Ibero-Amerika Institut für Wirtschaftsforschung
Instituto Ibero-Americano de Investigaciones Económicas
Ibero-America Institute for Economic Research
(IAI)

Georg-August-Universität Göttingen
(founded in 1737)

Diskussionsbeiträge · Documentos de Trabajo · Discussion Papers

Nr. 176

Determinants of the Growth Semi-Elasticity of Poverty Reduction

Stephan Klasen, Mark Misselhorn

September 2008

Platz der Göttinger Sieben 3 · 37073 Goettingen · Germany · Phone: +49-(0)551-398172 · Fax: +49-(0)551-398173

e-mail: uwia@gwdg.de · http://www.iai.wiwi.uni-goettingen.de

Determinants of the Growth Semi-Elasticity of Poverty Reduction

Stephan Klasen* and Mark Misselhorn†

September 4, 2008

Abstract

In this paper we examine the mathematical relationship between growth and distributional change on absolute (i.e. percentage point) changes in FGT poverty measures assuming a log-normal income distribution, which we argue to be a conceptually superior and more policy-relevant measure than the much used 'regular' growth elasticity of poverty reduction. We also test the empirical relationship of these semi-elasticities of growth and distributional change on poverty and find them to explain actual changes in poverty very well (in fact, much better than a related study by Bourguignon (2003) that studied the growth elasticity of poverty reduction). This is particularly the case when poverty depth and severity is considered. Using our results helps in interpreting past performance in poverty reduction and will allow a rapid and quite reliable prediction of the impact of growth and distributional change on (absolute) poverty reduction across countries, taking heterogeneity in country circumstances into account.

***JEL* Classification:** O1, I32, O2.

Key words: Poverty reduction, growth elasticity, growth semi-elasticity, income distribution

Acknowledgements: We would like to thank Francois Bourguignon, Andrea Cornia, Michael Grimm, Marcel Fafchamps, Ravi Kanbur, Amartya Sen, and participants at the 2005 EUDN workshop in Paris, the German Economics Association Meetings in 2006, the PEGNet meeting in 2006, the World Bank PREM research seminar in 2007, and two conferences in Göttingen for helpful comments and discussion.

---

*University of Göttingen, Department of Economics, Platz der Göttinger Sieben 3, 37073 Göttingen, Germany, email: sklasen@uni-goettingen.de.

† University of Göttingen, Department of Economics, Platz der Göttinger Sieben 3, 37073 Göttingen, email: m.misselhorn@mwm.ag.

1 Introduction

Prospects for poverty reduction in regions and on the global level, which are critical for assessing progress towards meeting the first Millennium Development Goal, have so fare relied largely on simple extrapolations (e.g. Ravallion and Chen, 2004). At the same time, we know quite a bit more about the impact of growth and distributional change on poverty reduction and these insights could be used to assess prospects for poverty reduction, depending on particular country circumstances and growth scenarios. To provide such assessments in a comparable manner for all countries, the relationship between growth, distributional change, and poverty reduction must be studied in a way that allows for country heterogeneity but remains tractable.

Discussions about the sensitivity of the incidence of poverty to economic growth have been going on for a number of years (e.g. World Bank, 2000; Ravallion and Datt 1998; Adams, 2000; Ram, 2006; Bresson, 2006; Bourguignon, 2003). Although most studies clearly show that growth reduces poverty, the size of this effect is still debated (e.g. Dollar and Kraay, 2002). Whereas different studies estimated the growth elasticity of poverty reduction to be somewhere between -2.0 and -3.0 (Ravallion and Chen, 1997; Bruno et al., 1998; World Bank 2000) a well known study by Bhalla (2002) estimated it to be about -5.0, meaning that a 1 percent increase in mean income reduces the poverty headcount by 5 percent.[1]

A related question concerns the impact of distributional change on poverty. While also here there has been some empirical work (e.g. reviewed in World Bank 2000 and Bourguignon, 2003), a purely data-driven approaches have usually yielded mixed and strongly varying estimates and are often only able to explain a small portion of the actual change in poverty. In particular, it has become increasingly clear that both the impact of growth and distribu-

[1] See also Ram (2006) for a discussion of the different estimates and their apparent inconsistencies.

tional change on poverty will depend on a number of factors, including the location of the poverty line and the initial level of inequality.

From an analytical point of view this is not very surprising, since an identity links changes in mean income, changes in the income distribution and reductions in poverty. This identity results in a non-linear relationship between economic growth and headcount poverty as well as between distributional changes and headcount poverty [2]. Although the identity has been known for quite a while, only a small number of studies has taken account of it, namely Ravallion and Huppi (1991), Datt and Ravallion (1992), Kakwani (1993) and Bourguignon (2003). All these studies are limited to the country level with the only exception being Bourguignon (2003). This is due to the fact that one needs to know the complete distribution of incomes on the household level. Bourguignon (2003) circumvents this problem by assuming that incomes are lognormally distributed and therefore the complete distribution of incomes is known as long as information on mean income and the Gini coefficient is available. With this simplifying assumption[3] one can mathematically determine the poverty elasticity to growth and distributional change and it will depend on initial inequality, as well as the location of the poverty line in relation to mean incomes. It turns out that this simplification fits the data extremely well (see Bourguignon, 2003) and this is also supported by our calculations using a similar (and partially overlapping) dataset used by Adams (2004) which is also based on the World Bank poverty monitoring database. Thus the assumption of log-normality achieves the goal of providing a simple, yet powerful tool to assess and project poverty

[2] In the following it will be shown that the identity can be used to calculate the influence of income and distribution changes on other poverty measures than the headcount poverty ratio as for example the FGT poverty measures.

[3] Bresson (2006) questions this simplifying assumption. Using a large sample of observations, he finds that some 2 parameter distributions might provide a better fit for the data, although there is not a single one that performs best overall. That study does not control, however, for the determinants of the growth elasticity considered here. Also, the question of how well one can predict poverty reduction using the lognormal assumption is largely an empirical issue that is directly addressed below.

reduction depending on country circumstances.

Using the same assumption as Bourguignon (2003) we propose an alternative measure to calculate the effects of income growth and distributional changes on poverty. Instead of studying the determinants of the percentage change in poverty (and the associated poverty elasticity of growth and distributional change), we propose to study the percentage point change in poverty (and the associated poverty semi-elasticity of growth and distributional change). We argue that there are two distinct advantages to study absolute rather than proportionate poverty reduction. The first set of arguments is conceptual. They relate to the fact that policy-makers are likely to be more interested in the percentage point changes in poverty in their country rather than percent changes[4]. Also, when the poverty incidence becomes small, large percentage changes in poverty incidence are easily achieved and it seems difficult to treat poverty reduction from an incidence of 2 to 1 percent in the same manner as poverty reduction from an incidence of 80 to 40%. Lastly, as discussed further below, it can be shown that in growing countries (and a constant real absolute poverty line such as the international dollar-a-day poverty line), the growth elasticity of poverty reduction will keep increasing, giving the misleading impression of growth not only being 'good for the poor', but becoming ever better for them over time.[5]

[4]One may argue that MDG1 is, at the global level, about percentage changes in poverty (i.e. a 50% reduction in poverty). Since this is a non-marginal change, one cannot, however, directly use the growth elasticity of poverty reduction to deduce the growth requirements with any reliability. Moreover, since progress has been and will continue to be uneven between countries, it will be much easier to understand progress if one reformulated the goal as an absolute reduction in the poverty incidence from 29% to 14.5% and then consider what absolute poverty reduction where would contribute by how much to this goal. In the case of MDG1, if interpreted at the global level, one would also have to consider where poverty incidence has fallen, particularly is it has fallen in the countries where the absolute number of poor is very large which depends not only on the poverty rate but also on population size.

