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How good is growth for the poor? The role of the initial income distribution in regional diversity in poverty trends

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Abstract

Using panel data of 58 developing countries for the period 1980-1998, this study shows that the responsiveness of the $2 a day poverty headcount measure to changes in mean income and inequality significantly decreases with initial inequality and the ratio poverty line over mean income - taken as proxies for the initial density of income near the poverty line. Variations in these proxies account for the large cross-regional differences in the income elasticity of poverty during the 1980s and 1990s. We find that the income elasticity of poverty in the mid 1990s equals –1.31 on average and ranges from –0.71 for Sub-Saharan Africa to –2.27 for the Middle East and North Africa, and that the Gini elasticity of poverty equals 0.80 on average and ranges from 0.01 in South Asia to 1.73 in Latin America. While variation in income growth accounts for most of the variation in poverty reduction across regions, the impact of variations in inequality and in elasticities of poverty is almost always too large to be ignored, and in particular in Eastern Europe and Central Asia.

Keywords: Panel data, Poverty, Income Growth, Inequality

JEL-codes: C23, I32, O15

I Introduction

The call for the eradication of poverty is stronger now than it ever has been before. The World Bank, the IMF, the UN and in particular UNDP, all development banks and nearly all multilateral and bilateral aid agencies profess themselves to be principally concerned with reducing the number and proportion of people who live in conditions of absolute poverty. However, in the case of some of the organizations mentioned, the professed concern with poverty reduction has not made much difference to their policy recommendations. Despite poverty reduction being the central objective, the principal focus of the policies that are pursued in the name of poverty reduction is on promoting economic growth: deregulating internal and external markets, providing macro-economic stability, encouraging private investment through a stable and transparent legal framework, and so forth. Poverty reduction is more popular than ever, but so is economic growth, with the difference that growth is no longer seen as an end in itself but as a means to an end: growth is held to be good for the poor.

This focus on growth has worried quite a few commentators, particularly among NGOs. There are not many people who would want to argue that it is better for the poor not to have growth, but that of course is not the issue. The issue is that in some situations the poor appear to benefit much more from growth than in other situations. For example, a given amount of growth appears to reduce poverty by more than twice as much in East Asia than it does in Sub-Saharan Africa (Besley and Burgess 2003), which region therefore seems doubly cursed: both by low levels of growth and by a low responsiveness of poverty to growth. Eastern Europe experienced not only economic contraction but also sharply rising inequality when it saw its poverty headcount measure skyrocket to unprecedented levels in the 1990s. Paradoxically, as inequality rose, the region's economic contraction appeared to be increasingly associated with *less* extra poverty. This suggests that for understanding diversity in poverty trends it is important to examine the role of the initial income distribution in the variation in responsiveness of poverty to growth.

The main contribution of this study is an empirical analysis of the role of the initial Gini index and the ratio poverty line over mean income - taken as proxies for the initial population density of income near the poverty line - in the responsiveness of an absolute poverty measure both to changes in mean income (economic growth or contraction) and to changes in inequality. The literature on especially the first link has been evolving rapidly since Ravallion and Sen's (1997) seminal paper[1]. However, as Bourguignon (2003) and Epaulard (2003) discuss in great detail, poverty, mean income and inequality are all aspects of one income distribution. As a consequence, the relationship between their changes depends on properties of the initial distribution and this needs to be taken into account explicitly when analyzing the responsiveness of poverty to changes in mean income or income inequality. In the methodological section of the paper we take Bourguignon (2003) as our point of departure and clarify how the responsiveness (or elasticity) of poverty to economic growth and changes in inequality depends on properties of the initial income distribution. We point out that such distributional effects on the growth impact on poverty are unlikely to be captured by the literature that uses a relative poverty measure as its dependent variable (Romer and Gugerty 1997, Timmer 1997, Gallup et al. 1999, and Dollar and Kraay 2002), which should caution against interpreting the findings of this literature as implying a uniform relationship between growth and poverty reduction.

The discussion of the methodological section suggests an econometric specification in which both the income and the inequality elasticity of poverty depend on the population density around the poverty line in the initial distribution. To estimate this model, we exploit unbalanced panel data containing information for 58 developing countries over the period 1981-1998. In the first empirical section of the paper we demonstrate that even simple proxies for the population density around the poverty line considerably improve the performance of models that aim to explain the changes in poverty by changes in mean income and changes in inequality. We also find that apparent regional variation in the income elasticity of poverty, as reported in Besley and Burgess (2003), is no longer significant when properties of the initial income distribution are taken into account. That is to say, poverty appears to respond very differently to growth in some regions than it does in others, but these apparent differences can be explained in terms of differences in initial income distribution.

[1] Some examples of literature that estimates the growth elasticity of poverty using an absolute poverty measure are Mosley et al. (2004), Bourguignon (2003), Besley and Burgess (2003), Epaulard (2003), Bhalla (2002), Ravallion (2001), De Janvry and Sadoulet (2000), Hanmer and Naschold (2000), Bruno et al. (1998), Ravallion (1997), and Ravallion and Chen (1997). Recent literature that estimates the growth elasticity of poverty using a relative poverty measure includes Dollar and Kraay (2002), Gallup et al. (1999), Deininger and Squire (1998), Romer and Gugerty (1997), and Timmer (1997). Foster and Székely (2001) is an example of a paper that does both.

Next, we use the parameter estimates to explain diversity in regional poverty trends during the 1980s and 1990s. These trends themselves, using the same data set, have been documented in detail in Chen and Ravallion (2001, 2004). We attribute the diversity in poverty trends to differential growth rates, responsiveness to growth, changes in inequality and responsiveness to inequality. For most regions the role of growth is quantitatively more important than the other effects, although not always much more so. Eastern Europe and Central Asia's experience is markedly different. The shape of its income distribution at the onset of its demise made it especially vulnerable to economic contraction and rising inequality. The effect on its poverty due to differential changes in income and inequality is dwarfed by the effect due to differential *responsiveness* to those changes.

In our model, initial inequality and the ratio poverty line over mean income are used as proxies for 'crowdedness' near the poverty line and thereby determine poverty elasticities. This has important implications for two strands of the literature, which will be highlighted in the concluding section. First, the literature that links prospects for pro-poor growth to existing levels of inequality is based on (potentially) restricted models (Ravallion 1997, 2001, Hanmer and Naschold 2000, Mosley et al. 2004). Overall initial inequality may be a poor proxy for population density near the poverty line when initial mean income is not controlled for. Second, our findings suggest a way forward for the two highly influential poverty projection studies that derive an optimal aid-allocation rule based on a universally constant growth elasticity of the $2/day poverty headcount measure (Collier and Dollar, 2001, 2002). The allocation may be fine-tuned by taking properties of aid-recipient countries' initial income distribution into account, since these properties impact on the growth elasticity of poverty reduction and are known at the time aid-allocation decisions are made.

II Empirical Methodology

Changes in poverty may in principle be decomposed precisely into a finite number of effects due to shifts of parameters of the distribution of income or consumption[2], when that distribution is perfectly known. In that case there would be a tautological relationship between our key variables of interest: changes in, respectively, poverty,

[2] From now on, 'income' is shorthand for 'income or consumption'.

mean income and inequality. In practice, not all parameters are known, and the distribution of income needs to be approximated. Decomposition methodologies with relatively intensive data requirements have been developed and applied to individual countries or regions within countries with good data availability[3]. For cross-country data sets in which a poverty measure, mean income and the Gini index of inequality are the only known aspects of the income distribution, cruder approximations are unavoidable, for example through imposing a functional form. Two recent contributions to the literature assume income to be log-normally distributed, and compute country-specific elasticities of poverty with respect to changes in mean income and Gini accordingly (Bourguignon 2003, Epaulard 2003). They show that such 'theoretical' values predict changes in poverty reasonably well and considerably better than *ad hoc* econometric specifications. An attractive alternative is to specify the terms that a well-behaving functional-form approximation requires for computing poverty elasticities *without imposing the functional form itself*. In other words, one may take advantage of the fact that the lognormal fits actual distributions reasonably well (Cowell 1999), and therefore contains valuable information about these, without requiring the growth and inequality elasticity of poverty reduction to be pre-determined by it. This is the approach we will take in this study. Through examining features of an approximately log-normally distributed income variable we identify the terms of the implied non-linear relationship between poverty changes, income growth and changes in inequality, and arrive at our econometric specification. An important advantage of such a formal starting-point is that the derived empirical model will do justice to the fact that poverty, Gini and mean income are inherently interrelated through their being aspects of one and the same income distribution.

