We compute the statistics of interest for that distribution.

2. We decide on a number t of longitudinal income observations to be drawn randomly and independently from that population.

3. For each of $h = 1, ..., H$, we draw a sample of t such observations and estimate the statistics of interest, with or without bias corrections.

4. We compute the average of the H statistics estimated in the previous step, and compare that average to the true population statistics calculated in step 1.

Note again that Step 2 above can be done with or without bias corrections. Recall that biases arise because of the finite number of periods, not because of a finite number of households.

The Monte Carlo evidence is shown on Figure 1 for both JR's chronic poverty and EDE transient poverty, for $\alpha = 3$, and for poverty lines z set to 1 and 1.5. The bias corrections work well in all cases, generally reducing by more (and often by much more) than 50% the biases of the naive estimators of chronic and transient poverty. This is true even for the smallest possible number $t = 2$ of time periods: in all cases (except for JR's chronic poverty with z=1.5), the biases are reduced by roughly by 50%. The percentage fall in the biases introduced by the corrections increases with t — although the absolute value of the corrections itself naturally falls with t. Analytical and bootstrap corrections seem to work equally well: EDE transient poverty with $\alpha = 3$ and $z = 1$ is better estimated on average with a bootstrap correction, but JR's chronic poverty with $\alpha = 3$ and $z = 1.5$ is on average estimated slightly better with an analytical correction.

4 Illustration: An application to China

We now illustrate the use of the methodology presented above with panel survey data from China.

We use *per capita* household income and weight households by their sampling weight times household size. All expenditures have been normalized by a consumption-based poverty line based on a 2100-calorie-diet plus *per capita* expenditures for durables and housing of individuals close to poverty line[7]. Asymptotic standard errors are computed taking full account of the survey design, *viz*, taking into account sampling stratification and clustering[8].

We first carry out a decomposition of total JR poverty using 8 time periods separated by a two-year interval between 1987 and 2001. As shown in Table

[7]This rounds up to a national poverty line of 850 RMB *per capita* in 2002, which is deflated to 1990 using provincial price deflators.

[8]The estimation was done using the freely available *DAD* program, which can be downloaded from www.mimap.ecn.ulaval.ca. STATA program files to carry out the estimation are also available upon request.

1, transient poverty is significantly more important than chronic poverty and it represents slightly less than two thirds of total poverty. As expected, the asymptotic and bootstrap bias corrections generate almost identical estimates (these results are rounded to the fourth decimals); with these corrections, transient poverty amounts to about 73% of total poverty. This is in line with the simulation results discussed in Section 3.3. (All of the estimates discussed from now onwards are bias corrected.)

Figures 2 and 3 show the sensitivity of the above results to the choice of the poverty line and of the parameter α. The left vertical axis shows the numerical value of the estimates while the right vertical axis displays the ratio of transient over chronic poverty. For $\alpha = 2$ in Figure 2, increasing the poverty line from 50% to 150% of the official poverty line naturally increases all of the poverty estimates, but the effect is stronger for chronic poverty. Said differently, transient poverty falls as a proportion of chronic poverty when the poverty line increases – chronic poverty exceeds transient poverty when the poverty line is above 1.25.

Opposite results are obtained in Figure 3 when α increases. As α rises, poverty measurement becomes more and more sensitive to the occurrence of very low incomes, and less to the levels of average incomes. This comes out clearly in Figure 3: for a poverty line set to 1, transient poverty is never lower than chronic poverty, and the ratio shown on the right vertical axis increases rapidly with α. Note here the graphical verification of the anomaly mentioned on page 6: all components of the JR decomposition fall numerically with increases in α.

As mentioned above on page 7, another potential criticism of JR's approach is that their estimator of chronic poverty may seem to be too sensitive to the occurrence of very large incomes in some time period. The estimation of JR chronic poverty basically supposes that average *uncensored* income is a good proxy of the ability of households to consume over time, in part because households are assumed to abide by the permanent income hypothesis. Credit constraints, risk aversion and behavioral difficulties to save can, however, render this invalid. An alternative empirical procedure would seem to be to use the average of incomes censored at the poverty line to capture chronic poverty. This would basically assume that individuals are able to smooth their consumption behavior when incomes are no greater than z, but that they are not able to save any of the excess incomes that would bring (*e.g.*, temporarily large or windfall) incomes above the poverty line.

