

Determinants of the Growth Semi-Elasticity of Poverty Reduction

Stephan Klasen* and Mark Misselhorn†

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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 distribution. We also test the empirical relationship of the derived semi-elasticities of growth and distributional change on poverty and find them to explain changes in poverty very well (in fact, better than a related study by Bourguignon (2003) that studied the 'regular' growth elasticity of poverty reduction). This relationship will allow us to predict where growth and distributional change will have the largest (absolute) impact on poverty reduction, which is very useful for predicting and analyzing progress towards meeting MDG1.

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*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: mark.misselhorn@wiwi.uni-goettingen.de.

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 far 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, 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, Ravallion and Squire, 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.

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), 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 distributional 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 ¹. 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, 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 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

¹In 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.

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 rather than percent changes ². 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), the growth elasticity of poverty reduction will keep going up, giving the misleading impression of growth not only being 'good for the poor', but becoming ever better for them over time.

The second set of arguments is empirical. We show below that one can estimate the semi-elasticities of growth and distributional change on poverty reduction much more precisely and does not need to make arbitrary assumptions about excluding data from countries with low poverty incidence. Also, such 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. Moreover, percentage changes in poverty are influenced much more by observations with low poverty incidence which are highly susceptible to measurement error in the left tail of the income distribution and could therefore bias the results.

In section 2 we briefly review the mathematical relationships between growth, distributional change, and poverty reduction under the log-normal

²One may argue that MDG1 is, at the global level, about percentage changes in poverty (i.e. a 50% reduction in poverty). But since progress will 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.

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).

include Fig. 1 somewhere here

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

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

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 y_t , the constant international poverty line z (e.g. the \$1 a day criterion) and the standard deviation of the lognormal distribution :

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

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:

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

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

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

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

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

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

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

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

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

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

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

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^* ³:

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

³It 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.

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

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

and with respect to changes in distribution

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

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 absolute changes in poverty measures and therefore semi-elasticities that policy makers at the national and international level are interested in. The amount 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, the growth elasticity of poverty reduction is highly sensitive to the location of the poverty line relative to mean incomes. For example the continuous progress in the economic development of developing countries will lead to an increase in the distance between poverty line and mean incomes, equivalent to a reduction in headcount poverty. This reduction of the level of poor will lead to general increases in the elasticity due to the lower base by which absolute poverty changes are

divided. 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 implemented 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. In fact, the opposite occurs. As countries grow richer, the ability of growth to achieve the same absolute poverty reduction becomes increasingly smaller which seems more plausible as it becomes increasingly difficult to improve the plight of few remaining desperately poor in a society.

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, 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). Also, all observations where poverty was 0 in the first period can also not be considered. Using the semi-elasticity, we can include all observations that are available and are not bound by such an arbitrary decision. In our case we can increase the number of growth spells from 102 to 125. In particular, we are able to include many growth spells from Eastern Europe and Central Asia which would otherwise be underrepresented in the dataset.

Another positive consequence of using semi-elasticities is a better fit when considering other poverty measures like poverty gap and squared poverty gap.

This is an issue that will become apparent in the empirical findings below.

4 Empirical Results

In the empirical section we test our ability to explain the determinants of absolute and relative poverty change using the above formulas. We do this using a slightly different data-set 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 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)

	Naive Model	Standard Model	Improved Standard		Identity Model 1	Identity Model 2
			Model 1	Model 2		
Intercept	-0.0035 <i>-0.50</i>	-0.0123 <i>-1.92</i>	0.0001 <i>0.01</i>	0.0069 <i>1.41</i>	0.0007 <i>0.15</i>	0.0096 <i>2.08</i>
Y = percentage change in mean income	-0.1769 <i>-6.53</i>	-0.1462 <i>-5.94</i>	0.2837 <i>4.06</i>	0.1612 <i>2.54</i>		
DGini = Variation in Gini coefficient		0.1947 <i>5.87</i>	0.2569 <i>9.31</i>	0.0168 <i>0.38</i>	0.2443 <i>9.83</i>	
Y * poverty-line/mean-income			-0.8954 <i>-6.95</i>	-0.8617 <i>-7.73</i>		
Y * initial Gini coefficient			-0.5602 <i>-2.88</i>	-0.3036 <i>-1.75</i>		
DGini * poverty-line/mean-income				0.0088 <i>2.26</i>		
DGini * initial Gini coefficient				0.0123 <i>3.01</i>		
Y * theoretical value of growth semi-elasticity under lognormal assumption					-0.9901 <i>-12.09</i>	-1.0419 <i>-13.29</i>
DSigma * theoretical value of poverty inequality semi-elasticity under lognormal assumption						0.7330 <i>10.87</i>
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

