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Removing the anonymity axiom in assessing pro-poor growth

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Abstract The recent focus on 'pro-poor growth' led also to an intense debate on how exactly to define and to measure pro-poor growth. All suggested measures have in common that they are based on the anonymity axiom. Such a perspective may provide a very incomplete picture given that the common objective of most studies investigating the pro-poorness of growth is to test whether specific policy reforms where beneficial to the *initially* poor or not. I suggest a new concept of pro-poor growth which removes the anonymity axiom, and, using an illustration based on data from Indonesia and Peru, I check whether the assessment of pro-poor growth is different when an anonymous and a non anonymous approach to pro-poor growth is used. I also suggest an original decomposition of poverty changes over time which links both concepts. The results show that the choice of the approach has a drastic impact on the interpretation of the data.

Key words anonymity axiom · convergence · decomposition · mobility · pro-poor growth.

1 Introduction

The recent focus on 'pro-poor growth' in development economics and politics led also to an intense debate on how exactly to define and to measure pro-poor growth

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(see e.g., [8, 16, 19]). A key point in this debate is whether pro-poor growth should be defined in 'absolute' or 'relative' terms of poverty reduction. According to the absolute definition growth is considered as being pro-poor whenever the incomes of the poor increase. In contrast, the relative definition requires that the growth rate of income is higher among the poor than among the non-poor, i.e., inequality must decrease. However, all suggested measures, whether they use the absolute or the relative definition, have in common that they are based on the anonymity axiom, i.e., two distributions are treated as equally good if, after income is redistributed among households, the overall distribution is the same.

Such a perspective may provide a very incomplete picture. The common objective of most studies investigating the pro-poorness of growth is to test whether specific policy reforms were beneficial to the *initially* poor or not. More generally, to evaluate the effectiveness of reforms one would like to know who benefited or lost and how much. One may also want to know whether individuals under the poverty line before and after the reform are roughly the same, in which case poverty is rather a chronic state, or whether mobility among the poor is high so that poverty is rather a transient phenomenon. Issues of chronic poverty and income mobility received considerable attention in the past (see e.g., [10, 12]), however so far they have not been considered in the framework of pro-poor growth.

The following example shows that these issues are of particular importance when assessing pro-poor growth. Take the simple case, where an income distribution observed in t can be divided into two equal sized groups: the 'poor' and the 'rich'. Let us further assume that between t and $t+1$ the poor see their incomes increase to a level which is above the level of the initially rich in t and the rich see their incomes decrease to a level which corresponds exactly to the level of the initially poor in t. Looking only at marginal distributions we would judge such a growth pattern as not pro-poor, both, according to the absolute and the relative definition. However, looking at the group-specific trajectories, this growth pattern could be judged as being pro-poor. This very simple example illustrates that postulating anonymity, when assessing pro-poor growth, may result in misleading conclusions regarding the impact of a specific policy on the incomes of the initially poor. Obviously deciding whether such a growth process can be called pro-poor or not depends on the value judgements one might want to accept. Ravallion [20] pointed out that 'anti-globalizers' seem to focus more on the losers amongst the poor and those vulnerable to poverty, whereas 'globalizers' focus more on the aggregate income distribution. This may explain why both groups reach so different conclusions concerning the distributional consequences of trade liberalization. Moreover, the *Millennium Development Goal One*, which requires to halve poverty by half before 2015, clearly focuses on aggregate poverty.

The objective of this paper is therefore to suggest a new concept of pro-poor growth which does not rely on the anonymity axiom and to illustrate how an assessment of pro-poor growth may change, depending on whether this or the usual concept of pro-poor growth is used. The reminder of the paper is organized as follows. Section 2 recalls the usual concept of pro-poor growth which is based on the anonymity axiom. Section 3 presents the new concept. Section 4 suggests a decomposition which links both concepts. Section 5 gives an empirical illustration based on Indonesian and Peruvian data. Section 6 concludes.

2 The measurement of pro-poor growth and the anonymity axiom

2.1 Concepts and measures of pro-poor growth

Recently various measures have been suggested to assess the pro-poorness of growth.[1] These measures can be divided into two broad categories, based respectively on the 'absolute' and 'relative' concepts of pro-poor growth. According to the absolute definition, growth is considered as pro-poor whenever the incomes below the poverty line increase. In contrast, the relative definition requires that incomes below the poverty line grow relatively more than those above the poverty line, i.e., inequality must decrease. The most popular measures of pro-poor growth seem to be the 'growth incidence curve' (GIC) and the 'rate of pro-poor growth' ($RPPG$). Both were suggested by Ravallion and Chen [21]. They are relatively intuitive and therefore convenient for illustrative purposes.

When comparing two income distributions observed in $t-1$ and t, the growth rate in income y of the pth quantile, $g_t(p)$ can be written as:

$$g_t(p) = \frac{y_t(p)}{y_{t-1}(p)} - 1. \tag{1}$$

Letting p vary from p_1 to $p_{\max}$, $g_t(p)$ traces out what Ravallion and Chen [21] called the 'growth incidence curve'. The growth rate in income of the pth quantile can equivalently be written using the slopes of the Lorenz curves $L'(p)$ observed in t and $t-1$ as well as the corresponding growth rate in mean income γ [21]:

$$g_t(p) = \frac{L'_t(p)}{L'_{t-1}(p)}(\gamma_t + 1) - 1. \tag{2}$$

The GIC can be used to assess the pro-poorness of growth according to both the absolute and the relative concept.

2.1.1 The absolute concept of pro-poor growth

When the absolute concept is chosen, Ravallion and Chen [21] suggest to compute the rate of pro-poor growth ($RPPG$). The $RPPG$ in t is equal to the area under the GIC up to the initial headcount index, H_{t-1} (which gives the proportion of all individuals having an income in $t-1$ below or equal to the poverty line z), divided by the initial headcount index:[2]

$$RPPG_t = \frac{1}{H_{t-1}} \int_0^{H_{t-1}} g_t(p)\mathrm{d}p. \tag{3}$$

[1] See, for instance McCulloch and Baulch [18], Kakwani, Khandker and Son [14], Kakwani and Pernia [15], Ravallion and Chen [21] and Klasen [16].

[2] Throughout the analysis I assume that there is no ambiguity about the poverty line. It is defined in absolute terms and remains constant in real terms over time.