To see how to account for this analytically, let $\dot{y}_{ij} = \min(y_{ij}, z)$ be income y_{ij} censored at z. We can then re-estimate all of the JR poverty components with $\dot{y}_{ij}$ instead of y_{ij}. It can be checked that the estimate of total poverty $\widehat{P}_\alpha(\mathbf{g})$ will remain unchanged, but the estimation of i's chronic poverty will now use $\widehat{\bar{\dot{y}}}_i = t^{-1}\sum_{j=1}^{t} \dot{y}_{ij}$ instead of $\widehat{\bar{y}}_i$, with corresponding changes to the estimation of aggregate chronic poverty and transient poverty.

To see what this does to the estimates, we carried out the JR decomposition with censored incomes and report the results in Table 2. As mentioned, this does not change total poverty, but it has a considerable impact on its two components. Bias-corrected chronic poverty increases from 27% to 53% of total poverty. Figure 3 shows that this change in empirical procedure has particularly large effects for low poverty lines. Chronic poverty is always larger with the censored approach – it is now larger than transient poverty whenever the poverty line exceeds approximately 0.9 (instead of 1.25). Similar results are obtained with changes in α.

Table 3 uses the same data to decompose total poverty but this time using the EDE approach, with and without bias corrections. (Recall that all EDE estimators have a money-metric cardinal value.) Again, the two bias-correction methods give very similar results and increase the estimates of transient poverty by about 15%, consistent again with the simulation results of Section 3.3. The differences with the JR approach are, however, important. For the same α and the same poverty line, transient poverty now represents at most 23% (21% without bias corrections) of total poverty. A social decision maker (SDM) would thus be willing to spend about 23% of total poverty to remove intra-individual inequality in poverty status. This is a significant departure from the JR estimates, which suggested for the same parameter values that transient poverty accounted for around 73% of total poverty.

The sensitivity of EDE total, transient and chronic poverty to the choice of poverty line and parameter α is shown in Figures 4 and 5 respectively. Total poverty naturally increases both with the poverty line and with α. For $\alpha = 2$ and a poverty line set to 1.5, total poverty is deemed to be equal in Figure 4 to about 28% of the poverty line – a similar result is obtained in Figure 5 with a poverty line set to 1 and $\alpha = 5$. The ratio of transient to chronic poverty never exceeds 0.3 and is a non-monotonic concave function of z and/or α. The ratio eventually tends to fall as the poverty line increase since as z rises it is the increase in the average poverty gap that tends to dominate, thus leading to an increase in chronic poverty $\Gamma_\alpha(\mathbf{g})$. The same ratio eventually tends to fall as α increases since it is then the inequality between households (as opposed to variability of poverty status within individuals) that tends to dominate, in the form of an increase in the cost $C_\alpha(\gamma_\alpha)$ and in chronic poverty.

Table 1: JR transient and chronic poverty, with and without bias corrections; $\alpha = 2$; asymptotic standard errors within parentheses

Components	**Without bias corrections**	**With bias corrections**	
		Analytical	Bootstrap
Transient P_α^T	0.0123	0.0136	0.0136
	(0.0014)	(0.0016)	(0.0015)
Chronic P_α^*	0.0063	0.0050	0.0050
	(0.0017)	(0.0016)	(0.0016)
Total P_α	0.0187	0.0187	0.0187
	(0.0028)	(0.0028)	(0.0028)

Table 2: JR transient and chronic poverty, with and without bias corrections, and using censored incomes for chronic poverty; $\alpha = 2$; asymptotic standard errors within parentheses