[5]In this context, it is interesting to note that, as argued by Ram (2006), many forward-looking assessments of poverty reduction appear to imply a falling growth elasticity of poverty reduction in future. This could only be the case if future growth was accompanied by increasing inequality as it has been in a growing number of countries recently. Without knowing the details of these projections, it is hard to verify this conjecture.

The second set of arguments is empirical. Proportionate poverty changes cannot be calculated when the poverty incidence was 0 in at the start or end of the spell. More seriously, proportionate poverty changes can be very large when the poverty incidence is small. For example, a change from 2 to 1 per cent headcount is a 50% reduction. As the elasticity formulas are for marginal changes, they are not appropriately applied to situations where the poverty changes are very large. For these reasons, in empirical assessments of the growth elasticity (e.g. Bourguignon, 2003; Adams, 2004; Kraay, 2006), these observations with low (or zero) poverty incidence are usually simply dropped and one cannot therefore say much about the poverty-growth nexus in these situations. When applied to the $ a day poverty line, this usually means that most observations from Eastern Europe and Central Asia, as well as some from the Middle East and North Africa, are excluded from consideration. Moreover, as we show below, the assumption of lognormality is empirically much less reliable when trying to estimate the determinants of the growth elasticity of poverty reduction, particularly when poverty depth and severity is considered.

In contrast, the lognormal assumption appears to work much better when estimating the impact of growth and distributional change on absolute (i.e. percentage point) poverty reductions. One does not need to make arbitrary assumptions about excluding data from countries with low poverty incidence. Also, such an empirical analysis will place more weight on countries with high poverty incidence which is desirable as these countries are the main concern of the international poverty reduction effort.

Our work is also related to a second literature which measures the actual historical contribution of growth and inequality change on poverty reduction. Starting with the decomposition work by Datt and Ravallion (1992), a recent contribution is by Kraay (2006) who examines to what extent past poverty reduction in the world (using the $ a day criterion) was due to a growth effect, a distribution effect, or an effect measuring differences in the impact of growth on poverty reduction. That paper found that in the longer term, poverty reduction was mostly a result of growth rather than distributional change, although that finding is sensitive to the length of the spell and the type of poverty measure. As that paper addresses a related but different question (the actual decomposed roles of growth and distributional change on poverty reduction, rather than an assessment of the respective elasticities), our analysis here should be seen as complementary. But since the study be Kraay also examines proportionate poverty reduction, it runs into similar problems as the growth elasticity papers and therefore also discards observations where poverty incidence was zero or low (below 2%) in the initial or final period. Thus such decompositions could also be usefully enriched when one considered absolute poverty reduction where such data discards would not be required.

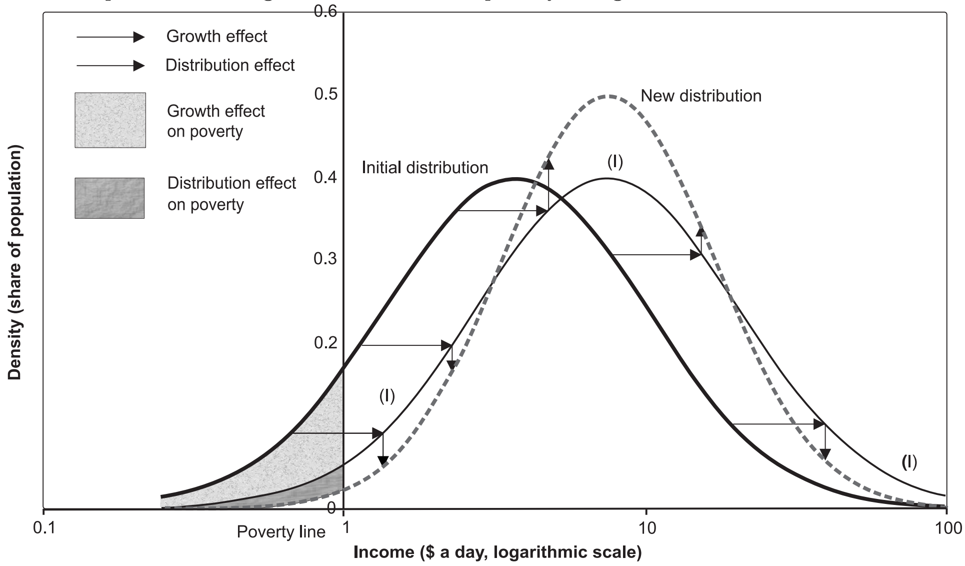
The paper is organized as follows. In section 2 we briefly review the mathematical relationships between growth, distributional change, and poverty reduction under the log-normal assumption, using both the proportionate as well as the absolute change in poverty. In section 3 we consider the relative merits of the elasticity versus the semi-elasticity in more detail. In section 4, we move to the data and study to what extent we are able to explain past absolute and relative poverty reduction with the log-normal assumption. In the last section we conclude and assess prospects for poverty reduction in different countries of the world, based on the existing income and distribution patterns.

2 The Influence of Income and Distribution Changes on Poverty Measures

As already mentioned by Bourguignon (2003), Datt and Ravallion (1992) and others, poverty reductions are either due to increases in mean income or changes in the distribution of relative incomes. Knowing this any change in headcount poverty can be decomposed into a) a "growth effect" that is the result of a proportional change in all incomes that leaves the distribution of relative incomes unaffected and b) a "distributional effect" that is only due to a change in the distribution of relative incomes leaving the mean income constant. These two effects are shown in Fig. 1 (from Bourguignon, 2003).

Figure 1

Decomposition of change in distribution and poverty into growth and distributional effects



Source: Bourguignon (2003).