II.A Three Aspects of One Distribution

The proportion of the population at time *t* with an income below the absolute poverty line *z* is equal to the probability that income Y_t is lower than the poverty line:

(1) $$H_t = \Pr(Y_t < z) \equiv F_t(z) .$$

[3] The papers that pioneered a growth/equity decomposition of poverty changes, using a parametric specification of the Lorenz curve, are Ravallion and Huppi (1991) for Indonesia, Datt and Ravallion (1992) for regions of Brazil and India, and Kakwani (1993) for Cote d'Ivoire. The decomposition methodology introduced in Datt and Ravallion (1992) has become very influential, sparking off a voluminous literature that applies their methodology. Contreras (2003) for Chile, Bigsten et al. (2003) for Ethiopia, Alwang et al. (2002) for Zimbabwe, and Gibson (2000) for Papua New Guinea are but a handful of recent examples that apply the Datt and Ravallion decomposition methodology to poverty changes in other contexts.

$F_t(.)$ is the distribution function of income. Following Bourguignon (2003) and Epaulard (2003) we assume a lognormal income distribution and in this case poverty is expressed as follows:

(2) $$H_t = \Phi\left(\frac{\log(z/\bar{y}_t)}{\sigma_t} + \frac{1}{2}\sigma_t\right),$$

where $\Phi(.)$ is the cumulative distribution function of the standard normal distribution, which is denoted by $\phi(.)$. The standard deviation of the logarithm of income is denoted by σ_t. Now the Gini in period *t*, denoted by G_t, is given by: $G_t = 2\Phi\left(\frac{\sigma_t}{\sqrt{2}}\right) - 1$.

Using a first-order approximation, we can decompose the relative change in poverty over time into an income growth and a redistribution effect:

(3) $$\frac{dH_t}{dt} = \frac{\partial H_t}{\partial \bar{y}_t}\frac{d\bar{y}_t}{dt} + \frac{\partial H_t}{\partial G_t}\frac{dG_t}{dt}.$$

In terms of elasticities we can rewrite Eq. (3) as follows:

(3’) $$\frac{dH_t}{dt} = \varepsilon_{\bar{y}}^{H}\,\frac{d\bar{y}_t}{dt}\frac{H_t}{\bar{y}_t} + \varepsilon_G^H\,\frac{dG_t}{dt}\frac{H_t}{G_t},$$

where $\varepsilon_{\bar{y}}^{H}$ denotes the (distribution-neutral) income elasticity of poverty and ε_G^H denotes the Gini elasticity of poverty. Figure 1 illustrates the decomposition by considering a move from an initial to a final distribution in two stages: by first shifting its mean and next its dispersion parameter[4]. The initial distribution shifts to the right such that its mean is identical to that of the final distribution but at first it does not change shape: the *relative* distribution remains unchanged. The area between the two identically shaped distributions to the left of the poverty line is the poverty reduction that results from the growth that has actually taken place, under the assumption that the relative distribution of income has not changed. The final distribution has a different shape from the initial distribution – the relative distribution *has* changed; in Figure 1 we illustrate for decreasing inequality. The area between the shifted initial and the final distribution is the poverty reduction resulting from a changing Gini.

[4] The figure has been used by a number of authors; our direct source is Bourguignon (2003).

Figure 1
Growth and direct redistribution effects on poverty

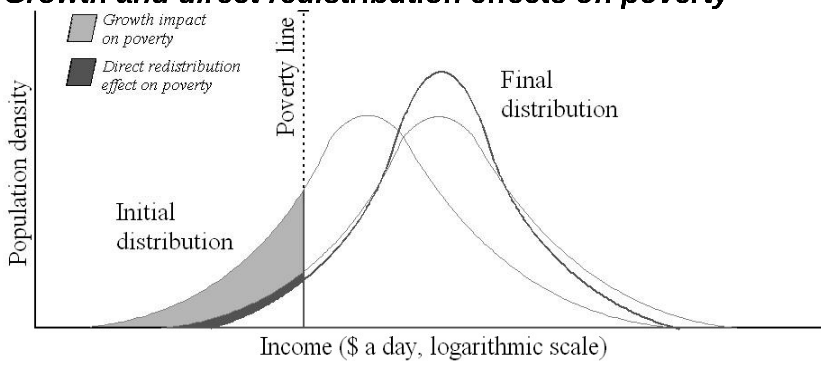
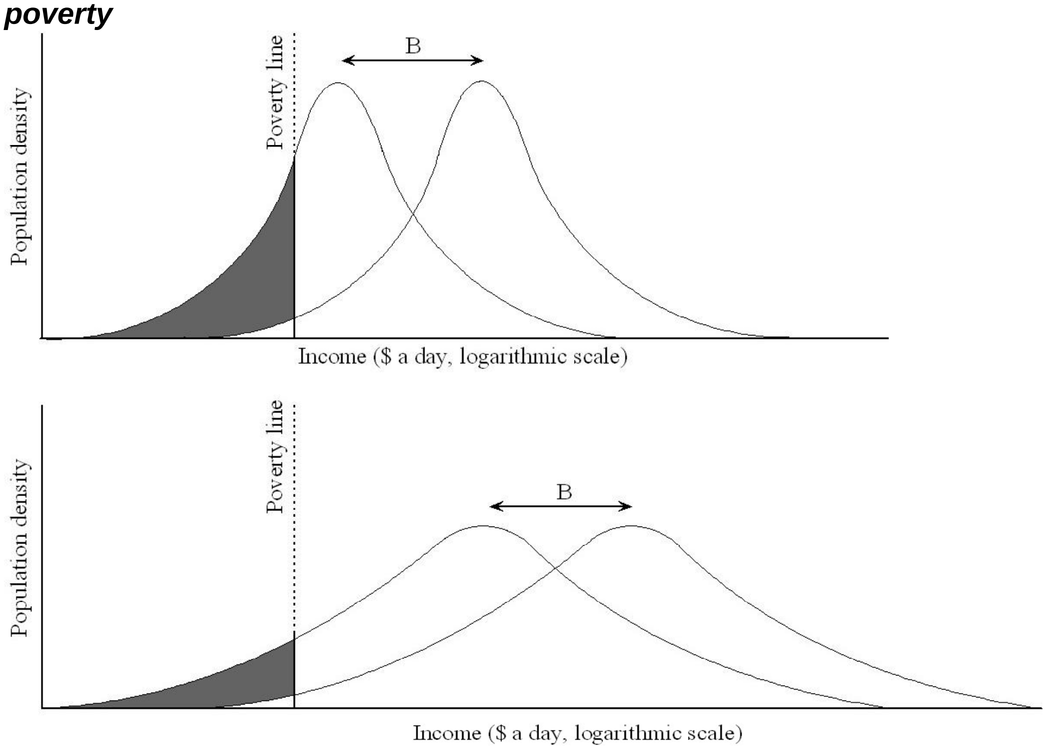


Figure 2
The role of the initial income distribution in the income growth effect on poverty



This study is not only interested in identifying the direct effects of changes in income and inequality on poverty, as illustrated in Figure 1, but also on identifying the indirect effects of redistribution as it changes the income elasticity of poverty, hence affects future poverty reduction through income growth. This is illustrated in Figure 2. An identically-sized spread-preserving shift *B* of mean income implies a much larger poverty headcount change for a distribution such as the one illustrated in the top panel of the figure than the one illustrated in the bottom panel. The difference in poverty reduction between these two illustrations in Figure 2 is due to differences in inequality and ratio poverty line over mean income. The idea of using proxies for the population density near the poverty line is the essence of the methodology used in this study to identify these (indirect) effects. To gain insights in how the initial income distribution affects the income elasticity we depend on normally distributed log-incomes, hence we use Eq.(2) as our definition of poverty, to derive the income elasticity of poverty:

$$\text{(4)} \qquad \varepsilon_{\bar{y}}^{H} = \frac{\partial H_t}{\partial \bar{y}_t}\frac{\bar{y}_t}{H_t} \equiv -\frac{1}{\sigma_t}\frac{\phi_t\left(\dfrac{\log(z/\bar{y}_t)}{\sigma_t}+\dfrac{1}{2}\sigma_t\right)}{\Phi_t\left(\dfrac{\log(z/\bar{y}_t)}{\sigma_t}+\dfrac{1}{2}\sigma_t\right)} \leq 0,$$

