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When Is Growth Pro-Poor? Cross-Country Evidence

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Abstract: Growth is pro-poor if the poverty measure of interest falls. According to this definition there are three potential sources of pro-poor growth: (a) a high rate of growth of average incomes; (b) a high sensitivity of poverty to growth in average incomes; and (c) a poverty-reducing pattern of growth in relative incomes. This paper empirically decomposes changes in poverty in a large sample of developing countries during the 1980s and 1990s into these three components. In the medium to long run, most of the variation in changes in poverty can be attributed to growth in average incomes, suggesting that policies and institutions that promote broad-based growth should be central to the pro-poor growth agenda. Most of the remainder of the variation in poverty is due to poverty-reducing patterns of growth in relative incomes, rather than differences in the sensitivity of poverty to growth in average incomes. Cross-country evidence provides relatively little guidance as to the policies and institutions that promote these other sources of pro-poor growth.

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1. Introduction

In the past few years, the term “pro-poor growth” has become pervasive in discussions of development policy. Despite the widespread use of the term, there appears to be much less consensus as to what exactly pro-poor growth means, let alone what its determinants are. According to one view, growth is pro-poor if the accompanying change in income distribution by itself reduces poverty (Kakwani and Pernia 2000). However, this definition is rather restrictive, as it implies that, for example, China’s very rapid growth and dramatic poverty reduction during the 1980s and 1990s was not pro-poor because the poor gained relatively less than the non-poor. A broader and more intuitive definition is that growth is pro-poor if the poverty measure of interest falls. Ravallion and Chen (2003) propose this definition and apply it to a particular poverty measure, the Watts index.

In this paper, I adopt the broader definition, and then apply standard poverty decomposition techniques to identify three potential sources of pro-poor growth: (a) a high rate of growth of average incomes; (b) a high sensitivity of poverty to growth in average incomes; and (c) a poverty-reducing pattern of growth in relative incomes. I implement this decomposition for several poverty measures, using household survey data for a large sample of countries in the 1980s and the 1990s. I then use variance decompositions to summarize the relative importance of these sources of pro-poor growth. Finally, I investigate the correlates of the sources of pro-poor growth in a large panel of observations on changes in poverty.

The main results of this paper are the following. First, regarding the relative importance of the three potential sources of pro-poor growth, I find that roughly half of the variation in short-run changes in poverty can be explained by growth in average incomes. In the medium to long run, between 66 and 90 percent of the variation in changes in poverty can be accounted for by growth in average incomes. Virtually all of the remainder is due to changes in relative incomes. In contrast, cross-country differences in the sensitivity of poverty to growth in average incomes account for very little of the variation in changes in poverty.

Second, I find some evidence that growth in average household survey incomes is correlated with several of the usual determinants of growth from the empirical growth literature, including institutional quality, openness to international trade, and size of government. Although the evidence documented here for the correlates of growth in household survey incomes is not especially compelling, I argue that this likely reflects the limited country coverage and presence of measurement error in the household survey data on which this paper is based.

Third, I find relatively little evidence that poverty-reducing patterns of growth in relative incomes are significantly correlated with a set of explanatory variables that the empirical growth literature has identified as significant determinants of growth in per capita GDP. The same is true for a number of other variables, that while not generally significant for growth, have been suggested in the literature as potentially reducing inequality.

Taken together, these results underscore the importance of growth in average incomes for poverty reduction. This in turn suggests that a policy package focusing on known determinants of growth in average incomes, such as the protection of property rights, stable macroeconomic policies and openness to international trade should be at the heart of pro-poor growth strategies. Moreover, the absence of compelling evidence that these factors are systematically correlated with the changes in income distribution that matter most for poverty reduction suggests that there are no obvious tradeoffs – policies that lead to growth in average incomes are unlikely to systematically result in adverse effects on poverty through their effects on relative incomes.