Formally the change in headcount poverty can be explained by the following decomposition identity:

$$\Delta H = H_{t'} - H_t = \left[\tilde{F}_t\left(\frac{z}{\bar{y}_{t'}}\right) - \tilde{F}_t\left(\frac{z}{\bar{y}_t}\right)\right] + \left[\tilde{F}_{t'}\left(\frac{z}{\bar{y}_{t'}}\right) - \tilde{F}_t\left(\frac{z}{\bar{y}_{t'}}\right)\right] \quad (1)$$

where Ht refers to the headcount poverty measure and F() refers to the cumulative distribution function of an actual income distribution. The first term refers to the growth effect while the second one to the distribution effect. Using the empirically plausible assumption proposed by Bourguignon (2003) that incomes are lognormally distributed, we no longer need to know the total distribution of individual incomes to calculate headcount poverty. The only information necessary is the mean income yt, the constant international poverty line z (e.g. the $1 a day criterion) and the standard deviation of the lognormal distribution :

$$H_t = \tilde{F}_t(log(z/\bar{y}_t) = \Pi \left[\frac{log(z/\bar{y}_t)}{\sigma} + \frac{1}{2}\sigma \right]. \tag{2}$$

wherein Π is the cumulative distribution function of the standard normal. The standard deviation of the lognormal distribution can be calculated from the Gini coefficient by the following equation:

$$\sigma = \sqrt{2} \left[\Pi^{-1} \left(\frac{G+1}{2} \right) \right] \tag{3}$$

Besides the headcount poverty ratio at a certain point in time, relative and absolute changes in poverty due to "growth effects" and "distributional effects" can be generated on the basis of changes in mean income and changes in the Gini coefficient. When considering relative changes in the headcount poverty ratio, the growth elasticity of poverty reduction is given by

$$\epsilon_y^H = \frac{\Delta H}{\Delta log(\bar{y}) H_t} = \frac{1}{\sigma} \lambda \left[\frac{log(z/\bar{y}_t)}{\sigma} + \frac{1}{2}\sigma \right]. \tag{4}$$

where λ is the hazard rate, which is the ratio of density function to the cumulative density function of the standard normal.

In contrast to Bourguignon, our focus will be on absolute (i.e. percentage point) changes in the headcount poverty ratio and therefore on semi-elasticities. As will be argued below this is a less misleading measure than elasticities. Using equation (1) the growth semi-elasticity of poverty reduction is

$$\kappa_y = \frac{1}{\sigma} \pi \left[\frac{log(z/\bar{y}_t)}{\sigma} + \frac{1}{2}\sigma \right] \tag{5}$$

and the semi-elasticity due to distributional changes in relative incomes is given by

$$\kappa_\sigma = \pi \left[\frac{log(z/\bar{y}_t)}{\sigma} + \frac{1}{2}\sigma \right] \cdot \left[\frac{1}{2} - \frac{log(z/\bar{y}_t)}{\sigma^2} \right], \tag{6}$$

where π is the density function of the standard normal.

When combined with the growth rate and the percentage change in the standard deviation, respectively these theoretical values of the semi-elasticities will identify the percentage point changes in the headcount poverty ratio either due to growth in mean income (5) or due to changes in the distribution of relative incomes (6) depending on the level of development and the existing distribution of incomes.

As mentioned before, it is also possible to calculate the elasticities and semi-elasticities for the other FGT-measures. According to formulas derived by Kakwani (1993) the elasticity η_{P_α} of FGT-measure P_α with respect to changes in mean income is

$$\eta_{P_\alpha} = \frac{\delta P_\alpha}{\delta \mu} \frac{\mu}{P_\alpha} = -\frac{\alpha[P_{\alpha-1} - P_\alpha]}{P_\alpha} \tag{7}$$

The elasticity ϵ_{P_α} of a FGT-measure with respect to a change in the distribution leaving the mean income unaffected can be denoted by the following equation

$$\epsilon_{P_\alpha} = \eta_{P_\alpha} + \frac{\alpha \mu P_{\alpha-1}}{z P_\alpha} \tag{8}$$

In combination with the assumption of lognormally distributed incomes this means that the elasticity of the poverty gap with respect to changes in mean come is the following and depends partly on the mean income of the poor $\bar{y}_t^*$ [6]:

[6] It should be noted that formula (9) differs from the formula cited by Bourguignon (2003), in which the mean income of the poor is not explicitly taken into consideration.

$$\epsilon_y^{PG} = -\frac{\Pi[\frac{log(z/\bar{y}_t)}{\sigma} + \frac{1}{2}\sigma]}{(\frac{z}{\bar{y}_t^*}) \cdot \Pi[\frac{log(z/\bar{y}_t)}{\sigma} + \frac{1}{2}\sigma] - \Pi[\frac{log(z/\bar{y}_t)}{\sigma} + \frac{1}{2}\sigma]} \tag{9}$$

Using the formulas derived by Kakwani (1993) we can also generate values for the semi-elasticities of the FGT-measures, which are with respect to income

$$\kappa_y^{P_\alpha} = \epsilon_y^{P_\alpha} * P_\alpha = -\alpha[P_{\alpha-1} - P_\alpha] \tag{10}$$

and with respect to changes in distribution

$$\kappa_\sigma^{P_\alpha} = \alpha P_\alpha + \alpha(\frac{\mu}{z} - 1)P_{\alpha-1}. \tag{11}$$

In tables A1-A4 in the appendix as well as Table 7 below, we have used these results to calculate elasticities and semi-elasticities with respect to growth and distributional change depending on initial inequality and the location of the poverty line with respect to mean income to illustrate the impact of the different formulas. These tables will be discussed in more detail below.

3 Growth Elasticity versus Semi-Elasticity

Economists usually tend to use elasticities to measure the influence of income/consumption growth on poverty changes. Although this information is clearly of some relevance it is actually texitabsolute changes in poverty measures and therefore semi-elasticities that policy makers at the national and international level are interested in. The number of persons leaving or entering poverty measured as a percentage of the total population is clearly of more interest than the same amount measured as a percentage of the poor. Stated differently the reduction of the percentage of the population that is living below the poverty line by 10 percentage points is clearly a lot. But the reduction of headcount poverty by 10% can be a lot, if the poverty rate is currently around 60%, but if it is only at 6% it is not really that much (only another 0.6% of the population are leaving poverty).

Moreover, as shown in the formulas above and in Table A1 in the appendix, the growth elasticity of poverty reduction is highly sensitive to the location of the poverty line relative to mean incomes. The higher mean income in a country is (relative to an international absolute poverty line), the larger the growth elasticity; as shown in Table A1, the effects are quite large. Middle-income countries will have much larger elasticities and regional comparisons of elasticities that have been regularly undertaken (e.g. Adams, 2004) will be biased in this sense. There is a further problem when comparing elasticities over time. Continued per capita growth in developing countries will lead to an increase in the distance between the absolute poverty line and mean incomes. Not only will such growth reduce absolute poverty, but as clear from the formulas above, the growth elasticity of poverty reduction will increase as well. This may lead policy makers to the conclusion that policies that were implemented in times with lower poverty rates were more successful in poverty reduction than policies that were implement during times of very high poverty rates, although these changes are purely a consequence of the way elasticities are calculated. To give an easy imaginary example, future economists might find that growth elasticities between 1980 and 2000 were a lot lower than in the following two decades. Therefore they might falsely come to the conclusion that the growth enhancing policies implemented in the last two decades were less successful than growth policies that are to be implemented in the future. In contrast, the semi-elasticity formulation will not have an in-built increase in the poverty impact of growth (see Table 7 below). In fact, the opposite occurs. As countries grow richer, the ability of growth to achieve the same absolute poverty reduction becomes increasingly smaller.[7]