Components	**Without bias corrections**	**With bias corrections**	
		Analytical	Bootstrap
Transient	0.0083	0.0094	0.0093
	(0.0009)	(0.0010)	(0.0010)
Chronic	0.0104	0.0092	0.0093
	(0.0021)	(0.0020)	(0.0020)
Total	0.0187	0.0187	0.0187
	(0.0028)	(0.0028)	(0.0028)

Table 3: EDE transient and chronic poverty, with and without bias corrections; $\alpha = 2$; asymptotic standard errors within parentheses

Components	**Without bias corrections**	**With bias corrections**	
		Analytical	Bootstrap
Average gap $\Gamma_1(\mathbf{g})$	0.0545	0.0545	0.0545
	(0.0103)	(0.0103)	(0.0103)
Cost of inequality $C_\alpha(\mathbf{g})$	0.0532	0.0540	0.0539
	(0.0068)	(0.0035)	(0.0035)
Transient $\Gamma_\alpha^T(\mathbf{g})$	0.0290	0.0331	0.0344
	(0.0020)	(0.0023)	(0.0024)
Chronic $\Gamma*(\mathbf{g})$	0.1077	0.1086	0.1085
	(0.0095)	(0.0093)	(0.0092)
Total $\Gamma_\alpha(\mathbf{g})$	0.1368	0.1418	0.1429
	(0.0103)	(0.0103)	(0.0102)