If $RPPG_t > 0$ growth is pro-poor in the absolute sense. If $RPPG_t < 0$, it is not. It should be noted that the $RPPG$ is derived from the mean of the growth rates at all quantiles up to the headcount index, which is not the same as the growth rate of mean income of the poor.

It can be shown that the $RPPG$ is directly linked to the Watts poverty index [24] when the latter is written in terms of quantile functions [21]:

$$W_{t-1} = \int_0^{H_{t-1}} \log\left[\frac{z}{y_{t-1}(p)}\right] \mathrm{d}p. \tag{4}$$

Hence, by differentiating W_t with respect to time (and for small changes in income between $t-1$ and t), one can see that:

$$-\frac{\mathrm{d}W_t}{\mathrm{d}t} = \int_0^{H_{t-1}} \frac{\mathrm{d}\log y_t(p)}{\mathrm{d}t} \mathrm{d}p = \int_0^{H_{t-1}} g_t(p)\mathrm{d}p, \tag{5}$$

i.e., the area under the GIC up to the headcount index gives (minus one times) the change in the Watts index. In the discrete case the absolute annualized change in the Watts index corresponds to the annualized $RPPG$. Given this property of the Watts poverty index, it will be used below for a decomposition of poverty changes over time.

2.1.2 The relative concept of pro-poor growth

When the relative concept is chosen, one can either look directly at the GIC to make an assessment or compare the $RPPG$ with the growth rate in the overall mean, γ. If $g_t(p) > \gamma_t$ for all p up to the initial headcount index, then growth is pro-poor according to the relative definition and, hence inequality falls for all inequality measures satisfying the Pigou–Dalton transfer principle. Conversely, if $g_t(p) < \gamma_t$ for all p up to the initial headcount index, then growth is not pro-poor according to the relative definition and, hence inequality rises. If $g_t(p) < \gamma_t$ for some p up to the initial headcount index and $g_t(p) > \gamma_t$ for some other p then one cannot in general infer whether growth is pro-poor in relative terms. In this case the $RPPG$ can be compared with the growth rate in the overall mean, γ. If $RPPG_t > \gamma_t$ growth is pro-poor in relative terms and inequality decreases and if $RPPG_t < \gamma_t$ growth is not pro-poor in relative terms and inequality increases. Then $RPPG_t = \gamma_t$ if all incomes grow at the same rate. In this case inequality remains constant.

If the relative concept of pro-poor growth is strictly taken, it paradoxically also implies to judge a growth process pro-poor, when $RPPG_t > \gamma_t$, but both $RPPG_t < 0$ and $\gamma_t < 0$, i.e., when incomes below the poverty line actually decrease and poverty rises. However, in this case it makes sense, as suggested by some authors, not to rely on the relative concept (see e.g., [8]).

2.2 The problem of postulating anonymity

The measures of pro-poor growth described previously, but also others suggested in the literature, have in common that they are based on the anonymity axiom, whether they use the absolute or relative definition. The anonymity axiom postulates that for an income distribution over n individuals enjoying each an income y_i, all permutations of personal labels have to be regarded as distributionally equivalent, i.e.:

$$(y_1, y_2, y_3, \ldots, y_n) \sim_I (y_2, y_1, y_3, \ldots, y_n) \sim_I (y_1, y_3, y_2, \ldots, y_n).$$

In other words, this axiom, sometimes also called ‘symmetry’, requires that the underlying social welfare function uses only the information about the income variable and not about some other characteristics (e.g., gender or ethnic origin) which might be available in a sample or a census of the population [5]. This assumption is usually invoked for welfare orderings, whether we look at inequality [1] or at poverty [11]. However, this axiom is neither trivial nor self-evident, and for certain purposes, such as measuring pro-poor growth, it could make sense to remove it.

The common objective of most studies investigating the pro-poorness of growth is to analyze whether specific policy reforms where beneficial to the *initially* poor or not. More generally, to evaluate the effectiveness of reforms one would like to know which groups benefited or lost and how much. Likewise, one would like to know, whether individuals under the poverty line before and after the reform are roughly the same, in which case poverty is rather a chronic state, or, in contrast, whether mobility among the poor is high, which implies that poverty is rather a transient phenomenon. This is why I argue that the measurement of pro-poor growth should not make use of the anonymity axiom. In what follows I suggest concepts using the absolute as well as relative definition of pro-poor growth, but removing the anonymity axiom.

3 Measuring pro-poor growth without postulating anonymity

So far it was (implicitly) assumed that one income distribution is observed in $t-1$, $(F(y_{i,t-1}))$ and one in t, $(F(y_{j,t}))$, where i and j do not refer necessarily to the same individuals or where at least no information is available to follow individuals over time. I have hitherto explicitly assumed that this information is available and that it is possible to infer the joint income distribution $F(y_{i,t-1}, y_{i,t})$ for a fixed population, i.e., individuals cannot only be ordered by their income level y, but also according to some other personal circumstances revealing their identity or membership to group Ω_h, where h is a criteria classifying individuals into up to $i = 1, \ldots, n$ groups. For instance, suppose we can order individuals, observed in $t-1$ and t, according to the group membership $\Omega_{p(y_{t-1})}$ defined by the income quantile $p(y_{t-1})$ they belonged to in $t-1$. This information allows to order individuals in ascending order according to their initial income quantile $p(y_{t-1})$ and to compute the quantile specific mean incomes and growth rates in income where each quantile comprises the same individuals in $t-1$ and t:

$$g_t(p(y_{t-1})) = \frac{y_t(p(y_{t-1}))}{y_{t-1}(p(y_{t-1}))} - 1. \tag{6}$$

As before, letting p vary from p_1 to $p_{\max}$, $g_t(p(y_{t-1}))$ traces out a GIC. To distinguish this GIC from the one defined by Ravallion and Chen [21], I denote it in what follows ‘IGIC’, for ‘Individual Growth Incidence Curve’. As for the GIC, the IGIC is a horizontal line if $g_t(p(y_{t-1})) = \gamma_t$ for all $p(y_{t-1})$, i.e., the individuals in each quantile see their incomes grow with the average growth rate. If $g_t(p(y_{t-1})) > 0$ ($g_t(p(y_{t-1})) < 0$) for all $p(y_{t-1})$, then each group is richer (poorer) in t than in $t-1$.