[7]While this will also bias assessments of the poverty impact of growth, this time in the opposite direction, this bias is arguably less problematic than the one of persistent

From an empirical point of view, there are further advantages to estimating the determinants of absolute rather than proportionate changes in poverty. In estimating the determinants of proportionate changes in welfare, all studies using proportionate changes in poverty must discard observations where poverty spells started or ended with a headcount of 0. In addition, most poverty spells with low initial or final poverty incidence are omitted as they generate very large proportionate changes and tend to drive and distort empirical assessments. For example, Bourguignon states that he had to 'eliminate all spells where the percentage change in poverty headcount was abnormally large in relative value' (Bourguignon 2003: 15). Adams (2004) and Kraay (2006) also discarded such spells for the same reason. Using the semi-elasticity, we can include all observations that are available and are not bound by such an arbitrary decision; thus we can consider the impact of growth and distributional change on poverty reduction in cases of high or low poverty incidence. In our case we can increase the number of growth spells from 102 to 125 in our empirical assessments. In particular, we are able to include many growth spells from Eastern Europe and Central Asia as well as the Middle East and North Africa which would otherwise be underrepresented in the dataset.

Lastly, when using semi-elasticities, the assumption of lognormality is leading to much more precise results, particularly when considering poverty measures like poverty gap and squared poverty gap. Thus this distributional assumption appears to be work better when studying absolute rather than proportionate poverty changes.

increase in the poverty impact of growth. In actual fact, it may be the case that poverty reduction becomes increasingly harder when the poverty incidence is reduced to very levels as these groups are hard to reach and hard to include in growth-processes. The declining semi-elasticity would capture this insight.

4 Empirical Results

In the empirical section we test our ability to explain the determinants of absolute and proportionate poverty change using the above insights and formulas, and apply them to the World Bank's \$ a day poverty line. We do this using a slightly different data-set than Bourguignon (2003) which is an updated version of the World Bank Poverty Monitoring data set also used by Adams (2004). To make our results easily comparable with those of Bourguignon we have used the same set of regressions and given them the same names. In Tab. 1 - 6 our first regression is the naïve model that tries to explain changes in poverty measures by changes in mean incomes only. In all cases growth clearly has a significant poverty reducing effect but only a relatively small part of the variation in poverty changes can be explained by a linear influence of mean income growth. The second regression in Tab. 1 - 6 is the so called standard model that also takes changes in the distribution of incomes (i.e. variations in the Gini coefficient) into consideration and improves the fit of all models.

Table 1: Explaining the evolution of poverty across growth spells
(dependent variable = **absolute** change in poverty headcount during growth spell)

	(1) Naive Model	**(2)** Standard Model	**(3)** Improved Standard Model 1	**(4)** Improved Standard Model 2	**(5)** Identity Model 1	**(6)** Identity Model 2
Intercept	-0.0035	-0.0123	0.0001	0.0069	0.0007	0.0096
	(-0.50)	(-1.92)	(0.01)	(1.41)	(0.15)	(2.08)
Y = percentage change in mean income	-0.1769	-0.1462	0.2837	0.1612		
	(-6.53)	(-5.94)	(4.06)	(2.54)		
DGini = Variation in Gini coefficient		0.1947	0.2569	0.0168	0.2443	
		(5.87)	(9.31)	(0.38)	(9.83)	
Y * poverty-line/mean-income			-0.8954	-0.8617		
			(-6.95)	(-7.73)		
Y * initial Gini coefficient			-0.5602	-0.3036		
			(-2.88)	(-1.75)		
DGini * poverty-line/mean-income				0.0088		
				(2.26)		
DGini * initial Gini coefficient				0.0123		
				(3.01)		
Y * theoretical value of growth semi-elasticity under lognormal assupmtion					-0.9901	-1.0419
					(-12.09)	(-13.29)
DSigma * theoretical value of poverty inequality semi-elasticity under lognormal assumption						0.7330
						(10.87)
R^2	0.2571	0.4207	0.6368	0.7331	0.6601	0.6906
Adj. R^2	0.2511	0.4112	0.6247	0.7196	0.6546	0.6856
Obs.	125	125	125	125	125	125

Note: t-values in parenthesis.

Table 2: Explaining the evolution of poverty across growth spells
(dependent variable = **relative** change in poverty headcount during growth spell)

	(1) Naive Model	**(2) Standard Model**	**(3) Improved Standard Model 1**	**(4) Improved Standard Model 2**	**(5) Identity Model 1**	**(6) Identity Model 2**
Intercept	0.5266	0.4782	0.3429	0.2278	0.3877	0.1903
	(2.46)	(2.37)	(1.76)	(1.23)	(2.18)	(1.58)
Y = percentage change in mean income	-4.1283	-4.5748	-21.3351	-22.3100		
	(-4.28)	(-4.99)	(-4.37)	(-5.20)		
DGini = Variation in Gini coefficient		5.3861	5.7352	36.5913	5.6641	
		(3.71)	(4.13)	(5.96)	(4.42)	
Y * poverty-line/mean-income			16.2323	17.2438		
			(2.98)	(3.61)		
Y * initial Gini coefficient			28.3531	29.1387		
			(2.82)	(3.30)		
DGini * poverty-line/mean-income				-30.5798		
				(-4.63)		
DGini * initial Gini coefficient				-44.7220		
				(-3.55)		
Y * theoretical value of growth elasticity under lognormal assupmtion					-2.0519	-1.6908
					(-7.72)	(-9.48)
DSigma * theoretical value of poverty inequality elasticity under lognormal assumption						1.1989
						(12.76)
R^2	0.1546	0.2580	0.3491	0.5110	0.4201	0.7374
Adj. R^2	0.1462	0.2430	0.3223	0.4801	0.4084	0.7321
Obs.	102	102	102	102	102	102

Note: t-values in parenthesis.

As shown in the formulas above, both changes in mean incomes as well as changes in distribution have a non-constant influence on changes in poverty measures. As the formulas show, the size of the effects depends on the position of the poverty line relative to mean income and on initial inequality. This non-linear influence of growth in mean incomes is considered by interacting growth with the initial poverty-line/mean-income ratio and the initial Gini coefficient (Improved Standard Model 1). By interacting changes in the Gini coefficient with the same two factors we also take account of the non-linear influence of changes in the distribution of incomes (Improved Standard Model 2). When taking these non-linear influences of growth and distribution changes into consideration we are able to explain more than 70% of the variation in absolute changes in headcount poverty (Table 1) and about 50% of the variation in relative changes in headcount poverty (Table 2). This is a considerably improvement. The greater explanatory power of the regressions of the absolute poverty change is also true if we restricted the data set to the 102 observations used in the relative regression.