Figure 1: Monte-Carlo simulations of the impact of bias corrections on

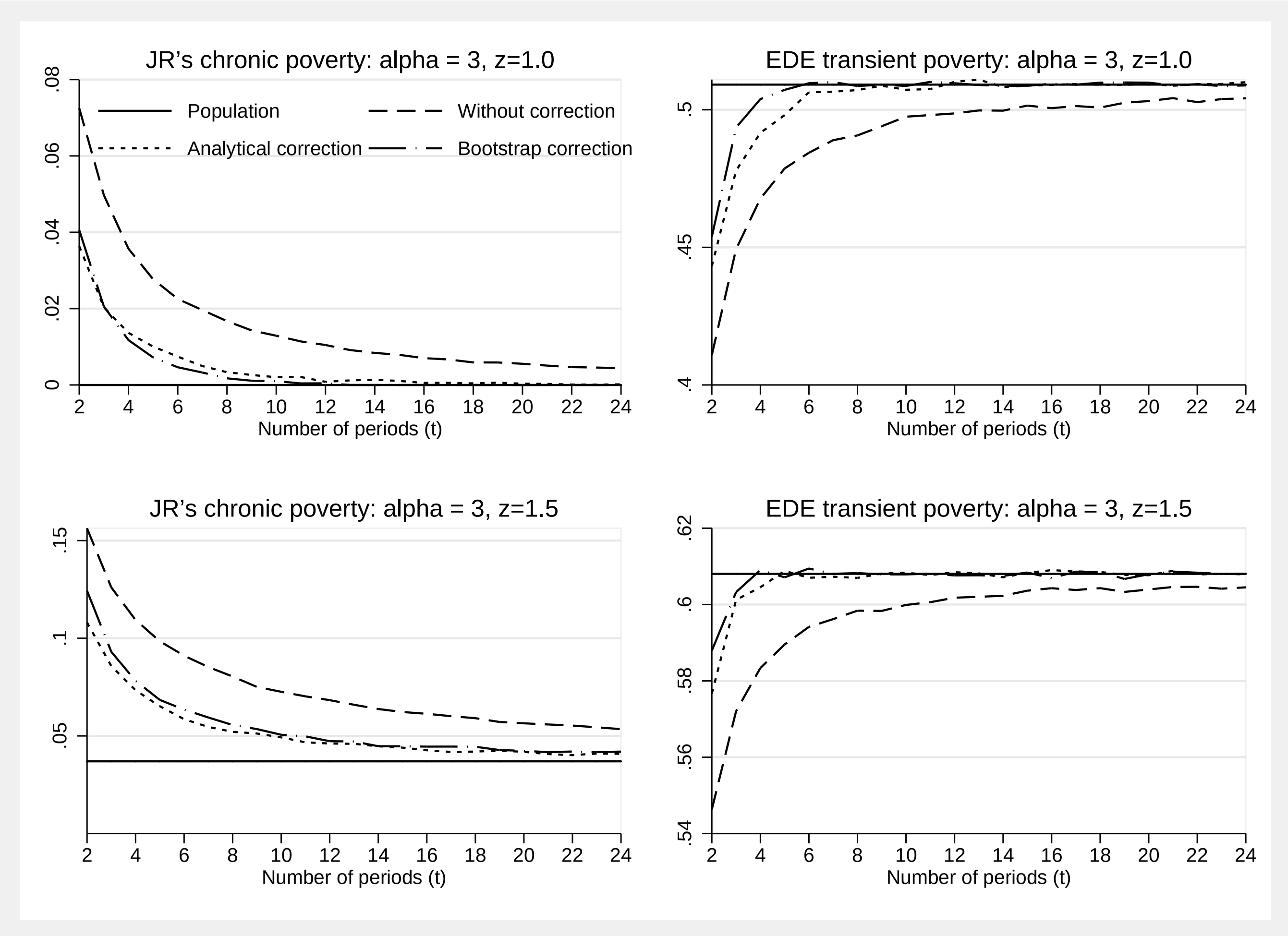


Figure 2: JR transient and chronic poverty according to the poverty line; $\alpha = 2$

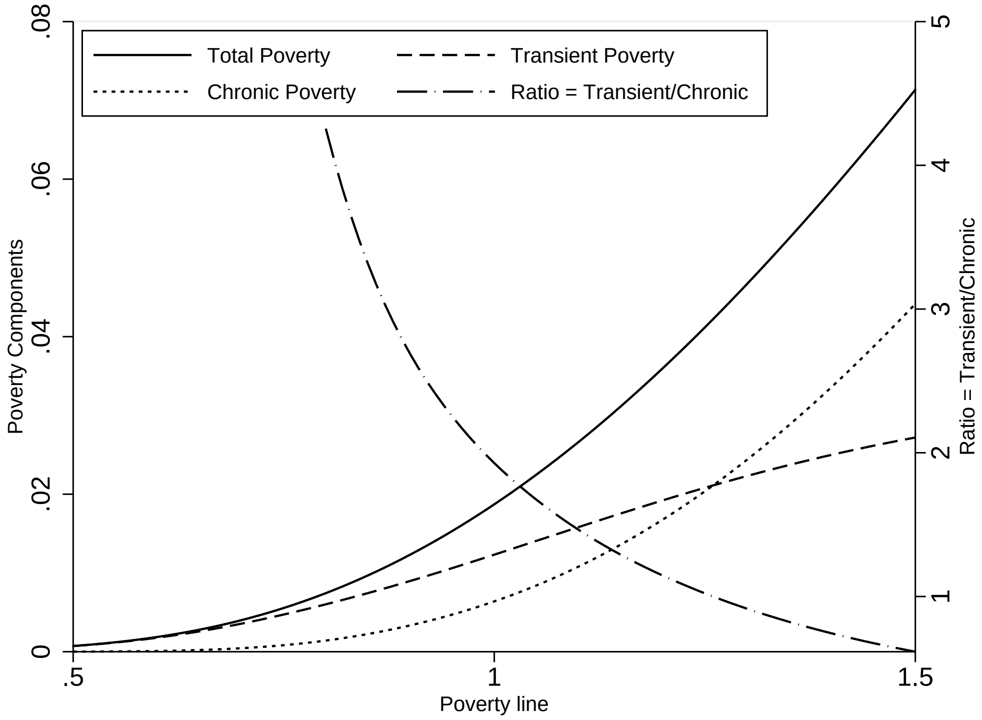


Figure 3: JR transient and chronic poverty according to the parameter α poverty line=1