As for the GIC, it is also possible to derive a rate of pro poor growth from the IGIC, by integrating the area under the IGIC up to the initial headcount index, H_{t-1}, divided by H_{t-1}. That means we integrate the growth of income for all those individuals who had an income below or equal to the poverty line z in $t-1$. Integrating over IGIC implies that we include the same individuals in $t-1$ and t, whether or not they still have in t an income below the poverty line z. Hence, this rate of pro-poor growth, $IRPPG$ in what follows (for Individual Rate of Pro-Poor Growth), can be written as:

$$IRPPG = \frac{1}{H_{t-1}} \int_0^{H_{t-1}} g_t(p_{t-1}) \mathrm{d}p_{t-1}. \tag{7}$$

Obviously, we may also have individuals who had an income above z in $t-1$, but who have one below z in t. These individuals would not enter the $IRPPG$. Hence, computing $IRPPG$ for the IGIC implies focusing on those initially poor. This can be taken as a special variant of the 'focus axiom' and might be justified on Rawlsian grounds [22].

3.1.1 The absolute concept of pro-poor growth when anonymity is removed

I define growth as pro-poor in absolute terms, if $IRPPG > 0$, i.e., if the incomes of the *initially* poor grow with a positive rate. Conversely, growth is defined as not pro-poor in absolute terms, if $IRPPG < 0$, i.e., if the incomes of the *initially* poor grow with a negative rate.

3.1.2 The relative concept of pro-poor growth when anonymity is removed

I define growth as pro-poor in relative terms if $g_t(p(y_{t-1})) > \gamma_t$ for all $p(y_{t-1})$ up to the poverty line (the initially poor). Conversely, if $g_t(p(y_{t-1})) < \gamma_t$ for all $p(y_{t-1})$ up to the poverty line, then growth is not pro-poor according to the relative definition. If $g_t(p) < \gamma_t$ for some $p(y_{t-1})$ under the poverty line in $t-1$ and $g_t(p) > \gamma_t$ for some other $p(y_{t-1})$ under the poverty line in $t-1$ then one cannot decide whether growth is pro-poor in relative terms. In this case, the $IRPPG_t$ can be compared with the growth rate in the overall mean, γ_t. If $IRPPG_t > \gamma_t$ growth is pro-poor and if $IRPPG_t < \gamma_t$ growth is not pro-poor according to my definition of relative pro-poor growth.

However, using the concept of the IGIC, it is not true anymore that if $g_t(p(y_{t-1}))$ is a decreasing (increasing) function for all $p(y_{t-1})$ then inequality falls (rises) over time for all inequality measures satisfying the Pigou–Dalton transfer principle. This is because individuals in t are not anymore ordered in ascending order of their income, i.e., going along the quantiles $p(y_{t-1})$ is not going along richer and richer individuals in t. In this case the IGIC would have an negative slope and the GIC a positive slope, i.e., inequality would increase. The difference is that the GIC compares two distributions quantile by quantile, whereas the IGIC reflects the transition between the distributions observed in $t-1$ and t, i.e., the IGIC takes into account income growth as well as the reranking of individuals.

4 A decomposition linking the rates of pro-poor growth with and without anonymity

As described previously, the rate of pro-poor growth, $RPPG$ is directly linked to the negative change over time in the Watts poverty index. This property can be used to derive a decomposition of changes in poverty over time which establishes a direct link between the concept of pro-poor growth under anonymity and that without anonymity.

The decomposition, which has to my knowledge not been proposed previously, consists in decomposing changes in the Watts poverty index into components summarizing income growth among the initially poor who crossed the poverty line, income growth among the initially poor who did not cross the poverty line, and income decline of the initially non-poor who fell below the poverty line. Hence, the first two components take into account, as does the $IRPPG$, only the income growth among the initially poor (or mobility among the poor) whereas the two last components measure income growth below the poverty line, i.e., what is measured by the $RPPG$. The difference between the two is determined by the income change among the initially non-poor and the income change among those who were not poor at the end. Obviously this decomposition can only be done when anonymity is removed.

Since poverty is usually defined over individuals and not over quantiles, I consider in what follows the individual as unit of analysis. Hence the absolute change in the Watts index between $t-1$ and t will include three additive components. The first component includes the absolute change in poverty due to the *movers*, those who were poor in $t-1$ and non-poor in t (while for those remaining under the poverty line (*stayers*) income is kept at the initial level of $t-1$). The second component gives the absolute change in poverty due to changes in income among the *stayers* (or chronically poor). The third component gives the absolute change in poverty due to the *joiners* who initially at time $t-1$ were not poor but became poor at time t.[3]

5 An empirical illustration for Indonesia and Peru

5.1 Data

To illustrate the implications of removing the anonymity axiom from measurements of pro-poor growth, I use longitudinal data for Indonesia and Peru.

For Indonesia, I use all three existing waves of the Indonesian Family Life Survey conducted by RAND, UCLA and the University of Indonesia's Demographic Institute in 1993 (IFLS1), 1997 (IFLS2) and 2000 (IFLS3). The IFLS is representative of 83% of the Indonesian population living in 13 of the nation's current 26 provinces. The IFLS is judged as having a very high quality, among other things, because individuals who moved are tracked to their new location and, where possible, interviewed there. Hence, this procedure ensured that the re-contact rate in the IFLS3 was 95.3% of IFLS1 households.[4] Using the three waves, I built two panels,

[3] A completely equivalent decomposition can be performed with the class of poverty measures suggested by Foster, Greer and Thorbecke [11]. Obviously, if the headcount index is decomposed the second component would always be zero.

[4] For details see Strauss et al. [23].

one from 1993 to 1997 (6,723 households; 31,324 individuals) and one from 1997 to 2000 (7,187 households; 32,314 individuals).[5] I use real household expenditure per capita as the welfare measure, or income measure in what follows. Expenditure is expressed in 1993 prices and adjusted by regional price deflators to the Jakarta price level.

For Peru I use the first (ENAHO1, 1997) and third wave (ENAHO3, 1999) of the Peruvian Encuesta Nacional de Hogares conducted by the Instituto Nacional de Estadística e Informática. The ENAHO is representative for the three rural and four urban areas of Peru. The 'panel-households' are only a sub-sample of all households interviewed. In total 3,027 households (14,948 individuals) have been followed over the first three waves. De Vreyer, Mesplé-Somps and Herrera [7] have shown that there seems to be no significant attrition bias. Attrition could be a problem if the fourth wave (2000) were used, because of a substantial drop out of many panel households. I use again real household expenditure per capita as the income measure. Expenditure is expressed in 1997 prices and adjusted by regional price deflators to the Lima price level.