While in these first four regressions no assumptions are made on how income growth interacts with the distance of the poverty line to mean income and the initial degree of inequality the fifth regression (Identity Model 1) assumes a joint effect of these three variables according to the theoretical (semi-)elasticity mentioned in section 2. The last regression model (Identity Model 2) further assumes a joint effect of a change in the distribution, the development level and the initial degree of inequality according to the theoretical (semi-)elasticity. As seen in Tables 1 and 2 the assumption of a lognormal distribution fits the data very well. Multiplying growth in mean incomes with the respective theoretical value for the (semi-)elasticity and multiplying a change in the distribution of incomes with its respective theoretical value for the (semi-)elasticity can explain in both cases about 70%

of the variation in absolute/relative changes in headcount poverty rates.[8]

Whereas the results for headcount poverty are very similar between the last regressions in Tables 1 and 2, the goodness of fit is a lot better when looking at absolute changes in poverty gap and squared poverty gap and therefore when semi-elasticities are considered (Tables 3 and 5). The R2 values in Tables 4 and 6, where relative changes in poverty gap and squared poverty gap are considered, respectively, are quite modest, suggesting that the lognormal assumption is no longer as suitable because the explanatory power of the Identity Models are in both cases considerably smaller than those of the Improved Standard Models. The likely reason for the poor fit when considering depth and distribution-sensitive poverty measures is related to the increasing importance of the left tail of the distribution in countries with low poverty incidence who in turn are very influential due to the large proportionate poverty changes observed.[9] It is quite likely that these far left tails of the distribution are particularly prone to measurement error. Or alternatively, the assumption of log-normality is probably particularly problematic the more one moves into the left tail of the distribution. In contrast, it is very encouraging to see that we are able to explain changes in the absolute poverty gap and poverty severity very well still with the log-normal assumption. Thus our simplifying assumption of log-normality works particularly well when trying to explain absolute changes in poverty. This much better fit implies that the lognormal assumption is quite suitable when studying absolute changes in poverty headcount, depth and severity. This is due to the fact that these absolute poverty changes are largest in countries with high poverty incidence and in these countries the depth and severity

[8]Please note that, according to the formulas, it would not be necessary to include a constant in regressions 6 and 7. As it turns out the constant is always substantively very close to 0, although sometimes statistically different from it.

[9]By reducing the least squares deviations of the dependent variable from the regression line, OLS is particularly influenced by observations that have particularly high or low values. When the dependent variable is proportionate poverty change, most such particularly high or low observations will be from countries with small initial poverty incidence.

of poverty is well approximated with the lognormal assumption. It is also reassuring to know that our empirical results include all observations and are not based on arbitrary selection rules, but are particularly influenced by observations with large poverty incidence which are the main countries of interest as far as poverty reduction is concerned.

Table 3: Explaining the evolution of poverty across growth spells
(dependent variable = **absolute** change in poverty gap ratio during growth spell)

	(1) Naive Model	(2) Standard Model	(3) Improved Standard Model 1	(4) Improved Standard Model 2	(5) Identity Model 1	(6) Identity Model 2
Intercept	-0.1893	-0.6600	0.1307	0.4616	0.0261	0.8068
	(-0.46)	(-1.72)	(0.43)	(1.85)	(0.08)	(3.30)
Y = percentage change in mean income	-8.0477	-6.4003	19.9626	10.6787		
	(-5.06)	(-4.33)	(4.96)	(3.31)		
DGini = Variation in Gini coefficient		10.4652	14.3797	-1.8911	12.1874	
		(5.25)	(9.06)	(-0.84)	(7.95)	
Y * poverty-line/mean-income			-59.2421	-56.7783		
			(-8.00)	(-10.02)		
Y * initial Gini coefficient			-31.0163	-11.8068		
			(-2.77)	(-1.34)		
DGini * poverty-line/mean-income				1.0293		
				(5.21)		
DGini * initial Gini coefficient				0.4677		
				(2.24)		
Y * theoretical value of growth semi-elasticity under lognormal assupmtion					-1.1187	-1.1476
					(-10.25)	(-12.82)
DSigma * theoretical value of poverty inequality semi-elasticity under lognormal assumption						1.7043
						(12.39)
R^2	0.1721	0.3247	0.6117	0.7771	0.5813	0.7185
Adj. R^2	0.1653	0.3137	0.5987	0.7657	0.5745	0.7139
Obs.	125	125	125	125	125	125

Note: t-values in parenthesis.

Table 4: Explaining the evolution of poverty across growth spells
(dependent variable = **relative** change in poverty gap ratio during growth spell)
[using all 102 observations]

	(1) Naive Model	**(2) Standard Model**	**(3) Improved Standard Model 1**	**(4) Improved Standard Model 2**	**(5) Identity Model 1**	**(6) Identity Model 2**
Intercept	0.8454	0.8022	0.7712	0.7688	0.7089	0.7008
	(2.72)	(2.63)	(2.46)	(2.24)	(2.26)	(2.22)
Y = percentage change in mean income	-4.5943	-4.9930	-2.4044	-2.6994		
	(-3.28)	(-3.60)	(-0.31)	(-0.34)		
DGini = Variation in Gini coefficient		4.8088	4.5001	7.2457	4.5035	
		(2.19)	(2.02)	(1.18)	(1.99)	
Y * poverty-line/mean-income			5.2923	5.5254		
			(0.60)	(0.63)		
Y * initial Gini coefficient			-10.7182	-10.3106		
			(-0.66)	(-0.63)		
DGini * poverty-line/mean-income				-0.1799		
				(-0.60)		
DGini * initial Gini coefficient				0.1376		
				(0.05)		
Y * theoretical value of growth elasticity under lognormal assupmtion					-0.7561	-0.6978
					(-2.52)	(-2.33)
DSigma * theoretical value of poverty inequality elasticity under lognormal assumption						1.7376
						(1.73)
R^2	0.0970	0.1388	0.1480	0.1516	0.0848	0.0761
Adj. R^2	0.0880	0.1214	0.1129	0.0980	0.0664	0.0574
Obs.	102	102	102	102	102	102

Note: t-values in parenthesis.

Table 5: Explaining the evolution of poverty across growth spells
(dependent variable = **absolute** change in squared poverty gap ratio during growth spell)

	(1) Naive Model	**(2)** Standard Model	**(3)** Improved Standard Model 1	**(4)** Improved Standard Model 2	**(5)** Identity Model 1	**(6)** Identity Model 2
Intercept	-0.0634	-0.3592	0.1867	0.3657	0.0322	0.6071
	(-0.21)	(-1.25)	(0.79)	(1.84)	(0.13)	(2.89)
Y = percentage change in mean income	-4.8698	-3.8330	14.0963	7.616		
	(-4.28)	(-3.54)	(4.63)	(3.03)		
DGini = Variation in Gini coefficient		6.5542	9.2103	-1.5160	7.3959	
		(4.48)	(7.65)	(-0.86)	(6.11)	
Y * poverty-line/mean-income			-40.5948	-38.7195		
			(-7.22)	(-8.74)		
Y * initial Gini coefficient			-20.8864	-7.6895		
			(-2.46)	(-1.12)		
DGini * poverty-line/mean-income				0.8811		
				(5.62)		
DGini * initial Gini coefficient				0.1419		
				(0.86)		
Y * theoretical value of growth semi-elasticity under lognormal assupmtion					-1.0922	-1.1214
					(-7.96)	(-9.29)
DSigma * theoretical value of poverty inequality semi-elasticity under lognormal assumption						1.4229
						(9.08)
R^2	0.1342	0.2611	0.5460	0.7232	0.4692	0.5892
Adj. R^2	0.1268	0.2485	0.5302	0.7085	0.4602	0.5821
Obs.	120	120	120	120	120	120

Note: t-values in parenthesis.