The income elasticity is always negative and, more importantly, one can show that the income elasticity of poverty is, in absolute terms, decreasing in the ratio of poverty line over mean income ($z/\bar{y}_t$) and the standard deviation of log-income σ_t (cf. Epaulard, 2003). As mentioned above, the Gini is a known function of σ_t, and positively correlated with σ_t. The elasticity of poverty with respect to inequality, σ_t in this case, is given by:

$$\text{(5)} \qquad \varepsilon_{\sigma}^{H} = \frac{\partial H_t}{\partial \sigma_t}\frac{\sigma_t}{H_t} \equiv \frac{\phi_t\left(\dfrac{\log(z/\bar{y}_t)}{\sigma_t}+\dfrac{1}{2}\sigma_t\right)}{\Phi_t\left(\dfrac{\log(z/\bar{y}_t)}{\sigma_t}+\dfrac{1}{2}\sigma_t\right)}\left(\frac{-\log(z/\bar{y}_t)}{\sigma_t}+\frac{1}{2}\sigma_t\right) \geq 0.$$

Note that $\varepsilon_{G}^{H} = \varepsilon_{\sigma}^{H}\dfrac{\partial \sigma_t}{\partial G_t}\dfrac{G_t}{\sigma_t}$, with the second term at the RHS always being positive. The inequality elasticity is positive unless a country has very low average income[5], and decreasing in the ratio of poverty line over mean income ($z/\bar{y}_t$) and the standard deviation of log-income σ_t (cf. Epaulard, 2003). To summarize the results above, based on the assumption of normally distributed log-income Eqs (4) and (5) show the way income and Gini elasticities of poverty vary with the (initial) level of inequality (we will use G_t) and with the ratio poverty line over mean income ($z/\bar{y}_t$) and it is this variation we wish to identify in the empirical analysis.

[5] The inequality elasticity of poverty is positive if $\bar{y}_t > z \times \exp\left(-\tfrac{1}{2}\sigma_t^2\right)$.

To conclude this section, it may be of interest to note that such distributional effects on the growth impact on poverty are unlikely to be captured by the studies that use as their dependent variable mean income of the poorest quintile (Romer and Gugerty 1997, Timmer 1997, Gallup et al. 1999, and Dollar and Kraay 2002). All these studies find the growth elasticity of the change in mean income of the poorest quintile to be remarkably close to unity[6], a finding that in the title of Dollar and Kraay's article is announced as 'growth is good for the poor'. Call the income of the poorest quintile $\bar{y}*$ and the corresponding income elasticity $\varepsilon_{\bar{y}}^{\bar{y}*}$. If the relative distribution of incomes remains unchanged then $\varepsilon_{\bar{y}}^{\bar{y}*}$ equals 1 by construction, hence empirically, when changes in inequality are controlled for, one ought to find that $\varepsilon_{\bar{y}}^{\bar{y}*}$ equals 1. To interpret such a result as 'growth is good for the poor' is to miss an important point. As Figure 2 and Eq. (4) illustrate, distribution-neutral income growth will reduce absolute poverty but the impact will vary in accordance with properties of the distribution of income. Hence, how good growth is for the poor will depend on the initial income distribution.

II.B Estimation Framework

The empirical studies that use an absolute poverty measure for exploring the link between growth and poverty (listed in Section I, footnote 1) tend to relate the logarithm of a poverty headcount measure to the logarithm of average income. The availability of panel data makes it possible to control for unobserved time-constant country-specific characteristics that may affect both poverty and income, i.e. country fixed effects, and identification of the poverty elasticity comes from changes over time in poverty and income (e.g. Ravallion and Chen 1997). The empirical studies referred to above differ primarily from each other in terms of the way in which they treat inequality. Some studies treat inequality as a separate dependent variable (e.g. Ravallion and Chen 1997), some as a separate independent variable (e.g. Besley and Burgess 2003), as in Eq. (6) below. Others interact inequality with changes in mean income (e.g. Ravallion 1997, 2000, Mosley et al. 2004), which can be considered a halfway house between Eq. (6) and Eq. (7), presented below.

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[6] Romer and Gugerty (1997) report this elasticity to be .9; Timmer (1997) finds it to be .8; Gallup et al. (1999) 1.2; and Dollar and Kraay (2002) 1.0.

The simplest possible way of identifying the (distribution-neutral) income elasticity of poverty, introduced in Eq. (3'), is by controlling for changes in the distribution of income, as measured by Gini. Bourguignon (2003) calls such an econometric model, the 'standard model', which is in essence the empirical equivalent of Eq. (3') and can be specified as follows:

(6) $$\Delta \log H_{it} = \alpha + \beta \Delta \log \bar{y}_{it} + \gamma \Delta \log G_{it} + \nu_{it},$$

where i is a country index, $\Delta \log H_{it} = \log H_{it} - \log H_{it-1}$, $\Delta \log \bar{y}_{it} = \log \bar{y}_{it} - \log \bar{y}_{it-1}$ and $\Delta \log G_{it} = \log G_{it} - \log G_{it-1}$. The error term is denoted by ν_{it}. We assume the ν_{it}'s are independently distributed over countries and we allow them to be correlated with the explanatory variables. We return to this latter issue below. We start by estimating Eq. (6), at first without and later including the term $\Delta \log G_{it}$, in order to assess (apparent) regional variation in the relationship between income growth and poverty changes (cf. Besley and Burgess 2003). All changes are annualised changes (see Section III.A) and *t-1* refers to one year before time *t*. A linear time trend is captured by the parameter α. The estimated parameters β and γ are referred to as, respectively, the income and inequality elasticity of poverty ($\varepsilon_{\bar{y}}^{H}$ and ε_{G}^{H}).

We next ask whether regional variation in the relationship between growth and poverty is still significant when extending Eq. (6) by including the distributional effects on the income and inequality elasticity of poverty developed in Section II.A. Put conversely, is the apparent regional variation in the relationship between growth and poverty reduction fully accounted for by differences in regional income distributions at the onset of growth? The considerations set out in Section II.A have several empirical implications. The effects on poverty of a change in mean income and a change in inequality depend on initial inequality and the ratio poverty line over initial mean income, in other words on both the *dispersion parameter* and the *location* of the initial income distribution. Extending Eq. (6) by taking into account these considerations yields the following preferred empirical specification:

(7) $$\begin{aligned} \Delta \log H_{it} = \; & \alpha + (\beta_1 + \beta_2 \log G_{it-1} + \beta_3 \log(z/\bar{y}_{it-1}))\Delta \log \bar{y}_{it} + \\ & (\gamma_1 + \gamma_2 \log G_{it-1} + \gamma_3 \log(z/\bar{y}_{it-1}))\Delta \log G_{it} + \\ & \eta_1 \log G_{it-1} + \eta_2 \log(z/\bar{y}_{it-1}) + \nu_{it}. \end{aligned}$$

The question of whether regional variation in the link between growth and poverty is robust to including the discussed distributional effects amounts to testing for the joint significance of regional interaction terms with $\Delta \log \bar{y}_{it}$. If regional variation is not significant then predicted regional growth elasticities can be computed using region-specific income distribution data and estimates of β_1, β_2, and β_3.

The error terms in Eqs (6) and (7) reflect the fact that, as discussed in section II.A, we crudely approximate the relationship between three variables ($\Delta \log H_{it}$, $\Delta \log \bar{y}_{it}$ and $\Delta \log G_{it}$). The error terms and the explanatory variables may be correlated for at least the following three reasons. Firstly, income and poverty measures are based on the same survey data and the error term is therefore possibly correlated with measurement errors of income. The resulting bias when not taking this possible correlation into account will differ by region or country since $\bar{y}_{it}$ is sometimes measured as income, sometimes as expenditures[7]. Secondly, unobserved time-varying characteristics that affect income growth (or consumption growth) may affect changes in poverty as well. Ignoring this may yield a standard omitted variable bias. Thirdly, the phenomenon that participation rates among richer groups in surveys tend to be lower than those among poorer groups would lead us to overstate poverty and understate income (cf. Deaton 2004). As survey methods improved (cf. Chen and Ravallion 2004), this bias would decrease over time, yielding a spurious relationship between changes in poverty and changes in mean income.