For both countries I use two alternative poverty lines: the first corresponds to the income, which separates the poorest 25% from the richest 75% of the income distribution in the base year (25% poverty line) and the second corresponds to the income, which separates the poorest 50% from the richest 50% of the income distribution in the base year (50% poverty line).

5.2 An assessment of pro-poor growth with and without postulating anonymity

Both countries, Indonesia and Peru, were quite seriously affected by economic shocks in the nineties. Hence, it is very interesting to see what the different concepts of pro-poor growth tell us about how the 'poor' fared during this period.

In Indonesia from 1993 to 1997 real GDP per capita increased by almost five percent per year. Table I shows, as one can expect, that household incomes increased and poverty could be significantly reduced. This very favorable dynamic was abruptly stopped by the economic crisis which started to be felt in the South-East Asia region in April 1997. However, the major impact did not hit Indonesia until December 1997/January 1998, just after IFLS2 was conducted. Then, in 1998, GDP per capita declined almost by twelve percent. The sustained crisis period continued then more than a year. Yet in 2000, when IFLS3 was conducted, the population had – benefiting from the pre-crisis positive dynamic – returned to roughly its pre-crisis living standard, and as Table I shows, with some people even a little better off.

Peru also felt the consequences of the crisis in South-East Asia and the EL Niño phenomenon and had in addition to face substantial institutional reforms. From 1997 on, macro-economic growth slowed down and became even negative in 1998 and 1999. Table I shows that real household income per capita, poverty and inequality remained more or less constant during that period.

For Indonesia, a look at the usual (cross-section) GICs (Figures 1 and 2, LHS), which postulate anonymity, shows that growth was in both sub-periods positive over

[5] The number of households is higher in the second period, because it includes so called 'split-off' households, i.e., individuals covered by the IFLS1, but who left their initial household and formed their own new household.

Table I Growth, poverty[a] and inequality

	Initial	Final	Initial	Final	Initial	Final
	Indon., nat. 1993–1997[b]		*Indon., nat. 1997–2000*		*Indon., urban 1997–2000*	
Annual growth in mean	0.079		0.019		0.011	
Watts (25% pline.)	0.096	0.029	0.091	0.075	0.086	0.091
Watts (50% pline.)	0.266	0.115	0.243	0.216	0.247	0.251
Gini-Coeff.	0.400	0.376	0.363	0.367	0.354	0.372
	Peru, nat. 1997–1999		*Peru, rural 1997–1999*			
Annual growth in mean	-0.008		-0.009			
Watts (25% pline.)	0.092	0.084	0.069	0.088		
Watts (50% pline.)	0.273	0.275	0.215	0.221		
Gini-Coeff.	0.367	0.366	0.325	0.327		

[a]Two poverty lines are used: the first corresponds to the income, which separates the poorest 25% from the richest 75% of the income distribution in the base year (25% poverty line) and the other corresponds to the income, which separates the poorest 50% from the richest 50% of the income distribution in the base year (50% poverty line). [b]Income growth and thus poverty reduction between 1993 and 1997 could be slightly over-estimated due to comparability problems between IFLS1 and IFLS2.

Source: IFLS1, IFLS2, IFLS3, ENAHO1, ENAHO3; computations by the author.

the whole income distribution and thus, according to the usual definition of absolute pro-poor growth, 'pro-poor'. No matter how one sets the poverty line, poverty decreased. During the period 1993–1997 the GIC indicates that growth rates up to the 80th percentile of the income distribution were even above the average growth rate and thus growth was also 'pro-poor' according to the usual relative definition. In consequence, inequality decreased (compare also the Gini coefficients in Table I). This was not the case during the period 1997–2000. This can also easily be seen by

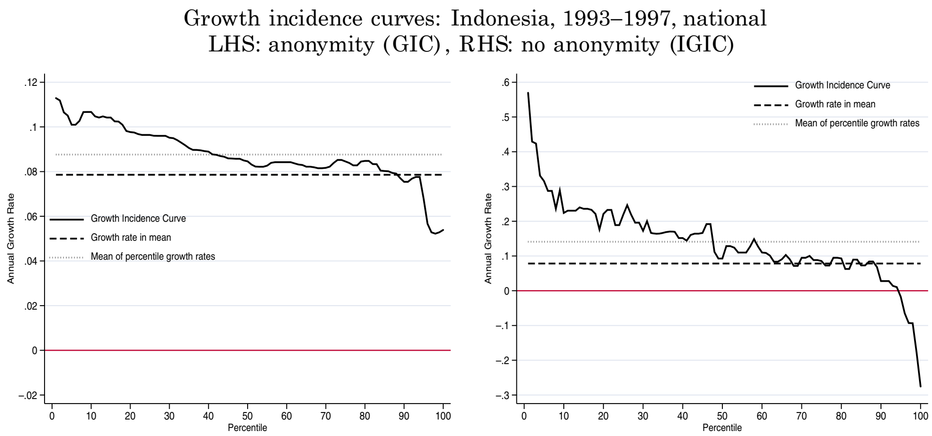

Figure 1 *Notes:* curves are smoothed using a three-period nonlinear smoother. *Source:* IFLS1, IFLS2, IFLS3; computations by the author.

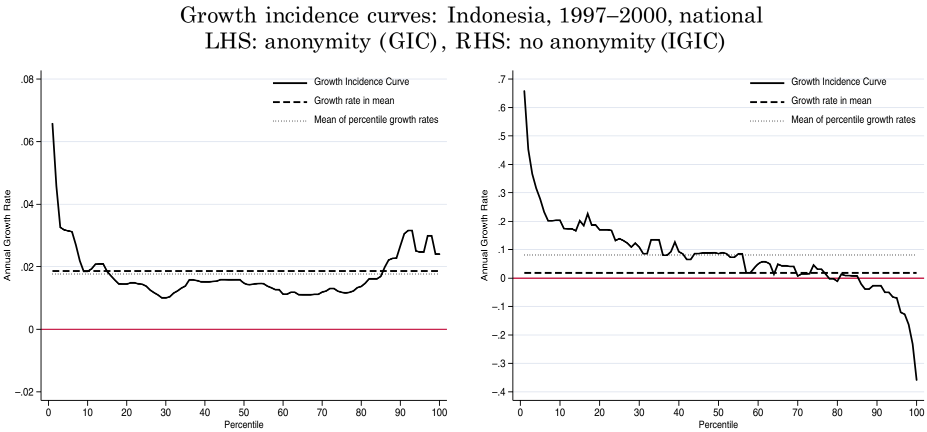

Figure 2 *Notes:* curves are smoothed using a three-period nonlinear smoother. *Source:* IFLS1, IFLS2, IFLS3; computations by the author.