Table 6: Explaining the evolution of poverty across growth spells
(dependent variable = **relative** change in squared poverty gap ratio during growth spell)
[using 96 observations for which data is available]

	(1) Naive Model	(2) Standard Model	(3) Improved Standard Model 1	(4) Improved Standard Model 2	(5) Identity Model 1	(6) Identity Model 2
Intercept	1.4112	1.3266	1.3740	1.2107	1.2402	1.2062
	(3.01)	(2.96)	(2.99)	(2.43)	(2.70)	(2.60)
Y = percentage change in mean income	-4.3469	-5.2351	8.6458	7.6383		
	(-2.08)	(-2.60)	(0.77)	(0.68)		
DGini = Variation in Gini coefficient		10.1417	9.5971	20.5698	9.4710	
		(3.20)	(3.00)	(2.36)	(2.91)	
Y * poverty-line/mean-income			-4.6689	-4.1046		
			(-0.37)	(-0.32)		
Y * initial Gini coefficient			-30.8061	-29.5108		
			(-1.32)	(-1.26)		
DGini * poverty-line/mean-income				-0.3548		
				(-0.84)		
DGini * initial Gini coefficient				-.2884		
				(-0.69)		
Y * theoretical value of growth elasticity under lognormal assupmtion					-0.2312	-0.1714
					(-1.07)	(-0.80)
DSigma * theoretical value of poverty inequality elasticity under lognormal assumption						1.9739
						(2.74)
R^2	0.0439	0.1390	0.1552	0.1725	0.0878	0.0793
Adj. R^2	0.0338	0.1205	0.1181	0.1168	0.0682	0.0595
Obs.	96	96	96	96	96	96

Note: t-values in parenthesis.

The preceding empirical results are very encouraging and allow us to generate tables for policy makers that could give a clear impression as to what percent point reduction in headcount poverty a 1% growth in mean incomes (assuming no change in income distribution) yields depending on the initial Gini coefficient and the level of development (Table 7). As the table shows, the highest growth semi-elasticity of poverty occurs in the Table when the Gini is 0.2 and the poverty line is at 90% of mean income. Thus a particularly poor country with a very equal income distribution can expect absolute large poverty reduction through (distribution-neutral) growth. In fact, 1 % growth will yield more than a one percentage point reduction in poverty.[10]

Table 7
Poverty/Growth ***semi-elasticity*** as a function of mean income and income inequality
(assumption: zero growth of mean income)

	Poverty line as a proportion of mean income									
Gini	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**
0.20	0.000	0.000	0.007	0.066	0.239	0.512	0.798	1.009	1.106	1.096
0.25	0.000	0.003	0.044	0.173	0.374	0.586	0.754	0.854	0.885	0.863
0.30	0.000	0.020	0.112	0.271	0.444	0.587	0.681	0.725	0.730	0.705
0.35	0.003	0.057	0.185	0.337	0.466	0.555	0.605	0.621	0.614	0.590
0.40	0.013	0.107	0.245	0.370	0.459	0.511	0.535	0.537	0.524	0.502
0.45	0.033	0.158	0.286	0.379	0.436	0.464	0.472	0.466	0.451	0.432
0.50	0.064	0.201	0.307	0.372	0.405	0.418	0.416	0.406	0.391	0.373
0.55	0.100	0.233	0.313	0.354	0.371	0.032	0.366	0.354	0.340	0.324
0.60	0.137	0.252	0.307	0.330	0.335	0.331	0.321	0.308	0.295	0.281
0.65	0.168	0.258	0.293	0.302	0.299	0.291	0.280	0.267	0.255	0.243
0.70	0.192	0.255	0.271	0.271	0.263	0.253	0.241	0.230	0.219	0.208

Similar easily interpretable tables can also be generated for changes in

[10] One may wonder why the semi-elasticity is smaller when the poverty line is equal to mean incomes. This is related to the fact that in a lognormal distribution, mean and mode are not at the same place. The largest impact will occur at the mode which is to the left of the mean in a lognormal distribution.

the distribution of incomes (see appendix table A4) as well as for other FGT-measures. From this table one can see that the impact of distributional change on absolute (percentage point) poverty reduction is particularly large for countries where the poverty line is about 60-70% of mean incomes and is larger the more equal the distribution. For poorer countries, the pay-off shrinks considerably as a reduction in inequality will not only push a lower number of people above the poverty line, but also push an increasing number of people from the right half of the distribution below the poverty line.

These tables contrast sharply with tables on the growth and distribution elasticity shown in Tables A2 and A3 which show uniformly that growth and inequality reduction will always be largest in countries where mean incomes are much higher than the poverty line and inequality is low.

Table 8 shows the elasticities and semi-elasticities for a number of individual countries to illustrate the difference with concrete country examples. When we study elasticities, by far the largest growth elasticities of poverty reduction are found in the transition countries where poverty incidence is very low. Conversely, the elasticities are lowest in Africa as well as India and rural China. In each case, this is largely due to the low mean incomes in these countries and regions, sometimes exacerbated by relatively high inequality. Also the distribution elasticities are much larger in transition countries and particularly low in poor African countries with relatively high inequality.

In contrast, the highest growth semi-elasticities are found in Bangladesh, Pakistan, India, Indonesia, Ethiopia, and rural China. These are all countries where income inequality is relatively low and mean incomes are quite close to the poverty line (of $ 365 a year). This not only generates a totally different picture on the impact of growth on poverty than suggested by the elasticities but it also puts into perspective recent debates about past poverty reduction performance in these countries. The large absolute poverty reduction achieved in India, Indonesia, Pakistan, Bangladesh, and rural China not only was a result of high, and in of these countries rather equitable, growth but it all occurred in situations where growth was having a particularly large impact on poverty reduction.[11] The results also suggest that Ethiopia could produce a similar poverty reduction feat if it was able to improve its growth performance.

Conversely, the countries with low elasticities include particularly the transition countries with little further scope for poverty reduction (such as the Slovak Republic and Latvia) as well as Brazil and urban China, where poverty is already quite low and high inequality (in the case of Brazil particularly) is making further absolute poverty reduction very difficult.