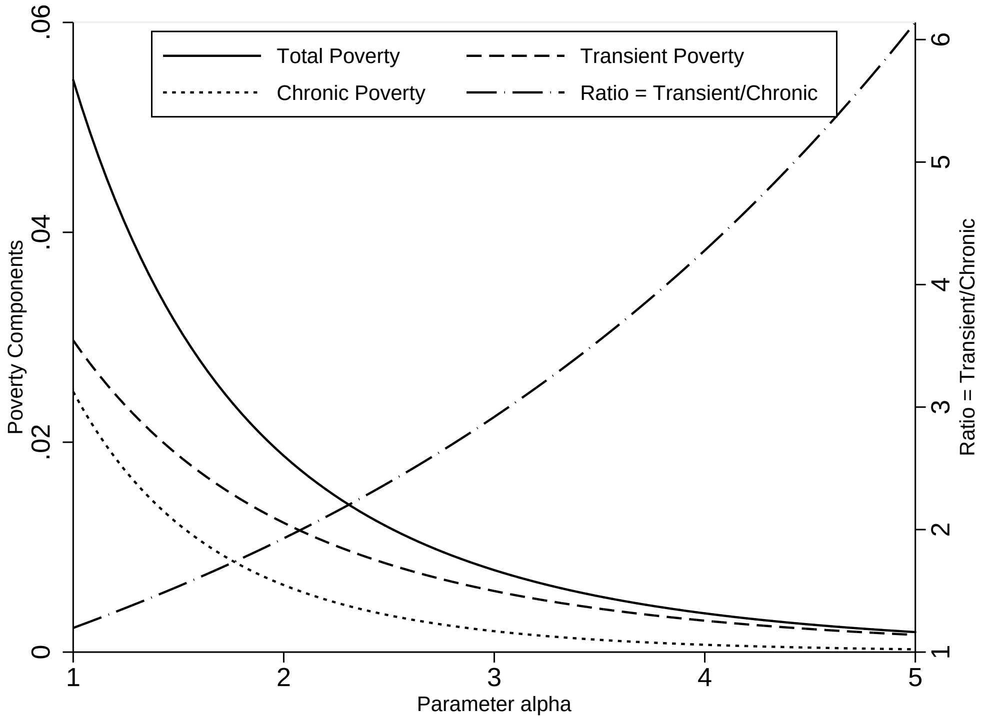


Figure 4: EDE transient and chronic poverty according to the poverty line
$\alpha = 2$