the fact that during the first period the mean of percentile growth rates was above the growth rate in mean, whereas it was below the growth rate in mean during the second period.[6] Table II shows the rates of pro-poor growth, $RPPG$, for both periods and alternative poverty lines. The rates computed under the anonymity axiom (first and third column), i.e., using the usual approach, consistently suggest that between 1993 and 1997 growth was highly and between 1997 and 2000 moderately pro-poor (in the absolute sense) for both poverty lines used.

However, the GICs and $RPPGs$ under anonymity completely hide the extent of income mobility as defined above. The cross-section measures of pro-poor growth only provide a comparison of marginal distributions, but are compatible with various movements of poor and non-poor individuals over time. One may want to know

Table II Annualized rates of pro-poor growth with and without postulating anonymity

	25% pline.		50% pline.	
	Anonymity ($RPPG$)	No anonym. ($IRPPG$)	Anonymity ($RPPG$)	No anonym. ($IRPPG$)
Indo., 1993–1997, national	0.103	0.268	0.096	0.220
Indo., 1997–2000, national	0.023	0.225	0.018	0.163
Indo., 1997–2000, urban	-0.007	0.172	-0.003	0.133
Peru, 1997–1999, national	0.007	0.206	-0.002	0.134
Peru, 1997–1999, rural	-0.003	0.218	-0.006	0.141

For the definitions of the poverty lines see note of Table I.
Source: IFLS1, IFLS2, IFLS3, ENAHO1, ENAHO3; computations by the author.

[6] The mean of the percentile growth rates is population weighted and thus gives more weight to the poorer population. Hence, if the mean of percentile growth rates lies above the growth rate in mean, the incomes of the poor grew relatively more than the mean income.

whether those individuals being poor after the crisis are the same individuals as those being poor before the crisis. Put differently, did post-crisis policies and reforms only help a few initially poor to escape poverty, or, instead, were these measures very favorable to the initially poor and helped many of them to substantially improve their living standard, but did in the same time hurt the initially richer households and pushed some of them below the poverty line? The usual pro-poor growth assessment does not allow to distinguish between both phenomena. From a political point of view, this might of course be crucial.

To answer these questions, I now turn to the IGICs, i.e., to the growth incidence curves, where growth rates for percentiles comprising the same individuals in both years are considered. Looking first at the Indonesian IGIC for the period 1993–1997 (Figure 1, RHS), one can state that the pattern of the IGIC is even 'more' pro-poor than that of the GIC, in the absolute and in the relative sense. The initial poor had higher absolute and higher relative growth rates than the marginal distribution on the RHS suggest. In fact the IGICs suggest 'convergence' of incomes or what is sometimes called 'regression towards the mean'. A look at the other IGICs for Indonesia as well as Peru (Figures 2–5), shows that this 'regression towards the mean' can be observed more or less for all spells considered. Measurement error might of course be a problem here and be responsible for the observed convergence. However, this problem should, at least partly, be under control, given that the data were trimmed (see the Appendix) but this issue will be addressed in more detail below.

Turning back to the Indonesian 1993/97-spell, one can state that the GIC hides the fact that the initially poor particularly benefited from income growth. This can also be seen when computing the mean growth rate for the 50% initially poor ($IRPPG$), which is 22% instead of the obtained 9.6%, when simply the mean of the growth rates at all percentiles up to the poverty line is computed (Table II). However, in this case both curves show at least qualitatively the same thing: pro-poor growth in the absolute as well as in the relative sense.

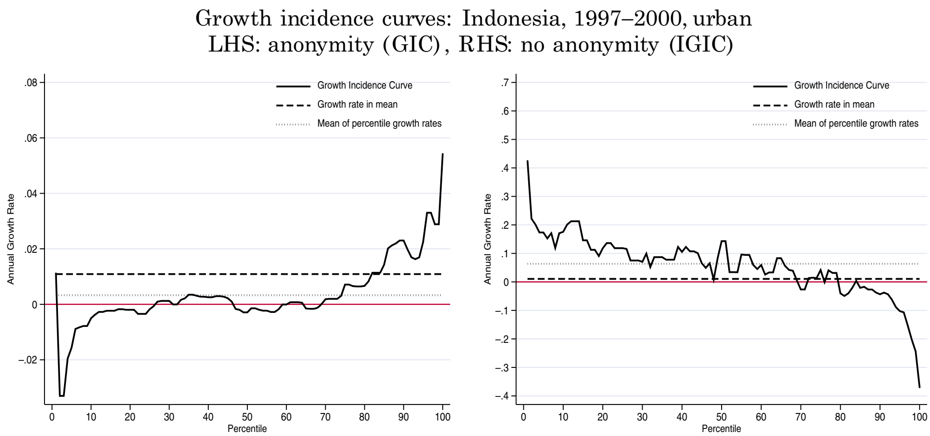

Figure 3 *Notes:* curves are smoothed using a three-period nonlinear smoother. *Source:* IFLS1, IFLS2, IFLS3; computations by the author.

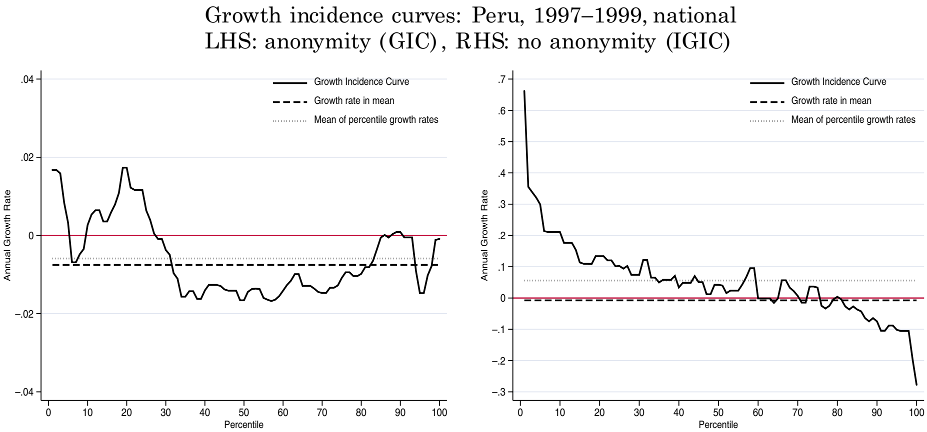

Figure 4 *Notes:* curves are smoothed using a three-period nonlinear smoother. *Source:* ENAHO1, ENAHO3; computations by the author.