The estimator employed in this study is a Generalized Method of Moments estimator and takes into account the endogeneity issues discussed above (see e.g. Davidson and MacKinnon 1993). We use, apart from lagged values of mean income and Gini, as extra instrument the change in GDP per capita (Δ log GDPpc$_{it}$) from the national accounts (corrected for PPP, as is $\bar{y}$ itself) to instrument the change in mean income (Δ log $\bar{y}_{it}$), as proposed by Ravallion (2001). Several interaction terms between this instrument and the initial income distribution and regional dummy variables are also included. The main assumption we make here is that measurement errors of GDPpc (i.e. in national account data) are not related to country-specific faults in the design and coverage of the household surveys from which poverty, mean income and Gini have been computed, which may cause the common survey measurement-error bias to arise. An additional instrument we use is change in the logarithm of the size of the population (Δ log pop$_{it}$). Clearly our choice of instruments

[7] In approximately 60% of cases expenditures are obtained, in 40% income – see Chen and Ravallion (2001, 2004) for details.

is restricted by the available data. The crucial testable assumption we need for consistency of the parameter estimates is that the instruments are orthogonal to the error terms (ν_{it}'s). Therefore, in order to validate the set of instruments, we present an over-identification test statistic – the Hansen J-statistic -, which is also considered to be a general model-specification test. The null-hypothesis of this test is that the instruments are orthogonal to the error terms.

III Data: Key Features and Regional Trends

III.A Data Set

The data set we use has been developed by Ravallion and Chen (1997) and has been regularly updated since on the World Bank website[8]. It has been described in some detail before (e.g. Ravallion and Chen 1997, Chen and Ravallion 2001); here we only rehearse its main features. The data set is based on nationally representative household surveys, mostly carried out by government statistical agencies. Values of all variables for one country/year are computed from one and the same underlying survey. The data set contains eight variables: mean income or mean consumption (normalised by household size), the Gini index of inequality (based on the same welfare measure), two poverty headcount, two poverty gap and two poverty gap square measures based on the \$1 and \$2/day poverty line, respectively[9]. Our indicator of choice is the \$2/day poverty headcount measure. The reason we prefer a measure of the *extent* (headcount) rather than the *intensity* (gap, gap square) of poverty is pragmatic. In Section II we have arrived at an econometric specification that naturally leads to the use of the headcount measure as dependent variable. Our preference for the \$2 rather than the \$1/day poverty line is likewise pragmatic. It allows for direct comparison of our results with the results of influential simulation studies (Collier and

[8] http://www.worldbank.org/research/povmonitor. Our data are almost identical to the ones used by Besley and Burgess (2003). Besley has helpfully made the data available online in a readily usable form: http://econ.lse.ac.uk/staff/tbesley/hgp/. We have modified the figures for Ghana and Jordan, as these appear to have been revised in the World Bank Poverty Monitoring Database as of November 2003.

[9] Strictly speaking, these poverty lines are now \$1.08 and \$2.16; Chen and Ravallion (2001) have re-assessed them to be consistent with World Bank 1993 PPPs. The poverty headcount measure is equal to the percentage of the population living in households with a per capita income lower than the poverty line; the poverty gap measure is equal to the average income shortfall of both the poor (poverty line minus actual income) and the non-poor (zero), expressed as a proportion of the poverty line; the poverty gap square measure is equal to the average income shortfall weighted by itself, again expressed as a proportion of the poverty line; cf. Foster et al. (1984).

Dollar 2001, 2002); and it leads to a slightly larger sample size, as there are less H_{it}=0 observations for Eastern Europe and Central Asia, which need to be discarded when these form the beginning of a spell, since the associated elasticity would be plus (for Gini) or minus (for mean income) infinity. The Pearson correlation between the $1 and the $2/day poverty headcount measure is 0.912.

The data contain information on 78 countries with in total 231 observations on the $2/day poverty headcount measure. We discard five observations because the poverty measure is equal to zero, two observations because the Gini is missing and two observations because mean income is missing. As noted in Section II.B, our instrument for survey-based mean income/consumption is GDP per capita based on purchasing power parity (PPP)[10]. As a result, we need to discard five observations for which we do not have GDP per capita data. We discard eighteen observations (countries) because there are no adjacent observations, hence we cannot construct a spell. We end up with 199 usable observations, from which we construct 141 spells over 58 countries. Usable observations by country and year are listed in Table A1; summary statistics presented in Table A2. For a cautious interpretation of the results that follow, it is important to be aware of the uneven regional coverage of the data set: see Table A1 and Table A3 for details. For example, 45 spells (32% of the total) are from Eastern Europe and Central Asia, and only 6 (4% of the total) from the Middle East and North Africa. Note also in Table A3 that over 70% of spells are three years or shorter, over 90% five years or shorter, and the duration of the remaining less than 10% is between six and fourteen years. For this reason we base our estimations on annualised changes rather than lumping together changes over time intervals of widely varying lengths.

III.B Regional Trends in Mean Income, Inequality and Poverty

Figures A1-A3 show the regional trends in poverty, mean (real, per capita) income and the Gini index of inequality during the 1980s and 1990s, as present in our data set. A linear trend is included, based on a Least-Squares fit and weighted by population size. Table 1 summarises these trends.

[10] Data source: World Bank, World Development Indicators CD ROM 2002. It is expressed in international dollars, which have the same purchasing power over GDP as the U.S. dollar has in the United States.

(i) East Asia experienced considerable income growth and poverty reduction, especially during the 1990s, and a modest rise in inequality. More than one third of usable observations for this region are for China (Table A1). Both because of the composition of the data set and especially because of China's size, East Asia's growth/poverty reduction story is here therefore very much a Chinese story.

(ii) In Eastern Europe and Central Asia poverty and inequality rose sharply, whilst the economy contracted severely. The region went from being the lowest-inequality region (Gini = 26) to being a high-inequality region (Gini = 45). Inequality trends are often described as sluggish (e.g. Atkinson and Bourguignon, 2000), but this is belied by this region's experience.

(iii) Latin America saw some growth, some poverty reduction and slightly falling inequality.

(iv) The Middle East and North Africa experienced economic contraction, rising poverty and falling inequality. It should be remembered, though, that the region is underrepresented in our data set (see Tables A1 and A3).

(v) In South Asia mean income and inequality rose somewhat, and poverty fell somewhat.

(vi) In Sub-Saharan Africa mean income fell somewhat, and both Gini and poverty rose somewhat.

The picture for all six regions together is very much like that of East Asia but it is important to realise that this averages across considerable diversity of experiences in the different regions. The key question we address in the remainder of the paper is to what extent diversity in regional poverty trends can be attributed to (1) diversity in economic growth, (2) diversity in changes in inequality, (3) diversity in poverty's responsiveness to economic growth, and (4) diversity in poverty's responsiveness to changes in inequality. Below we disentangle the effects of regional mean income and inequality trends on regional poverty trends, using parameter estimates of Eq. (7) as well as information about properties of region-specific initial income distributions. In order to justify this exercise, we first need to show that heterogeneity in the relationship between growth and poverty, as apparent in jointly significantly different regional income elasticities of poverty in estimates of Eq. (6), is accounted for by differences in initial regional income distributions.

Table 1
Regional trends in poverty, mean income and inequality (% change)

	Poverty (headcount,$2/day)		Mean income (real, per capita)		Inequality (Gini index)	
	1980s	1990s	1980s	1990s	1980s	1990s
East Asia	-9	-28	15	32	5	13
Eastern Europe and Central Asia	81	117	-8	-43	14	42
Latin America	-4	-10	3	7	-1	-2
Middle East and North Africa	-	54	-	-43	-	-21
South Asia	-1	-1	4	5	4	5
Sub-Saharan Africa	1	2	-4	-7	5	7
All regions	-10	-19	13	18	7	10

Note: population-weighted trends

IV Empirical Results

The methodology developed above will be applied in order to answer two related questions. Is the considerable apparent heterogeneity in the poverty elasticity with respect to income driven by properties of the initial income distribution? If so, what is the impact of properties of the initial income distribution on the roles of changes in mean income and inequality, respectively, in explaining observed regional poverty trends? In Section IV.A we build our preferred model (Eq. (7)) in stages, so that the additional influence of each of its ingredients may be clearly seen. In particular, we show that apparent heterogeneity in growth's impact on poverty, as evidenced by significantly different regional elasticities in relatively simple specifications, does not survive a more complete specification that does justice to changes in poverty, mean income and inequality reflecting shifts in one and the same underlying income distribution. In Section IV.B we present and discuss the income and inequality elasticities of poverty reduction implied by our estimation results. In Section IV.C we disentangle the effects of regional mean income and inequality trends on regional poverty trends, using information about properties of the initial income distribution. Although we will carry out the decomposition for all individual regions, the most illuminating cases will be regions with strong movements in all three variables and for which data availability is good. These requirements make Eastern Europe and Central Asia stand out as the most interesting case study.