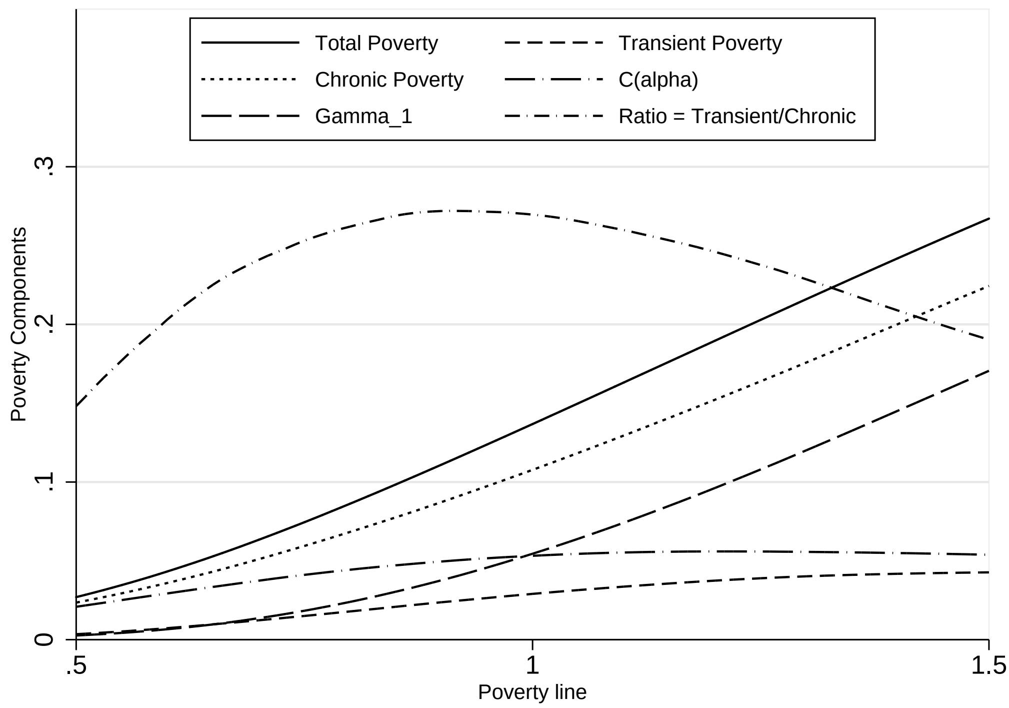


Figure 5: EDE transient and chronic poverty according to the poverty line