Comparing the GIC and IGIC for the period 1997–2000, one can state that whereas the GIC is U-shaped, suggesting that for the very poor and the very rich growth was higher than growth in mean, the IGIC has a clear negative slope (again suggesting regression towards the mean) and, in contrast to the GIC, growth in mean is significantly below the mean of percentile growth rates. Therefore in this case, whether the 'poor' benefited from growth or not depends on whether we postulate or remove the anonymity axiom. This shows up also when computing rates of pro-poor growth (see Table II). The corresponding rates are around 2% for the GIC, but exceed 15% when computed for the IGIC.

The contrast between both curves is even greater when they are drawn solely for the urban sample. Whereas postulating anonymity leads to a GIC (Figure 3,

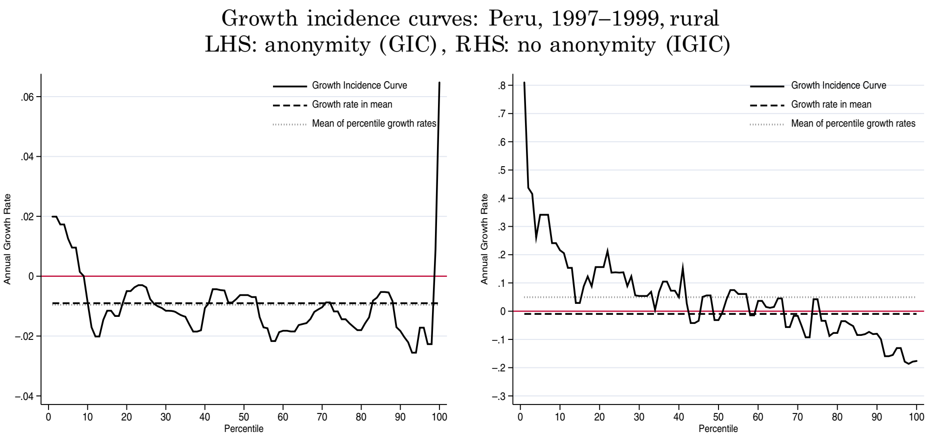

Figure 5 *Notes:* curves are smoothed using a three-period nonlinear smoother. *Source:* ENAHO1, ENAHO3; computations by the author.

LHS) which is clearly anti-poor in the relative and absolute sense (see also the $RPPG$ in Table II), the IGIC (Figure 3, RHS) clearly indicates pro-poor growth according to the definition suggested in this paper, i.e., growth rates are positive up to the 70th percentile and even higher than the growth rate in mean up to the 65th percentile. That means that if we remove the anonymity axiom and consider individual trajectories through time, we obtain a GIC which is exactly the opposite to that derived when we do the usual cross-section comparison. Likewise the rates of pro-poor growth computed for both poverty lines are negative for the GIC, but significantly positive for the IGIC (Table II).

The Peruvian example is also interesting. Whereas the GIC (Figure 4, LHS) shows positive growth only for the poorest five percentiles and between the 15th and the 25th percentile and negative growth for all others, the IGIC (Figure 4, RHS) indicates positive growth rates up to the 75th percentile. As for Indonesia, the slope of the IGIC is clearly negative, indicating higher growth rates for the poor and thus again convergence. Likewise, whereas the mean of percentile growth rates lies below the growth rate in the mean for the GIC, it lies not only above the growth rate in the mean for the IGIC, but is also positive (about 5%). This contrast is even more pronounced if only rural areas are considered (see Figure 5). At the national level as well as for rural areas, the $RPPG$s are close to zero or even negative, whereas the $IRPPG$s are clearly positive (Table II), thus showing that the initially poor improved their situation, and that growth was pro-poor according to my definition.

Using the decomposition suggested in Section 4 can give additional insights on how people moved across the income distribution and how the GIC is related to the IGIC. Taking for instance urban Indonesia during the period 1997–2000 (Table III), the absolute change in the Watts poverty measure (using the 50% poverty line) was 0.005. This change is the result of (a) a decrease by −0.032 due to a rise of income

Table III Decomposition of changes in poverty using the Watts measure

	Watts (25% pline.)			Decomposition		
	Initial	Final	Change	*mover*	*stayer*	*joiner*
Indo., 1993–1997, national	0.096	0.029	-0.067	-0.072	-0.008	0.012
Indo., 1997–2000, national	0.091	0.075	-0.017	-0.045	-0.003	0.032
Indo., 1997–2000, urban	0.086	0.091	0.005	-0.032	0.004	0.033
Peru, 1997–1999, national	0.092	0.088	-0.004	-0.030	-0.002	0.027
Peru, 1997–1999, rural	0.069	0.068	0.001	-0.035	0.000	0.036
	Watts (50% pline.)			Decomposition		
	Initial	Final	Change	*mover*	*stayer*	*joiner*
Indo., 1993–1997, national	0.266	0.115	-0.151	-0.120	-0.053	0.021
Indo., 1997–2000, national	0.243	0.216	-0.027	-0.061	-0.012	0.047
Indo., 1997–2000, urban	0.247	0.251	0.004	-0.047	0.003	0.048
Peru, 1997–1999, national	0.273	0.275	0.002	-0.034	0.003	0.040
Peru, 1997–1999, rural	0.215	0.221	0.006	-0.047	0.004	0.049

For the definitions of the poverty lines see note of Table I. Note that the absolute annualized change in the Watts index divided by the initial headcount rate corresponds to the negative annualized $RPPG$ shown in Table II. Small discrepancies can arise for very large changes in income, given that the equivalence of the change in the Watts poverty index and the $RPPG$ relies on the approximation that $\log(x + \mathrm{d}x) - \log(x) \approx \mathrm{d}x/x$.