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

	Naive Model	Standard Model	Improved Standard		Identity Model 1	Identity Model 2
			Model 1	Model 2		
Intercept	0.5266 <i>2.46</i>	0.4782 <i>2.37</i>	0.3429 <i>1.76</i>	0.2278 <i>1.23</i>	0.3877 <i>2.18</i>	0.1903 <i>1.58</i>
Y = percentage change in mean income	-4.1283 <i>-4.28</i>	-4.5748 <i>-4.99</i>	-21.3351 <i>-4.37</i>	-22.3100 <i>-5.20</i>		
DGini = Variation in Gini coefficient		5.3861 <i>3.71</i>	5.7352 <i>4.13</i>	36.5913 <i>5.96</i>	5.6641 <i>4.42</i>	
Y * poverty-line/mean-income			16.2323 <i>2.98</i>	17.2438 <i>3.61</i>		
Y * initial Gini coefficient			28.3531 <i>2.82</i>	29.1387 <i>3.30</i>		
DGini * poverty-line/mean-income				-30.5798 <i>-4.63</i>		
DGini * initial Gini coefficient				-44.7220 <i>-3.55</i>		
Y * theoretical value of growth elasticity under lognormal assumption					-2.0519 <i>-7.72</i>	-1.6908 <i>-9.48</i>
DSigma * theoretical value of poverty inequality elasticity under lognormal assumption						1.1989 <i>12.76</i>
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

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 considerable 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.

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 that the increasing importance of the left tail of the distribution where observations from countries with low poverty incidence are particularly influential and particularly prone to measurement error in the left tail of the distribution. An alternative way of phrasing the issue is that the assumption of log-normality is probably particularly error-prone the more one moves into the left tail of the distribution. In the relative poverty change regressions, the left tail from low incidence countries are particularly influential and this might therefore explain the poor fit. 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.

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

	Naive Model	Standard Model	Improved Standard		Identity Model 1	Identity Model 2
			Model 1	Model 2		
Intercept	-0.1893 <i>-0.46</i>	-0.6600 <i>-1.72</i>	0.1307 <i>0.43</i>	0.4616 <i>1.85</i>	0.0261 <i>0.08</i>	0.8068 <i>3.30</i>
Y = percentage change in mean income	-8.0477 <i>-5.06</i>	-6.4003 <i>-4.33</i>	19.9626 <i>4.96</i>	10.6787 <i>3.31</i>		
DGini = Variation in Gini coefficient		10.4652 <i>5.25</i>	14.3797 <i>9.06</i>	-1.8911 <i>-0.84</i>	12.1874 <i>7.95</i>	
Y * poverty-line/mean-income			-59.2421 <i>-8.00</i>	-56.7783 <i>-10.02</i>		
Y * initial Gini coefficient			-31.0163 <i>-2.77</i>	-11.8068 <i>-1.34</i>		
DGini * poverty-line/mean-income				1.0293 <i>5.21</i>		
DGini * initial Gini coefficient				0.4677 <i>2.24</i>		
Y * theoretical value of growth semi-elasticity under lognormal assumption					-1.1187 <i>-10.25</i>	-1.1476 <i>-12.82</i>
DSigma * theoretical value of poverty inequality semi-elasticity under lognormal assumption						1.7043 <i>12.39</i>
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

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]

	Naive Model	Standard Model	Improved Standard		Identity Model 1	Identity Model 2
			Model 1	Model 2		
Intercept	0.8454 <i>2.72</i>	0.8022 <i>2.63</i>	0.7712 <i>2.46</i>	0.7688 <i>2.24</i>	0.7089 <i>2.26</i>	0.7008 <i>2.22</i>
Y = percentage change in mean income	-4.5943 <i>-3.28</i>	-4.9930 <i>-3.60</i>	-2.4044 <i>-0.31</i>	-2.6994 <i>-0.34</i>		
DGini = Variation in Gini coefficient		4.8088 <i>2.19</i>	4.5001 <i>2.02</i>	7.2457 <i>1.18</i>	4.5035 <i>1.99</i>	
Y * poverty-line/mean-income			5.2923 <i>0.60</i>	5.5254 <i>0.63</i>		
Y * initial Gini coefficient			-10.7182 <i>-0.66</i>	-10.3106 <i>-0.63</i>		
DGini * poverty-line/mean-income				-0.1799 <i>-0.60</i>		
DGini * initial Gini coefficient				0.1376 <i>0.05</i>		
Y * theoretical value of growth elasticity under lognormal assumption					-0.7561 <i>-2.52</i>	-0.6978 <i>-2.33</i>
DSigma * theoretical value of poverty inequality elasticity under lognormal assumption						1.7376 <i>1.73</i>
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