poverty line = 1

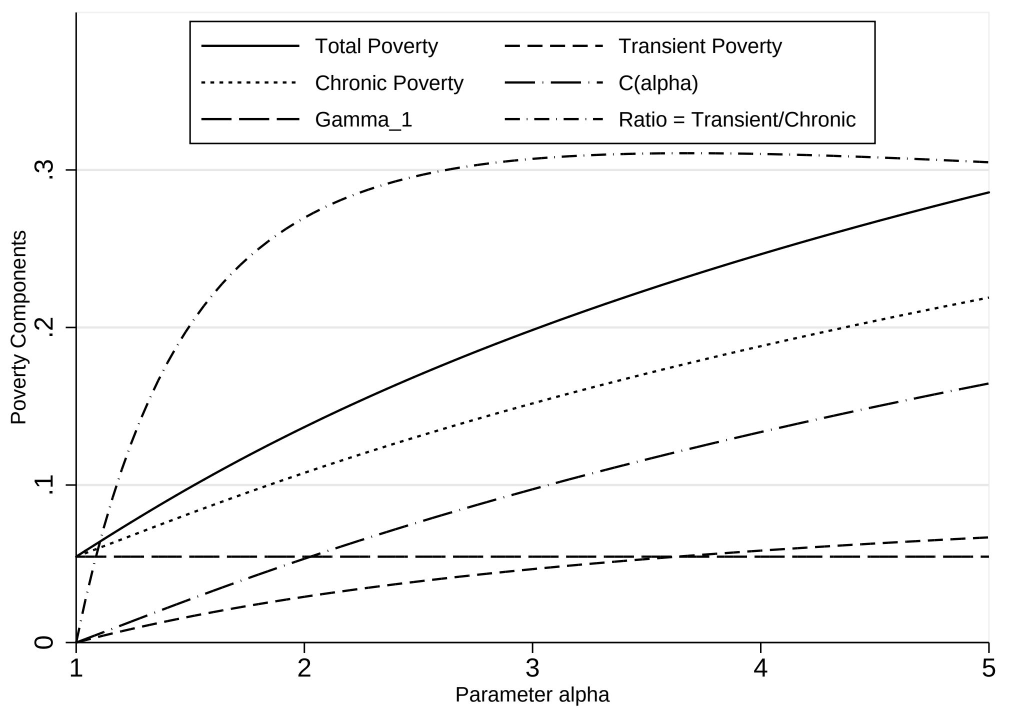
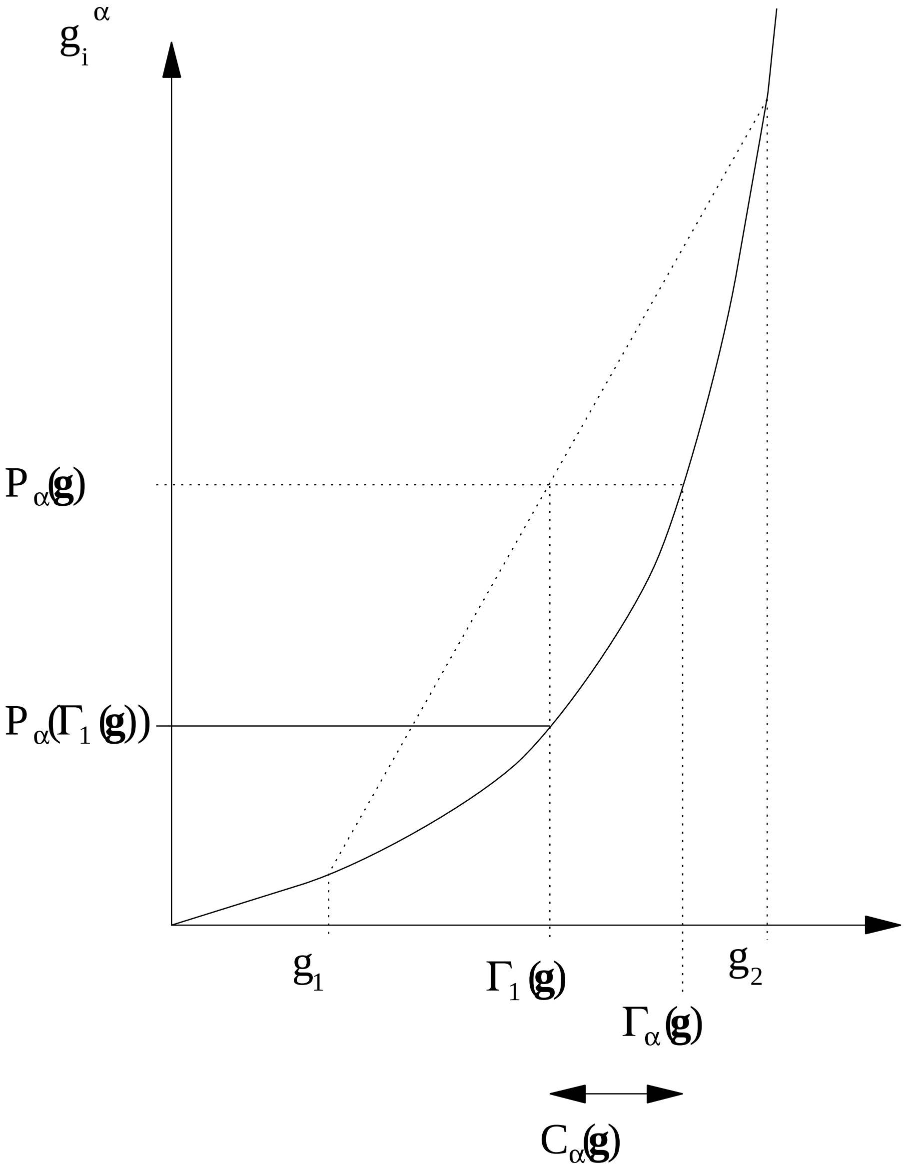