Source: IFLS1, IFLS2, IFLS3, ENAHO1, ENAHO3; computations by the author.

of individuals who crossed the poverty line (*movers*), (b) an increase by 0.003 due to a decrease of income of those initially poor and who were not able to cross the poverty line (*stayers*), and (c) an increase by 0.048 due to a decrease of income of individuals who fell below the poverty line (*joiners*). The link of this decomposition with the $RPPG$ can be seen when one divides the absolute annualized change in the Watts index by the initial headcount index (50%). One then obtains the negative of the $RPPG$ noted in Table II: $\frac{0.004/3}{0.5} = 0.003$. In contrast, the $IRPPG$ integrates not the total change in the Watts, but instead considers only the change in income of the initially poor, i.e., that of *movers* and *stayers*. Or, put differently, and as stated previously, the role of the joiners is ignored. Again, this highlights the fact that the definition of pro-poor growth adopted in this paper, focuses on those initially poor.

All decompositions in Table III show that there is an intense mobility among the initially poor, i.e., even small changes in poverty (positive and negative) are associated with many initially poor people crossing the poverty line and many initially non-poor people falling below the poverty line. Given that this phenomenon even arises when income growth is very low, as for urban Indonesia (1997–2000), or almost zero as for Peru, shows that this mobility arises indeed from both sources defined by Fields and Ok [10]: transfers of income among individuals and a change in the total amount of income available.

5.3 Robustness of the results to measurement error

The above results are all based on a sample of expenditures declared by households ('income' in what follows). Apparent outliers have been withdrawn from the sample using the Mahalanobis distance measure (see the Appendix). It is likely, however, that the remaining data are still affected by measurement errors. When drawing the usual GIC, the problem of measurement error is a less critical issue, given that we only compare marginal income distributions. The problem, however, can be more serious, when drawing the IGIC, which is based on a joint income distribution, even though this issue is likely to be less acute because the growth rates are computed over percentiles and not individuals (this is also true for the GIC). In this sub-section, I will analyze the robustness of the negative slope of the IGICs to the existence of measurement error. To do this, I follow the approach suggested by Fields, Cichello, Freije et al. [9].

It is assumed that the income reported by household i in year t is given by the sum of unobserved true income Y^*_{it} and a measurement error component μ_{it}:

$$Y_{it} = Y^*_{it} + \mu_{it}, \tag{8}$$

where μ_{it} may be correlated with true income. Following Fields et al. [9], it is assumed that measurement error in the initial period $t-1$ is a linear function of true income, plus a white-noise disturbance term, u_{t-1}. If the average true income in the initial period is denoted as $\bar{Y}^*_{t-1}$ and if δ_{t-1} represents the correlation between true base year income and measurement error, measurement error in the initial year reported income can be written as:

$$\mu_{it-1} = \delta_{t-1}(Y^*_{it-1} - \bar{Y}^*_{t-1}) + u_{it-1}. \tag{9}$$

Given that the measurement errors may be correlated over time, a serial correlation coefficient ρ is defined. Measurement error in the final period can then be written as:

$$\mu_{it} = \delta_t (Y^*_{it} - \bar{Y}^*_t) + \rho u_{it-1} + u_{it}. \tag{10}$$

The relationship between households' income in the initial period and their subsequent income change, when income is measured without error, is the coefficient from a regression of true income change on true initial income. This coefficient measures the extent of convergence or divergence in true income and can be expressed as:[7]

$$\beta^* = \frac{\mathrm{Cov}[Y^*_t - Y^*_{t-1}, Y^*_{t-1}]}{\mathrm{Var}[Y^*_{t-1}]}. \tag{11}$$

The OLS estimate from a regression of reported income change on reported base year income is denoted:

$$\beta = \frac{\mathrm{Cov}[Y_t - Y_{t-1}, Y_{t-1}]}{\mathrm{Var}[Y_{t-1}]}. \tag{12}$$

As shown in Fields et al. [9], Eqs. (8) through (12) now yield:

$$\begin{aligned}\beta = \beta^* \frac{\mathrm{Var}[Y^*_{t-1}]}{\mathrm{Var}[Y_{t-1}]}(1+\delta_{t-1})(1+\delta_t) - \frac{\mathrm{Var}[u_{t-1}](1-\rho)}{\mathrm{Var}[Y_{t-1}]} \\ + \frac{\mathrm{Var}[Y^*_{t-1}]}{\mathrm{Var}[Y_{t-1}]}(1+\delta_{t-1})(\delta_t - \delta_{t-1}).\end{aligned} \tag{13}$$

To give these three terms an interpretation, two additional assumptions have to be made according to Fields et al. [9]. First, a particular household's propensity to misreport income is assumed to decline or remain constant over time, such that $\rho \leq 1$. Second, measurement error is assumed partially correlated with true income, such that δ_{t-1} and δ_t are both > -1. Both assumptions are consistent with empirical evidence (see [2]).

Under these assumptions, the second term of Eq. (13) indicates that the measurement error in initial income contributes to an apparent negative correlation between base-year income and subsequent income change. This is due to the fact that the measurement error of the initial period enters of course also the computed income change. However, this bias is partly offset if measurement errors are serially correlated. The first term of Eq. (13) corresponds to the standard attenuation bias caused by the stochastic independent variable. This attenuation bias is aggravated if measurement error is negatively correlated with true income in each period. As Fields et al. [9] emphasize, this attenuation bias counteracts the effects of the second term by raising the value of β towards zero, whenever the true relationship

[7] It should, however, be noted that 'mean-reversion' ($\beta < 0$) is not sufficient but only necessary to prove convergence, under some circumstances the rate of convergence is even independent of the degree of mean-reversion. Put differently, 'mean-reversion' and convergence are, as shown by Lichtenberg [17], not completely equivalent. Given, that in the case of Indonesia inequality did not rise in the relevant period, it seems however likely that mean reversion and convergence took indeed place.

between initial income and income change is negative, i.e., under convergence. Finally, the third term will be relatively small, unless the correlation coefficient between measurement error and true income changed substantially between periods.

From Eq. (13) Fields et al. [9] derive the following expression:

$$\frac{\mathrm{Var}[u_{t-1}]}{\mathrm{Var}[Y^*_{t-1}]} = \frac{\beta^*(1+\delta_{t-1})(1+\delta_t) + (1+\delta_{t-1})(\delta_t - \delta_{t-1}) - \beta(1+\delta_{t-1})^2}{1-\rho+\beta}, \tag{14}$$

which gives the variance of stochastic measurement error, relative to the variance of true income, given the observed regression coefficient on reported income β and a particular value of the unknown coefficient on true income, β^*. Setting β^* equal to zero can then give the minimum amount of measurement error required to overturn the negative relationship between initial income and income change.