The highest distribution semi-elasticities are found in Indonesia, Lithuania, Turkmenistan, Bangladesh, Ethiopia, and rural China. The list is similar but shows that the pay-off to distributional change in terms of absolute poverty reduction is relatively larger in richer and quite equal countries such as Indonesia or Turkmenistan. Conversely, distributional change will have a relatively low pay-off in the transition countries with very low poverty incidence, but also in Zambia and Niger where the ratio of the poverty line to mean incomes is close to 1 or above 1, thus lowering the impact of distributional change on poverty. As these particular countries grow, we would, according to the results in Table A4, expect the effect of distributional change on absolute poverty to first increase and then decrease with further economic growth.

[11] For debates about poverty reduction in these countries, see for example, Bhalla 2002; Bhalla 2003; Deaton 2003a, Deaton 2003b, Ravallion and Chen, 2007; Besley and Cord, 2007.

Table 8

Country Comparisons of Elasticities and Semi-Elasticities

Country	Headcount poverty	Headcount poverty (theo.)	Gini Coeff.	Mean Income	Growth semi-elasticity	Distribution semi-elasticity	Growth elasticity	Distribution elasticity
Brazil 1997	5.10	5.11	51.7	3250	0.106	0.278	2.070	5.435
India 1997	44.03	39.91	37.8	599	0.553	0.528	1.386	1.322
China (Urban) 1998	0.98	4.30	40.3	1875	0.122	0.301	2.841	7.001
China (Rural) 1998	24.14	34.08	40.3	706	0.491	0.568	1.439	1.666
Slovak Republic 1993	0.00	0.00	19.5	3014	0.000	0.000	16.694	100.343
Latvia 1995	0.00	0.11	28.5	2179	0.007	0.025	6.479	23.189
Lithuania 1993	16.47	19.01	33.6	814	0.441	0.659	2.321	3.464
Bangladesh 1992	35.86	35.94	28.3	539	0.730	0.637	2.032	1.771
Indonesia 1998	26.33	21.10	31.5	734	0.504	0.693	2.387	3.286
Niger 1995	61.42	64.83	50.6	434	0.384	0.225	0.592	0.347
Ethiopia 1995	31.25	33.39	40.0	710	0.491	0.575	1.471	1.721
Zambia 1993	69.16	72.12	46.2	344	0.386	0.110	0.535	0.152
Turkmenistan 1993	20.92	20.42	35.8	839	0.432	0.640	2.114	3.136
Pakistan 1993	33.90	34.03	34.2	619	0.585	0.607	1.720	1.785

5 Conclusion

To summarize our results we find generally strong support for the assumption of lognormally distributed incomes when studying the growth-inequality-poverty nexus. At the same time, we find that this assumption is particularly accurate when studying absolute poverty reduction.

The use of semi-elasticities instead of elasticities has considerable conceptual advantages. By looking at absolute changes (i.e. percentage point changes) in headcount poverty, poverty gap and squared poverty gap we can study the poverty reduction experience of a wider set of countries, obviating the need for arbitrary data trimming. The generation of semi-elasticities needs no additional information and can be achieved by simple modifications of the formulas derived in Kakwani (1993). The use of semi-elasticities leads to high explanatory power of past poverty reduction even for distributionally sensitive measures such as the poverty gap and the squared poverty gap. With our measure we come to drastically different interpretations of the prospects for poverty reduction in the future as well as on explaining the record of poverty reduction in different countries.

We should end the paper with two important caveats. While it is conceptually relatively straight-forward to assess the impact of distribution-neutral growth on absolute and proportionate poverty reduction, it is conceptually less clear how to interpret our results of distributional change on poverty reduction. In these cases, we consider proportionate changes in the Gini coefficient while maintaining the lognormal assumption. This is a rather abstract way to model distributional change and in principle, there are infinite ways such distributional change could come about. This should be borne in mind when interpreting the findings.

Moreover, in all the analysis here (following the literature to which we are contributing), we are assuming that growth and distributional change can be separated and separately assessed in their impact on poverty. While this is true in an ex post accounting sense, it is clear from a policy perspective, the two issues are not easily separable as most policies one can think of will typically have simultaneous effects on growth and on distribution.[12] To what extent different policies affect growth and/or distribution has not been analyzed here. All we are did here was to provide policy-makers with ways to determine the poverty impact of different growth and distributional change scenarios on poverty reduction, depending on initial inequality and the location of the poverty line; we believe that this is a useful way to analyze past poverty reduction, project future poverty reduction, and consider different growth/distribution scenarios and their impact on poverty. The harder question concerning the type of policies that will deliver such growth-distribution scenarios remains an area of active research (e.g. Grimm et al., 2007; Besley and Cord, 2007; Kraay, 2006).

[12]In principle, one can of course use our approach here to combine growth and distributional effects of a policy by considering their combined effect on poverty.

References

Adams, Richard H. (2004), Economic Growth, Inequality and Poverty: Estimating the Growth Elasticity of Poverty, *World Development* 32(12): 1989-2014.

Besley, T. and L. Cord (2007), *Delivering on the Promise of Pro-Poor Growth*, London: Palgrave Macmillan.

Bhalla, Surjit S. (2003), Recounting the Poor: Poverty in India, 1983-1999, *Economic and Political Weekly* 37(4): 338-349.

Bhalla, Surjit S. (2002), *Imagine There is No Country: Poverty, Inequality and Growth in the Era of Globalization*, Washington: Institute for International Economics.

Bhalla, Surjit S. (2001), How to Over-Estimate Poverty: Detailed Examination of the NSS 1993 Data, *Paper presented for the 50th Anniversary of the National Sample Survey.*

Bourguignon, Francois (2003), The Growth Elasticity of Poverty Reduction: Explaining Heterogeneity across Countries and Time Periods. In T. Eichler and S. Turnovsky (eds.), *Growth and Inequality*, Cambridge: MIT Press.

Bresson, L. (2006), Poverty: Looking for the Real Elasticities. Mimeographed, Clermont-Ferrant, Department of Economics.

Datt, Gaurav and Martin Ravallion (1992), Growth and Redistribution Components of Changes in Poverty Measures: A Decomposition with Application to Brazil and India in the 1980s, *Journal of Development Economics* 38(2): 275-295.

Deaton, Angus (2003a), Adjusted Indian Poverty Estimates for 1999-2000, *Economic and Political Weekly* 37(4): 322-326.

Deaton, Angus (2003b), Prices and Poverty in India: 1987-2000, *Economic and Political Weekly* 37(4): 362-368.

Grimm, Michael, Stephan Klasen and Andrew McKay (2007), *Determinants of Pro-Poor Growth: Analytical Issues and Findings from Country Cases*, Houndsmills: Palgrave Macmillan.

Kakwani, Nanak (1993), Poverty and Economic Growth with Application to Côte d'Ivoire, *Review of Income and Wealth* 39(2): 121 - 139.

Kraay, Aart (2006), When is growth pro-poor? Evidence from a panel of countries. *Journal of Development Economics* 80:198-227.

Ram, R. (2006), Growth Elasticity of Poverty: Alternative Estimates and a Note of Caution, *KYKLOS* 59:601-610.