IV.A Estimation Results

Table 2 presents two models. The first estimates an all-sample growth elasticity of poverty across all 141 spells. The point estimate of -2.32 (standard error 0.50) is *not* an estimate of $\varepsilon_{\bar{y}}^{H}$, which is defined for a constant Gini, but is what Ravallion and Chen (1997) call, an 'empirical' elasticity, that is an elasticity consistent with actual changes in the Lorenz curve. Its value is lower than their reported -3.12 (standard error 1.19), but their estimations are based on only 42 spells; it is reasonably close to (less than one standard error away from) the value of -2 that Collier and Dollar (2001, 2002) use in their policy simulations. However, the results of the first model presented in column 1 have to be interpreted with caution since the model does not pass the model specification test, i.e. the Hansen J-statistic is significant. All further models (see also Table 3) pass the model specification test. We also examined the first stage regressions and the excluded instruments show high explanatory power with respect to the endogenous variables. These results are in support of the choice of instruments (cf. Bound et al., 1995).

The second model estimates a region-specific income elasticity of poverty, in the spirit of Besley and Burgess (2003). As do Besley and Burgess, we find strong evidence for heterogeneity in the income elasticity of poverty: the hypothesis of equality of regional interaction terms with changes in log mean income is rejected with considerable conviction (F-test, last row of Table 2). In contrast with Besley and Burgess, this model finds that poverty's responsiveness to changes in mean income is of the same order of magnitude in Sub-Saharan Africa as it is in East Asia (they find it to be much lower in Sub-Saharan Africa) – but see Section IV.B below for the predictions of our preferred model.

Table 2
The Income Elasticity of Poverty: Regional Variation (Both models are estimates by GMM)

Dependent variable: Δ log \$2/day poverty headcount measure

Explanatory variables	Parameter Estimates (Standard Errors)	Parameter Estimates (Standard Errors)
Δ log mean income	-2.32	
	(0.50)	
Δ log mean income x a region specific dummy variable		
East Asia		-1.02
		(0.11)
Eastern Europe and Central Asia		-3.04
		(0.40)
Latin America		-0.77
		(0.37)
Middle East and North Africa		-8.16
		(5.29)
South Asia		-0.41
		(0.14)
Sub-Saharan Africa		-1.17
		(0.25)
N	141	141
R^2	0.52	0.58
Hansen J-Statistic	8.19[a]	8.78[b]
Equal income elasticity across regions(F-test)[c]		8.81

Notes: Standard errors in parentheses. Regional dummy variables are included in the model in the second column.

[a] Critical value is $\chi_{0.05}(2) = 5.99$. Instruments: $\Delta\ log\ GDPpc_{it}$, $log\ \bar{y}_{it-1}$ and $\Delta\ log\ pop_{it}$.

[b] Critical value is $\chi_{0.05}(7) = 14.1$. Instruments: regional dummy variables, $\Delta\ log\ GDPpc_{it}$ and $log\ \bar{y}_{it-1}$ interacted with regional dummy variables, and $\Delta\ log\ pop_{it}$.

[c] F-test statistic, critical value is F(5,129)=2.29.

Table 3
The Income and Inequality Elasticity of Poverty: Impact of Properties of the Initial Income Distribution (All models are estimated by GMM)

Dependent variable: Δ log \$2/day poverty headcount measure

Explanatory variables	Parameter estimates (standard errors)	Parameter estimates (standard errors)	Parameter estimates (standard errors)
Δ log mean income			-8.077 (1.440)
Δ log mean income x log initial Gini		1.88 (0.66)	2.770 (0.311)
Δ log mean income x log (poverty line/initial mean income)		0.71 (0.38)	0.926 (0.205)
Δ log Gini	1.54 (0.33)	-4.63 (3.85)	-1.741 (0.894)
Δ log Gini x log initial Gini		-0.42 (0.73)	-0.697 (0.238)
Δ log Gini x log (poverty line/initial mean income)		-1.80 (0.42)	-1.357 (0.097)
log initial Gini		-0.07 (0.07)	-0.071 (0.024)
log (poverty line/initial mean income)		0.00 (0.02)	-0.001 (0.006)
Δ log mean income x a region specific dummy variable			
East Asia	-1.61 (0.14)	-5.52 (2.94)	
Eastern Europe and Central Asia	-2.64 (0.44)	-6.22 (2.92)	
Latin America	-0.93 (0.24)	-5.49 (3.22)	
Middle East and North Africa	-7.19 (4.38)	-6.82 (5.15)	
South Asia	-1.37 (3.04)	-3.84 (4.21)	
Sub-Saharan Africa	-1.42 (0.60)	-5.41 (3.18)	
N	141	141	141
R^2	0.63	0.73	0.73
Hansen J-Statistic	16.77[a]	13.62[b]	19.98[c]
Equal income elasticity across regions (F-test) [d]	2.91	0.97	

Notes: Standard errors in parentheses. Regional dummy variables are included in the models in the first and second columns. The term 'initial' refers to a variable's value at the beginning of a spell.

[a] Critical value is $\chi_{0.05}(12) = 21.0$. Instruments: regional dummy variables, Δ *log GDPpc* $_{it}$, *log* $\bar{y}_{it-1}$ and *log* G_{it-1} interacted with regional dummy variables, and Δ *log pop* $_{it}$.

[b] Critical value is $\chi_{0.05}(12) = 21.0$. Instruments: regional dummy variables, Δ *log GDPpc* $_{it}$, *log* $\bar{y}_{it-1}$ and *log* G_{it-1} interacted with regional dummy variables, Δ *log pop* $_{it}$, *log* $\bar{y}_{it-1}$ x *log* G_{it-1}, *log* $\bar{y}_{it-1}$ x *log*$(z/\bar{y}_{it-1})$, Δ *log GDPpc* $_{it}$ x *log* G_{it-1}, *log GDPpc* $_{it-1}$ x *log* G_{it-1} and *log* G_{it-1} x *log* G_{it-1},

[c] Critical value is $\chi_{0.05}(22) = 33.9$. Instruments: same as listed in [b].

[d] F-test statistic, critical value is 2.29.

Table 3 presents three models that take into account the distribution of income. The first is the final model of Table 2 with the change in the logarithm of Gini added, i.e. $\Delta \log G$ (standard model, Eq. (6)). Its coefficient is highly significant and suggests a Gini elasticity of 1.54. Adding $\Delta \log G$ to the model changes the order of magnitude of the growth elasticity of poverty reduction for most regions. The reason is that the coefficient on $\Delta \log \bar{y}$ may now be interpreted properly as an estimate of $\varepsilon_{\bar{y}}^{H}$: the 'empirical' elasticity reported in Table 2 picks up changes in Gini that coincide with growth, which are now controlled for. The hypothesis of 'no regional effects' is still rejected in the first model in Table 3; region-specific growth elasticities are jointly significant.

The second model examines whether this heterogeneity across regions is robust to adding the terms developed in Section II, so this specification now takes into account that the income and Gini elasticities depend on initial inequality, using the Gini index from the previous period, and the distance between mean income and the poverty line, using the ratio poverty line over mean income. Table 3, second column, last row, shows that the hypothesis of equal growth elasticities across regions is now no longer rejected. Naturally, the coefficients on $\Delta \log G$ and on the regional interaction terms with $\Delta \log \bar{y}$ are no longer directly interpretable as poverty elasticities since one has to take the extra interaction terms into account when calculating elasticities (see Eqs. (8) and (9) below).