Table IV shows the OLS estimates of β, when for each of the five spells analyzed above, $Y_{it} - Y_{it-1}$ is regressed on Y_{it-1} (without controlling for any other variables, i.e., test of unconditional convergence). Moreover, Table III reports the minimum threshold for each spell, which is computed for different combinations of ρ and the δs (as in Fields et al. [9], it is assumed that δ_{t-1} and δ_t are equal). The chosen parameters ρ and δ correspond to the lower and upper bounds found in various validation studies on earnings declarations summarized in Bound et al. [2]. The correlation coefficient between measurement error and true earnings usually seems to lie between −0.05 and −0.4. A reasonable range for serial correlation goes according to these studies from 0.1 to 0.2. These orders of magnitude are derived from declarations on annual earnings and do not necessarily apply to the expenditure data used in this study, but should however, given the wide range of parameters tested, serve as reasonable bounds.

Table IV Ratio of measurement error to true income variance implying zero correlation between true initial income and true income change

		Indonesia			Peru	
δ	ρ	1993–1997,nat. $\beta = -0.684$	1997–2000,nat. $\beta = -0.686$	1997–2000,urb. $\beta = -0.696$	1997–1999,nat. $\beta = -0.442$	1997–1999,rur. $\beta = -0.441$
0	0	2.165	2.185	2.289	0.792	0.789
0	0.1	3.167	3.206	3.412	0.965	0.961
0	0.2	5.897	6.018	6.692	1.235	1.228
-0.1	0	1.753	1.770	1.854	0.642	0.639
-0.1	0.1	2.565	2.597	2.764	0.782	0.778
-0.1	0.2	4.776	4.874	5.421	1.000	0.995
-0.2	0	1.385	1.398	1.465	0.507	0.505
-0.2	0.1	2.027	2.052	2.184	0.618	0.615
-0.2	0.2	3.774	3.851	4.283	0.790	0.786
-0.4	0	0.779	0.786	0.824	0.285	0.284
-0.4	0.1	1.140	1.154	1.228	0.347	0.346
-0.4	0.2	2.123	2.166	2.409	0.444	0.442

Source: Computations by the author.

In Indonesia, for divergence to have taken place, the variance of measurement error would need to be at least 75–670% of the variance of true incomes, depending on the correlation between measurement error and both true income and past measurement error. In Peru, measurement error with a variance that ranges from 28 to 125% of true income could already be responsible for the observed estimates of convergence. Bound et al.[2] report for the ratio of the variance of measurement error to the variance of true income a usual range of 0.1–0.3. That means that the observed convergence to the mean and the resulting negatively sloped IGICS can be considered as highly robust against measurement error for the case of Indonesia. However, for the case of Peru, it cannot not be excluded with certainty that measurement error is responsible for the observed convergence.

6 Conclusion

The assessment of pro-poor growth for Indonesia and Peru, with and without postulating the anonymity axiom, has shown that postulating anonymity, that is considering the usual cross-sectional growth incidence curves, does not allow one to draw any conclusion about how the *initially* poor were affected by macroeconomic shocks and policy reforms. The shape of almost all growth incidence curves constructed using the panel dimension of the data and without postulating anonymity, shows that growth for the initially poor was generally stronger than the usual cross-section growth incidence curve suggested. This also holds, at least for Indonesia, after the potential bias due to measurement error has be taken into account. Put differently, almost each spell considered indicated substantial upward mobility among the initially poor arising from redistribution from the initially non-poor to the poor and general income growth. An extreme case occurred in urban Indonesia during the period 1997–2000, where removing anonymity results in an exactly reversed growth incidence curve.

The concept of absolute and relative pro-poor growth suggested in this paper might be seen as an extreme position since it focuses on those initially poor without taking into account what happens to those who initially were not poor. This value judgement is obviously debatable. Hence, to be clear, the objective is not to question the utility of cross-section comparisons of income distributions, but to illustrate and highlight that they should be complemented by some kind of longitudinal analysis to better understand the sources of changes in poverty and to identify the losers and winners of specific shocks and reforms. Usual measurements of pro-poor growth, whether they rely on an absolute or a relative definition, are not appropriate to analyze such an issue. In consequence, when postulating anonymity and interpreting growth incidence curves, one should be explicit about what exactly is measured. This is often not the case.

Unfortunately, in most cases, especially for developing countries, panel data are not available so that one is usually forced to postulate anonymity when comparing income distributions over time. A solution to this problem can be to rely on micro-simulation methods or some kind of counterfactual analysis.[8] Such methodologies

[8]See e.g., Bourguignon and Ferreira [3], Cogneau, Grimm and Robilliard [4] or Cunha, Heckman and Navarro [6].

are obviously more time intensive than simple income distribution analyses. They have, however, the advantage of giving the possibility to solve the usual problem inherent in ‘before-after-comparisons’ by isolating which distributional change is due to a specific shock or policy and which one is due to other changes.

Appendix: elimination of outliers

To eliminate the influence of outliers the data were trimmed. I use a method similar to that used by Jenkins and Van Kerm [13]. For each pair of years analyzed, I discarded an observation if the *Mahalanobis* distance between its two log per capita income values (y_{it-1}, y_{it}) exceeded a critical value equal to the mean plus two times the standard deviation of the distribution of the *Mahalanobis* distances in the two-year sample. The vector of the household’s *Mahalanobis* distances for each pair of years can be computed by the following equation:

$$MD = \left[\mathrm{diag}[|(y-m)S^{-1}(y-m)'|]\right]^{1/2} \tag{15}$$

where y is a $N \times 2$ matrix containing the two vectors of incomes of both years, m is a 1×2 matrix containing the mean incomes of both years, and S is the 2×2 variance-covariance matrix of the two income vectors. Income is in logarithmic terms and expressed on a per capita basis.

The advantage of using this concept is that the *Mahalanobis* distance identifies not only outlier incomes in each year but also outlier changes in income between years. Applying this concept, between four and five percent of the observations in each two-year sample were excluded (in addition to a few observations for which no information on expenditures was available).

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