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

	Naive Model	Standard Model	Improved Standard		Identity Model 1	Identity Model 2
			Model 1	Model 2		
Intercept	-0.0634 <i>-0.21</i>	-0.3592 <i>-1.25</i>	0.1867 <i>0.79</i>	0.3657 <i>1.84</i>	0.0322 <i>0.13</i>	0.6071 <i>2.89</i>
Y = percentage change in mean income	-4.8698 <i>-4.28</i>	-3.8330 <i>-3.54</i>	14.0963 <i>4.63</i>	7.616 <i>3.03</i>		
DGini = Variation in Gini coefficient		6.5542 <i>4.48</i>	9.2103 <i>7.65</i>	-1.5160 <i>-0.86</i>	7.3959 <i>6.11</i>	
Y * poverty-line/mean-income			-40.5948 <i>-7.22</i>	-38.7195 <i>-8.74</i>		
Y * initial Gini coefficient			-20.8864 <i>-2.46</i>	-7.6895 <i>-1.12</i>		
DGini * poverty-line/mean-income				0.8811 <i>5.62</i>		
DGini * initial Gini coefficient				0.1419 <i>0.86</i>		
Y * theoretical value of growth semi-elasticity under lognormal assumption					-1.0922 <i>-7.96</i>	-1.1214 <i>-9.29</i>
DSigma * theoretical value of poverty inequality semi-elasticity under lognormal assumption						1.4229 <i>9.08</i>
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

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]

	Naive Model	Improved Standard Model		Improved Standard Model 2	Identity Model 1	Identity Model 2
		Model 1	Model 2			
Intercept	1.4112 <i>3.01</i>	1.3266 <i>2.96</i>	1.3740 <i>2.99</i>	1.2107 <i>2.43</i>	1.2402 <i>2.70</i>	1.2062 <i>2.60</i>
Y = percentage change in mean income	-4.3469 <i>-2.08</i>	-5.2351 <i>-2.60</i>	8.6458 <i>0.77</i>	7.6383 <i>0.68</i>		
DGini = Variation in Gini coefficient		10.1417 <i>3.20</i>	9.5971 <i>3.00</i>	20.5698 <i>2.36</i>	9.4710 <i>2.91</i>	
Y * poverty-line/mean-income			-4.6689 <i>-0.37</i>	-4.1046 <i>-0.32</i>		
Y * initial Gini coefficient			-30.8061 <i>-1.32</i>	-29.5108 <i>-1.26</i>		
DGini * poverty-line/mean-income				-0.3548 <i>-0.84</i>		
DGini * initial Gini coefficient				-2884 <i>-0.69</i>		
Y * theoretical value of growth elasticity under lognormal assumption					-0.2312 <i>-1.07</i>	-0.1714 <i>-0.80</i>
DSigma * theoretical value of poverty inequality elasticity under lognormal assumption						1.9739 <i>2.74</i>
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

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 yields depending on the initial Gini coefficient and the level of development (Table 7).

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

	<i>Poverty line as a proportion of mean income</i>									
<i>Gini</i>	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	0.371	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 the distribution of incomes as well as for other FGT-measures. From this table one can see that the impact of growth on absolute (percentage point) poverty reduction is particularly large for countries where the poverty line is close to mean incomes and middle levels of inequality (Gini of about 0.4). When inequality is lower, the impact is smaller as the mass close to the poverty line is smaller due to the low inequality (most mass is between the poverty line and mean income), while at higher levels of inequality, the elasticity is again smaller as the mass of people is again smaller, this time due to high overall

inequality. 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 effects are found in the transition countries where poverty incidence is very low. In contrast, the highest semi-elasticities are found in Bangladesh, Ethiopia, Pakistan, and India. Thus we could expect that growth and pro-poor distributional change will lead to the largest effects on absolute poverty reduction in these countries and thus to the largest impact on poverty reduction at the global level. 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 India's success in reducing poverty (e.g. Deaton, xxx; Ravallion, XXX, Bhalla, xxx). It appears that India was benefiting from being precisely in the situation where its growth will have the largest absolute impact on poverty.

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 strong support for the assumption of log-normally distributed incomes. On the other hand they show that the use of semi-elasticities instead of elasticities has considerable advantages aside from the fact that semi-elasticities are less prone to misinterpretations. By looking at absolute changes (i.e. percentage point changes) in headcount poverty, poverty gap and squared poverty gap we can increase the number of observations by about 20%. The generation of semi-elasticities needs no additional information and can be achieved by simple modifications of the formulas derived in Kakwani (1993). Besides the use of semi-elasticities leads to very high R2 values even for distributionally sensitive measures like poverty gap and 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.

References

- Adams, Richard H. (2004). Economic Growth, Inequality and Poverty: Estimating the Growth Elasticity of Poverty. *World Development* 32(12): 1989-2014.
- 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.
- 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.
- Kakwani, Nanak (1993). Poverty and Economic Growth with Application to Côte d'Ivoire. *Review of Income and Wealth* 39(2): 121 - 139.
- 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)

<i>Gini</i>	<i>Poverty line as a proportion of mean income</i>									
	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 10
Poverty/Distribution change *elasticity* as a function of mean income and income inequality
(assumption: no change in distribution)

<i>Gini</i>	<i>Poverty line as a proportion of mean income</i>									
	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
(assumption: no change in distribution)

<i>Gini</i>	<i>Poverty line as a proportion of mean income</i>									
	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)

<i>Gini</i>	<i>Poverty line as a proportion of mean income</i>									
	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