The third and final model therefore omits regional interaction terms with mean income growth. Furthermore, not reported here, the hypothesis of equal intercepts across regions is not rejected, suggesting a common linear time trend in poverty across regions, and therefore separate regional dummy variables are also omitted from the final model. The resulting model is the exact specification arrived at in Section II (Eq. (7)). The results of this final model show that the absolute value of the income elasticity of poverty significantly decreases with initial Gini and with the ratio poverty line over mean income. Likewise, the inequality elasticity of poverty significantly decreases with initial Gini and with the ratio poverty line over mean income. These findings support the idea developed in Section II that these two interaction terms jointly proxy for population density near the poverty line (ceteris paribus, when either one of them is higher, population density near the poverty line is higher) and should therefore lower (absolute) values of poverty elasticities.

IV.B Predicted Elasticities of Poverty

The final model estimated above (Table 3, last column) allows for heterogeneity in the poverty elasticity with respect to income and Gini through the initial distribution of income, as approximated by the initial value of the Gini index and the ratio of initial mean income and the poverty line. The initial distribution of income varies widely across regions and the implications of this are examined in this section. An impression of the diversity in elasticities both across regions and over time implied by our model may be gauged from Tables 4 and 5. The income elasticities of poverty presented in Table 4 are computed using parameter estimates of Eq. (7), as

$$\hat{\varepsilon}^{H}_{\bar{y}it} = \hat{\beta}_1 + \hat{\beta}_2 \log G_{it-1} + \hat{\beta}_3 \log(z / \bar{y}_{it-1}). \tag{8}$$

The findings presented in the table have some very interesting implications for the literature that estimates or makes use of the income elasticity of poverty. The point estimate of this elasticity for the mid 1990s for all regions of -1.31 is six standard errors away from the value of -2 that Collier and Dollar (2001, 2002) use for all countries in their aid-allocation rule for 1996. But perhaps more important than that is the regional diversity implied by our model. For example, in the mid 1990s, poverty is twice as responsive to changes in mean income in Eastern Europe and Central Asia than in Sub-Saharan Africa; the income elasticity of poverty reduction is seven standard errors higher from the point of view of the former region. Similarly, the respective predicted income elasticities and standard errors for East Asia and Sub-Saharan Africa for the mid 1990s are consistent with Besley and Burgess' (2003) finding that poverty is twice as responsive to economic growth in the former region. The properties of the initial income distribution that determine the income elasticity of poverty are known at the time aid-allocation decisions are made, and should therefore influence the aid-allocation rule. The findings presented here also bear on the literature that links pro-poor growth to inequality measured with the Gini index (Ravallion 1997, 2001, Hanmer and Naschold 2000, Mosley et al. 2004). Note in Table 4 that the income elasticity of poverty is of the same order of magnitude in Latin America as it is in East Asia. The literature just mentioned would have predicted a much lower responsiveness of poverty to income growth in Latin America because of its higher levels of inequality as measured with the Gini index. However, the Gini index is a poor proxy for population density near the poverty line. Even with limited data availability, this population density can be approximated more closely by also including in one's specification the distance between mean income and the poverty line. Previous models that include Gini but not the ratio poverty line over mean income reach therefore potentially the wrong conclusion about prospects for pro-poor growth, as the example just given of Latin America illustrates.

Table 4
Predicted Income Elasticities of Poverty across Time and Regions

	Mid 1980s	1990	Mid 1990s
All regions	-1.50	-1.43	-1.31
	(0.17)	(0.15)	(0.12)
East Asia	-1.32	-1.31	-1.25
	(0.20)	(0.17)	(0.12)
Eastern Europe & Central Asia	-3.47	-3.01	-1.46
	(0.19)	(0.16)	(0.11)
Latin America	-1.06	-1.12	-1.25
	(0.17)	(0.18)	(0.18)
Middle East & North Africa	-2.10	-2.10	-2.27
	(0.09)	(0.09)	(0.14)
South Asia	-1.30	-1.22	-1.11
	(0.26)	(0.25)	(0.23)
Sub-Saharan Africa	-1.15	-0.97	-0.71
	(0.15)	(0.16)	(0.18)

Note: Standard errors in parentheses.

The model implies considerable inter-temporal diversity in poverty's responsiveness to growth for Eastern Europe & Central Asia only. The predicted elasticity for the mid 1990s is less than half that for the mid 1980s, or approximately fifteen (1990s) standard errors lower. This confirms more rigorously the casual observation of Section I that, as inequality rose, the economic contraction of the region became increasingly associated with less extra poverty (per percentage point of contraction, that is).

Table 5
Predicted Gini Elasticities of Poverty across Time and Regions

	Mid 1980s	1990	Mid 1990s
All regions	0.51	0.63	0.80
	(0.10)	(0.12)	(0.14)
East Asia	0.28	0.45	0.79
	(0.10)	(0.11)	(0.14)
Eastern Europe & Central Asia	2.46	2.25	1.39
	(0.20)	(0.19)	(0.19)
Latin America	1.58	1.63	1.73
	(0.24)	(0.24)	(0.24)
Middle East & North Africa	1.56	1.56	1.11
	(0.16)	(0.16)	(0.12)
South Asia	-0.05	-0.02	0.01
	(0.08)	(0.08)	(0.09)
Sub-Saharan Africa	0.50	0.41	0.26
	(0.12)	(0.13)	(0.14)

Note: Standard errors in parentheses.

Table 5 reports on the responsiveness of poverty to changes in inequality, i.e. the Gini elasticity of poverty, using parameter estimates from Eq. (7):

(9) $$\hat{\varepsilon}^{H}_{Git} = \hat{\gamma}_1 + \hat{\gamma}_2 \log G_{it-1} + \hat{\gamma}_3 \log(z / \bar{y}_{it-1}).$$

The table shows that the overall responsiveness significantly increased from 0.51 in the mid 1980s to 0.80 in the mid 1990s, which is largely due to a tripling in East Asia. Noteworthy is that overall, poverty in South Asia remains impervious to changes in inequality. The strongest trend is that observed for Eastern Europe and Central Asia, where the Gini elasticity of poverty was at its peak in the mid 1980s, and has been steadily falling ever since the fall of the Berlin Wall in 1989. This region's sharply rising inequality, as shown in Table 1, implied that the vicinity of the poverty line in the population density function of income became less 'crowded', and hence, over time, both rising inequality and economic contraction pushed proportionately fewer people below the poverty line. Note that the isolated effect of the increasing ratio of the poverty line to mean income worked in the opposite direction: this effect on its own increased the predicted size of (absolute) values of poverty elasticities. However, in the case of this region the effect is dwarfed by the unprecedented increase in inequality.

IV.C Explaining Regional Diversity in Poverty Trends

Using parameter estimates of Eq. (7) (Table 3, last column), we may attribute diversity in regional poverty trends to diversity in growth ($\Delta \log \bar{y}$), in poverty's responsiveness to growth ($\varepsilon_{\bar{y}}^{H}$), in changes in Gini ($\Delta$ log G), and in poverty's responsiveness to changes in Gini (ε_{G}^{H}). The idea is simply to first compute predicted poverty changes for each region as if that region had the (population-weighted) average initial income distribution characteristics for the world as a whole, and next compute the additional influence of that region's actual characteristics. Denoting initial Gini and initial mean income for the world as a whole by $\overline{G}_0$ and $\bar{y}_0$, respectively, we may decompose as follows:

$$
\begin{aligned}
\Delta \log H_{it} = {} & (\hat{\beta}_1 + \hat{\beta}_2 \log \overline{G}_0 + \hat{\beta}_3 \log(z / \bar{y}_0)) \Delta \log \bar{y}_{it} + \\
& (\hat{\beta}_2 (\log G_{it-1} - \log G_0) + \hat{\beta}_3 (\log(z / \bar{y}_{it-1}) - \log(z / \bar{y}_0)) \Delta \log \bar{y}_{it} + \\
& (\hat{\gamma}_1 + \hat{\gamma}_2 \log \overline{G}_0 + \hat{\gamma}_3 \log(z / \bar{y}_0)) \Delta \log G_{it} + \\
& (\hat{\gamma}_2 (\log G_{it-1} - \log G_0) + \hat{\gamma}_3 (\log(z / \bar{y}_{it-1}) - \log(z / \bar{y}_0)) \Delta \log G_{it}
\end{aligned} \quad . \tag{10}
$$

The first line of Eq. (10) describes the effect on poverty of growth alone, the second an additional effect of regional and intertemporal variation in the growth elasticity of poverty, the third that of changes in Gini alone, and the fourth an additional effect of regional and intertemporal variation in the Gini elasticity of poverty.