Ravallion M. and S. Chen (2007), China's (uneven) progress against poverty, *Journal of Development Economics* 82:1-42.

Ravallion, M. and S. Chen (1997), What can new survey data tell us about recent changes in distribution and poverty, *The World Bank Economic Review* 11: 357-382.

Ravallion, M. and M. Huppi (1991), Measuring changes in poverty: A methodological case study of Indonesia during an adjustment period, *The World Bank Economic Review* 5: 57-82.

World Bank (1991), Growth, Poverty Alleviation and Improved Income Distribution in Malaysia: Changing Focus of Government Policy Intervention. Report 8667-MA, Washington: World Bank.

6 Appendix

Table A1
Poverty/Growth ***elasticity*** as a function of mean income and income inequality
(assumption: no change in distribution)

	Poverty line as a proportion of mean income									
Gini	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**
0.20	17.864	12.629	9.635	7.570	6.025	4.817	3.852	3.071	2.435	1.919
0.25	11.262	8.004	6.156	4.892	3.952	3.223	2.640	2.169	1.783	1.465
0.30	7.672	5.484	4.253	3.416	2.798	2.319	1.938	1.628	1.373	1.161
0.35	5.505	3.958	3.095	2.511	2.082	1.750	1.485	1.270	1.092	0.944
0.40	4.095	2.962	2.334	1.912	1.602	1.363	1.172	1.017	0.888	0.779
0.45	3.126	2.274	1.806	1.492	1.262	1.085	0.943	0.828	0.731	0.650
0.50	2.430	1.778	1.422	1.184	1.010	0.876	0.769	0.681	0.608	0.546
0.55	1.912	1.407	1.132	0.950	0.817	0.033	0.632	0.564	0.508	0.460
0.60	1.515	1.121	0.908	0.767	0.664	0.584	0.521	0.469	0.425	0.388
0.65	1.203	0.895	0.729	0.619	0.540	0.478	0.429	0.388	0.354	0.325
0.70	0.953	0.712	0.583	0.498	0.437	0.389	0.351	0.320	0.293	0.271

Table A2
Poverty/Distribution change ***elasticity*** as a function of mean income and income inequality
(assumption: no change in mean incomes)

	Poverty line as a proportion of mean income									
Gini	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**
0.20	118.003	58.991	34.102	20.715	12.734	7.731	4.525	2.462	1.152	0.344
0.25	60.082	30.389	17.835	11.049	6.970	4.379	2.685	1.563	0.818	0.330
0.30	34.510	17.691	10.555	6.675	4.322	2.806	1.796	1.110	0.640	0.316
0.35	21.519	11.197	6.799	4.391	2.917	1.954	1.302	0.849	0.530	0.303
0.40	14.233	7.527	4.655	3.071	2.091	1.444	0.998	0.683	0.455	0.289
0.45	9.835	5.291	3.335	2.247	1.568	1.114	0.797	0.568	0.400	0.275
0.50	7.024	3.848	2.472	1.702	1.216	0.887	0.654	0.484	0.357	0.261
0.55	5.142	2.871	1.881	1.322	0.966	-0.038	0.548	0.419	0.322	0.246
0.60	3.833	2.183	1.459	1.046	0.781	0.598	0.466	0.367	0.291	0.231
0.65	2.892	1.681	1.146	0.839	0.640	0.501	0.399	0.322	0.262	0.215
0.70	2.196	1.304	0.907	0.677	0.527	0.421	0.343	0.283	0.236	0.199

Table A3

Theoretical values of ***headcount poverty*** as a function of mean income and income inequality

	Poverty line as a proportion of mean income									
Gini	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**
0.20	0.00	0.00	0.07	0.87	3.96	10.63	20.71	32.86	45.43	57.11
0.25	0.00	0.04	0.72	3.53	9.46	18.19	28.56	39.36	49.66	58.91
0.30	0.00	0.37	2.64	7.94	15.88	25.30	35.12	44.55	53.15	60.74
0.35	0.05	1.44	5.99	13.41	22.38	31.73	40.71	48.93	56.22	62.58
0.40	0.31	3.60	10.52	19.36	28.64	37.52	45.62	52.79	59.05	64.46
0.45	1.07	6.93	15.83	25.42	34.56	42.80	50.03	56.31	61.72	66.37
0.50	2.64	11.31	21.62	31.43	40.14	47.66	54.10	59.60	64.30	68.33
0.55	5.25	16.54	27.67	37.31	45.44	98.65	57.94	62.75	66.84	70.34
0.60	9.02	22.45	33.85	43.06	50.51	56.59	61.62	65.82	69.38	72.41
0.65	13.98	28.88	40.13	48.71	55.43	60.81	65.21	68.86	71.94	74.56
0.70	20.10	35.75	46.47	54.29	60.26	64.96	68.78	71.93	74.57	76.82

Table A4

Poverty/Distribution change ***semi-elasticity*** as a function of mean income and inequality (assumption: zero growth of mean income)

	Poverty line as a proportion of mean income									
Gini	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**
0.20	0.000	0.000	0.025	0.180	0.504	0.822	0.937	0.809	0.523	0.196
0.25	0.000	0.012	0.129	0.390	0.659	0.796	0.767	0.615	0.406	0.194
0.30	0.001	0.065	0.278	0.530	0.686	0.710	0.631	0.495	0.340	0.192
0.35	0.012	0.161	0.407	0.589	0.653	0.620	0.530	0.415	0.298	0.189
0.40	0.045	0.271	0.490	0.595	0.599	0.542	0.455	0.360	0.269	0.186
0.45	0.105	0.367	0.528	0.571	0.542	0.477	0.399	0.320	0.247	0.182
0.50	0.185	0.435	0.534	0.535	0.488	0.423	0.354	0.289	0.230	0.178
0.55	0.270	0.475	0.520	0.493	0.439	0.037	0.318	0.263	0.215	0.173
0.60	0.346	0.490	0.494	0.451	0.395	0.339	0.287	0.241	0.202	0.167
0.65	0.404	0.486	0.460	0.409	0.354	0.304	0.260	0.222	0.189	0.160
0.70	0.441	0.466	0.421	0.367	0.317	0.273	0.236	0.204	0.176	0.152

Table A5

Descriptives of Regions

Region	Headcount poverty	Headcount poverty (theo.)	Gini Coeff.	Mean Income	P0 relative growth	P0 absolute growth	Income growth	Gini growth
East Asia and Pacific	16.46	20.68	39.74	1105	-3.45	-7.93	11.48	2.53
Europe and Central Asia	2.47	2.55	29.41	2235	1.70	220.04	-12.97	18.20
Latin America and Caribbean	14.77	16.26	51.47	2011	-0.14	47.92	3.10	0.96
Middle East and North Africa	1.93	4.74	37.44	1909	-0.16	-11.43	-9.14	-8.16
South Asia	34.35	32.09	32.44	646	-1.68	-1.04	3.92	4.20
Sub-Saharan Africa	35.88	34.51	43.20	900	2.39	21.10	-7.08	-0.76