Figure 6: The cost of inequality and variability in poverty gaps



References

[1] Atkinson, A.B. (1970), On the Measurement of Inequality, *Journal of Economic Theory*, vol. 2, 244–263.

[2] Atkinson, A. B., B. Cantillon, E. Marlier and B. Nolan (2002), *Social Indicators – The EU and Social Inclusion*, Oxford University Press, Oxford.

[3] Bane, M. J., and D. T. Ellwood (1986), Slipping into and out of Poverty; The

Dynamics of Spells, *Journal of Human Resources*, vol. 21, 1–23.

[4] Baulch, B. and J. Hoddinott (2000) (eds.), *Economic Mobility and Poverty Dynamics in Developing Countries*, London: Frank Cass.

[5] Bourguignon, F., Goh, C.-c., and Kim, D. I. (2004), Estimating Individual Vulnerability to Poverty with Pseudo-Panel Data, Washington DC, World Bank.

[6] Breen, Richard, and Pasi Moisio (2003), Poverty Dynamics Corrected for Measurement Error, mimeo.

[7] Calvo, C., and S. Dercon (2005), Measuring Individual Vulnerability, paper presented at the International Conference on The many dimensions of poverty, International Poverty Centre, Brasilia, Brazil, 29–31 August.

[8] Chaudhuri, S., J. Jalan, and A. Suryahadi (2002), Assessing Household Vulnerability to Poverty from Cross-sectional Data: A Methodology and Estimates from Indonesia, Columbia University, Discussion Paper 0102-52.

[9] Christiaensen, L. and K. Subbarao (2004), Toward an Understanding of Household Vulnerability in Rural Kenya, World Bank Policy Research Working Paper 3326.

[10] Chronic Poverty Research Centre (2004), *The Chronic Poverty Report 200405*, Institute for Development Policy and Management, University of Manchester.

[11] Foster, J. E., J. Greer and E. Thorbecke (1984), A Class of Decomposable Poverty Measures. *Econometrica,* vol. 52, 761–765.

[12] Gaiha, R. (1988), Income Mobility in Rural India, *Economic Development and Cultural Change*, vol. 36, 279–302

[13] Gaiha, R. (1989), Are the Chronically Poor also the Poorest in Rural India?, *Development and Change*, vol. 20, 295–322.

[14] Hulme, D., and A. McKay (2005) Identifying and Measuring Chronic Poverty: Beyond Monetary Measures, paper presented at the International Conference on The many dimensions of poverty, International Poverty Centre, Brasilia, Brazil, 29–31 August.

[15] Jarvis, Sarah, and Stephen P. Jenkins (1997), Low Income Dynamics in 1990s Britain, *Fiscal Studies*, vol. 18, 123–142.

[16] Kamanou, G., and J. Morduch (2004), Measuring Vulnerability to Poverty, chapter in Dercon, S. (ed.), *Insurance against Poverty*, Oxford University Press.

[17] Kolm, S. C. (1969), *The Optimal Production of Justice*, H. Guitton and J. Margolis.

[18] Ligon, E., and L. Schechter (2003), Measuring Vulnerability, *The Economic Journal*, vol. 113, C95–C102.

[19] Ravallion, M. (1988), Expected Poverty under Risk-Induced Welfare Variability, *The Economic Journal*, vol. 98, 1171–1182.

[20] Rendtel, Ulrich, Rolf Langeheine, and Roland Bernsten (1998), The Estimation of Poverty Dynamics Using Different Household Income Measures, *Review of Income and Wealth*, vol. 44, 81–98.

[21] Suryahadi, A., and S. Sumarto (2003), Poverty and Vulnerability in Indonesia Before and After the Economic Crisis, *Asian Economic Journal*, vol. 17, 45–64.

[22] Watts, H.W. (1968), ‘An Economic Definition of Poverty, in D.P. Moynihan (ed.), *On Understanding Poverty*, New York: Basic Books.

[23] World Bank, (2001), World Development Report 2000/2001 – Attacking Poverty, New York, Oxford University Press.

5 Appendix

Proof of Theorem 1.

Note first from equations (6), (10), and (13) that

$$C_\alpha(\gamma_\alpha) = \Gamma_\alpha(\gamma_\alpha) - \Gamma_1(\gamma_\alpha) = \Gamma_\alpha(\mathbf{g}) - \Gamma_1(\gamma_\alpha). \tag{29}$$

Using (11) and (12), note also that

$$\Gamma_\alpha^T(\mathbf{g}) = n^{-1}\left[\sum_{i=1}^{n} \gamma_\alpha(\mathbf{g}_i) - \gamma_1(\mathbf{g}_i)\right] \tag{30}$$

$$= \Gamma_1(\gamma_\alpha) - \Gamma_1(\mathbf{g}). \tag{31}$$

(Line (31) follows from (2), (7) and (13).) Hence, regrouping terms, we obtain

$$\Gamma_\alpha(\mathbf{g}) = \Gamma_1(\mathbf{g}) + C_\alpha(\gamma_\alpha) + \Gamma_\alpha^T(\mathbf{g}). \tag{32}$$

■