Table 6 presents the results of the decomposition. For most regions, the largest effect on poverty is due to growth alone, although the size of the other effects is non-negligible. Variations in the growth elasticity explain most of the *diversity* in regional poverty trends, whilst changes in the Gini have an additional significant, generally poverty-increasing effect, as both on average and in most regions inequality rose (Table 1). Most notable is the region Eastern Europe and Central Asia, which suffered a considerable extra increase in poverty – in addition to that due to its severe economic contraction – from its sharply rising inequality, and from the contraction and rising inequality being compounded by a relatively high population density near the poverty line at the onset of its demise.

Table 6
Explaining Regional Diversity in Poverty Trends 1980-1998

	% change in poverty headcount measure ($\Delta \log H_{it}$)due to			
	income growth		changes in inequality	
	Variation in growth [a)]	Variation in the growth elasticity of poverty [b)]	Variation in Gini [c)]	Variation in the Gini elasticity of poverty [d)]
East Asia	-71.1	9.0	9.3	-2.0
	(6.0)	(0.8)	(1.4)	(0.2)
Eastern Europe & Central Asia	76.5	80.5	28.1	99.9
	(7.4)	(11.0)	(4.5)	(5.3)
Latin America	-14.6	3.9	-1.7	-3.8
	(1.2)	(2.0)	(0.3)	(0.4)
Middle East & North Africa	64.9	25.6	-10.4	-21.6
	(7.3)	(7.2)	(2.1)	(1.6)
South Asia	-13.1	2.2	4.8	-5.2
	(1.1)	(0.6)	(0.7)	(0.3)
Sub-Saharan Africa	17.2	-5.3	6.2	-0.8
	(1.4)	(0.5)	(0.9)	(0.4)
All regions	-46.4	1.3	8.9	1.3
	(3.8)	(0.6)	(1.3)	(0.2)

Notes: Standard errors in parentheses; decomposition procedure described in text and Eq. (10).
[a)] Actual growth times fixed income elasticity
[b)] Actual growth times (region/period-specific – fixed) income elasticity
[c)] Actual changes in Gini times fixed Gini elasticity
[d)] Actual changes in Gini times (region/period-specific – fixed) Gini elasticity
Key to interpretation: The region-specific elasticities used are reported in tables 4 and 5. The fixed elasticities are the ones reported for 'all regions, mid 1980s' in these tables. Adding columns 1 and 2 gives the total effect on poverty of income growth and adding columns 3 and 4 gives the total effect of the change in inequality as measured by the Gini index.

V Conclusions

Using panel data of 58 developing countries for the period 1980-1998 we have shown that poverty's responsiveness to income growth and changes in inequality significantly decreases with initial inequality and the ratio poverty line over mean income- taken as proxies for the initial density of income near the poverty line. Our measure of inequality is the Gini index. Furthermore, we have shown that variations in initial Gini and the ratio poverty line over mean income account for the large cross-regional variation in the income elasticity of poverty during the 1980s and 1990s (Table 3). In other words, the higher the population density of income near the poverty line the more responsive the poverty headcount measure will be to changes in mean income and inequality. Based on our estimates we calculate that, conditional on the initial density of income near the poverty line in the mid 1990s, the income elasticity of poverty ranges from –0.71 for Sub-Saharan Africa to –2.27 for the Middle East and North Africa and centres on the all-region average of –1.31 for Eastern Europe, South and East Asia, and Latin America (Table 4). The Gini elasticity of poverty ranges from 0.01 in South Asia to 1.73 in Latin America and is equal to 0.80 across all regions (Table 5).

Our empirical findings have the following implications for the existing literature. First and foremost, our findings bear on the literature that exclusively emphasises economic growth as the ‘royal avenue’ for poverty reduction. Although variation in income growth accounts for most of the variation in poverty reduction over time and across regions, the impact on poverty reduction of changes in inequality and variation in the income and Gini elasticities of poverty is significant and almost always too large to be ignored. In Eastern Europe and Central Asia their combined effect is much larger than the impact of growth alone (Table 6).

Second, the findings presented here should refine the emerging aid-allocation literature in which the growth elasticity of poverty reduction influences the optimal aid-allocation rule. Rather than a universal constant, which it is typically assumed to be, it varies in a predictable fashion with country characteristics, which are known at the time aid-allocation decisions are made. An optimal aid-allocation rule therefore depends on properties of aid-recipient countries’ initial income distributions, and given the size of their effect on poverty elasticities, quite possibly in a major way.

Third, the empirical literature that links the prospects for pro-poor growth to levels of inequality is based on a rather restrictive model since it omits the ratio poverty line over mean income as an important proxy for the population density of income near the poverty line. As a consequence, such a model would predict a larger growth elasticity of poverty reduction for a lower-inequality region, which is only legitimate when initial mean income is held constant. As can be seen in Figure A2, mean income varies considerably over time and across regions and therefore we find a growth elasticity of poverty reduction for Latin America that is of the same order of magnitude as that for East Asia, while these two regions have very different levels of inequality (see Figure A3).

Table A1
Usable observations by region, country and year

East Asia	
China	1985, 1990, 1992, 1993, 1994, 1995, 1996, 1997, 1998
Indonesia	1984, 1987, 1990, 1993, 1996, 1998
Philippines	1985, 1988, 1991, 1994, 1997
Thailand	1981, 1988, 1992, 1996, 1998
Eastern Europe and Central Asia	
Belarus	1988, 1993, 1995, 1998
Bulgaria	1992, 1994, 1995
Estonia	1988, 1993, 1995
Hungary	1989, 1993
Kazakhstan	1993, 1996
Kyrgyz Republic	1993, 1997
Latvia	1993, 1995, 1998
Lithuania	1993, 1994, 1996
Poland	1990, 1992, 1993
Romania	1989, 1992, 1994
Russian Federation	1993, 1996, 1998
Slovak Republic	1987, 1998, 1992, 1993
Turkey	1987, 1994
Turkmenistan	1988, 1993
Ukraine	1988, 1992, 1995, 1996
Central and Latin America	
Brazil	1985, 1988, 1989, 1993, 1995, 1996, 1997
Chile	1987, 1990, 1992, 1994
Colombia	1988, 1991, 1995, 1996
Costa Rica	1986, 1990, 1993, 1996
Dominican Republic	1989, 1996
Ecuador	1988, 1994, 1995
El Salvador	1989, 1995, 1996
Guatemala	1987, 1989
Honduras	1989, 1990, 1992, 1994, 1996
Jamaica	1988, 1989, 1990, 1993, 1996
Mexico	1984, 1989, 1992, 1995
Panama	1989, 1991, 1995, 1996, 1997
Paraguay	1990, 1995
Peru	1985, 1994, 1996
Venezuela, RB	1981, 1987, 1989, 1993, 1995, 1996
Middle East and North Africa	
Algeria	1988, 1995
Egypt, Arab Rep.	1991, 1995
Jordan	1987, 1992, 1997
Morocco	1985, 1990
Tunisia	1985, 1990

South Asia	
Bangladesh	1984, 1985, 1988, 1992, 1996
India	1983, 1986, 1987, 1988, 1990, 1992, 1994, 1995, 1996, 1997
Nepal	1985, 1995
Pakistan	1987, 1990, 1993, 1996
Sri Lanka	1985, 1990, 1995
Sub-Saharan Africa	
Cote d'Ivoire	1985, 1986, 1987, 1988, 1993, 1995
Ethiopia	1981, 1995
Ghana	1987, 1989, 1992
Kenya	1992, 1994
Lesotho	1986, 1993
Madagascar	1980, 1993
Mali	1989, 1994
Mauritania	1988, 1993, 1995
Niger	1992, 1995
Senegal	1991, 1994, 1995
Tanzania	1991, 1993
Uganda	1989, 1992
Zambia	1991, 1993, 1996

Table A2
Summary Statistics

	Mean	Median	Std. Deviation	Minimum	Maximum
Poverty headcount	44.09	38.77	28.34	0.22	91.70
Gini	40.87	40.19	10.62	19.49	63.42
Mean income	124.39	108.48	69.59	28.70	349.96
GDP pc PPP	3,658	3,300	2,256	412	9,732
Duration spell	3.06	3.00	2.18	1	14

Table A3
Data Coverage by Region and Duration of Spell (% of total no. of spells)

Duration (in years):	Region: EA	ECA	LAC	MENA	SA	SSA	Total
1	4.3	4.3	8.6		4.3	2.9	24.5
2	2.2	5.8	7.9		2.2	4.3	22.3
3	5.8	4.3	6.5		3.6	3.6	23.7
4	1.4	2.9	3.6	0.7	1.4		10.1
5	0.7	2.2	1.4	2.9	1.4	2.2	10.8
6			2.2				2.2
7	0.7	0.7	0.7	0.7		0.7	3.6
9			0.7				0.7
10					0.7		0.7
13						0.7	0.7
14						0.7	0.7
Total	15.1	20.1	31.7	4.3	13.7	15.1	100.0

Notes: N = 141 spells. EA = East Asia (no Pacific countries included in the final data); ECA = Eastern Europe & Central Asia; LAC = Latin America & Caribbean; MENA = Middle East & North Africa; SA = South Asia; SSA = Sub-Saharan Africa.

Figure A1
Regional trends in poverty, 1980-1998

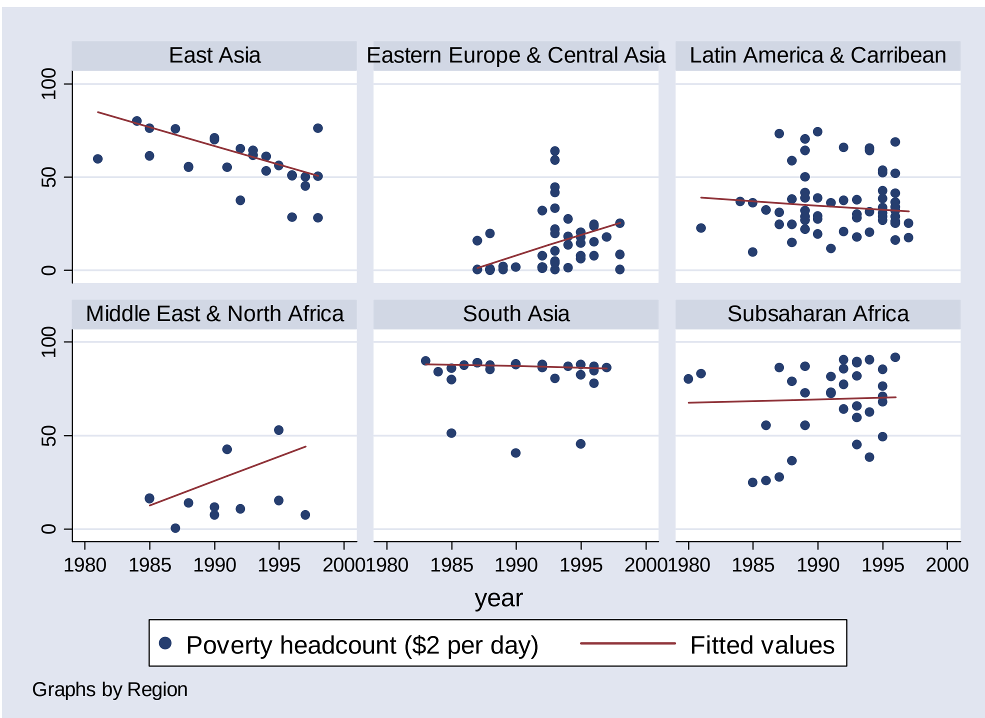


Figure A2
Regional trends in mean income, 1980-1998

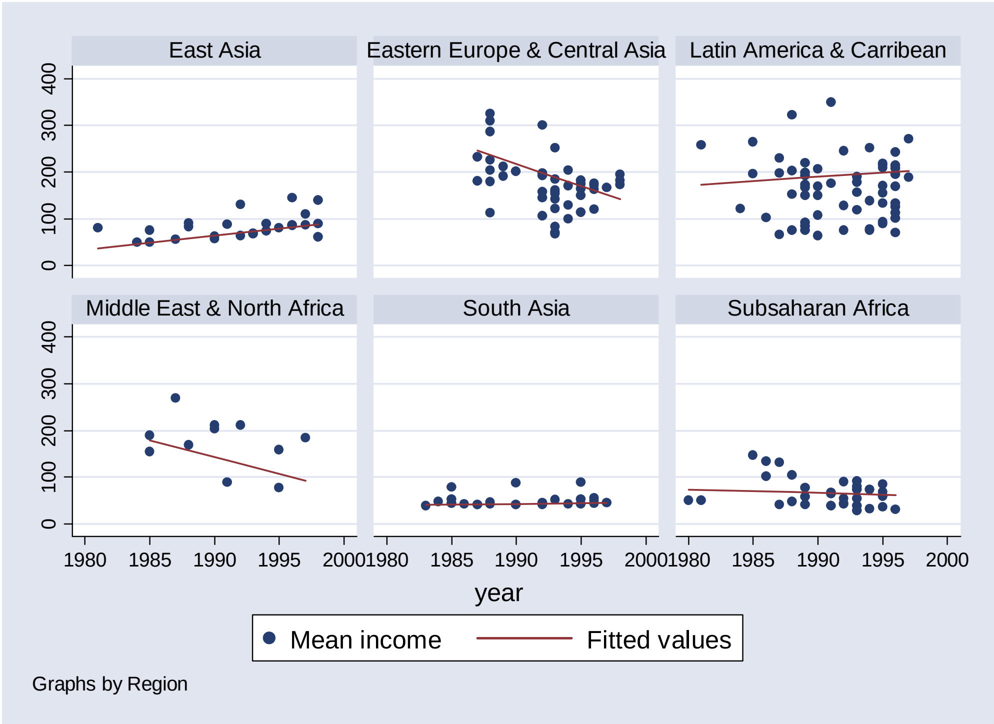
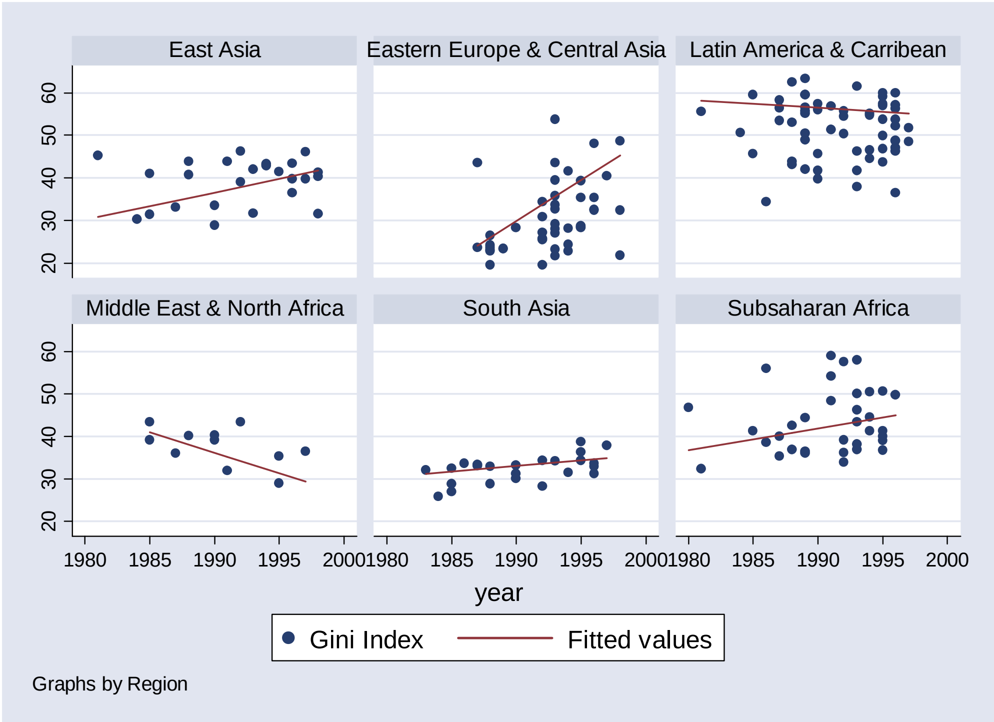


Figure A3
Regional trends in inequality, 1980-1998



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