This does not mean that growth in average incomes is sufficient for poverty reduction. Rather, the results presented here suggest that cross-country evidence is unlikely to be very informative about the policies and institutions that are likely to lead to poverty-reducing patterns of growth in relative incomes. This suggests that more micro-level and case-study research may be useful in shedding light on the determinants of poverty-reducing distributional change.

This paper is related to a growing empirical literature on growth, inequality, and poverty. Most immediately, this paper builds on Dollar and Kraay (2002). In that paper, we defined the poor as those in the bottom quintile of the income distribution, and empirically investigated the determinants of growth in incomes of the poorest quintile. In a large panel of countries, we found that growth in incomes of the poor tracked growth in average incomes roughly one-for-one. Since the growth rate of average incomes of the poor is just the sum of the growth rate of average incomes and the growth rate of the first quintile share, our paper showed that neither average incomes, nor a large set of other control variables, were significantly correlated with changes in the first quintile share. That paper contributed to a growing literature on the determinants of inequality, including Li, Squire and Zhou (1998), Gallup, Radelet and Warner (1998), Spilimbergo, Londono and Szekely (1999), Leamer, Maul, Rodriguez and Schott (1999), Easterly (1999), Barro (2000), Foster and Szekely (2001), and Lundberg and Squire (2003).

This paper differs from Dollar and Kraay (2002), as well as much of the existing literature on determinants of inequality, in two key respects. First, instead of looking at relative poverty measures or inequality, here I focus primarily on changes in absolute poverty measures as the dependent variable.[1] As is well understood, changes in absolute poverty measures are complicated and non-linear functions of underlying changes in average income and income distributions.[2] The second contribution of this paper is to empirically construct the exact measures of distributional change that matter for changes in poverty for a large sample of countries, rather than simply looking at common summary statistics of inequality such as the Gini coefficient or quintile shares. This means that I can empirically study the contributions of growth and distributional change to changes in poverty, without having to make restrictive assumptions about the shape of the underlying income distribution.[3]

Despite these differences, the main conclusions of this paper are similar to those in Dollar and Kraay (2002). In particular, both papers find that growth in average incomes matters a great deal for reductions in both relative and absolute poverty. Both

[1] A notable early exception is Ravallion and Chen (1997), who estimate regressions of changes in absolute poverty on changes in mean incomes using a panel of household surveys from developing countries.
[2] See for example Bourguignon (1999) for a lognormal example.
[3] For example, Lopez (2003) investigates the determinants of growth and change in the Gini coefficient, and then draws conclusions regarding the likely effects on poverty by assuming that the distribution of income is lognormal, so that there is a one-to-one mapping between the Gini coefficient and the Lorenz curve.

papers also find little evidence that common determinants of growth, as well as a number of other variables, are robustly correlated with patterns of distributional change that matter for poverty reduction.

The rest of this paper proceeds as follows. Section 2 reviews standard poverty decomposition techniques and uses them to illustrate the channels through which growth and distributional change matter for changes in a number of poverty measures. Section 3 describes the dataset of changes in poverty in a large sample of developing countries on which the empirical analysis is based. Section 4 provides evidence on the relative importance of the sources of pro-poor growth, as well as evidence on some of the correlates of these sources. Section 5 concludes.

2. Empirical Framework

In this section I use standard techniques to decompose the change in poverty into three components: (a) growth in average incomes; (b) the sensitivity of poverty to changes in average incomes; and (c) changes in relative incomes. Let $y_t(p)$ denote the income of the p^{th} percentile of the income distribution at time t. This can be written as a function of average income, μ_t, and the Lorenz curve, $L_t(p)$, i.e. $y_t(p) = \mu_t \cdot \frac{dL_t(p)}{dp}$. Let P_t denote the following generic additive poverty measure:

$$(1) \qquad P_t = \int_0^1 f(y_t(p)) \cdot dp$$

This notation captures a number of different poverty measures. For example, if $f(y_t(p),\theta) = \left(\frac{z - y_t(p)}{z}\right)^\theta$ up to the headcount, $H_t = y_t^{-1}(z)$ where z is the poverty line, and zero afterwards, we have the Foster-Greer-Thorbecke class which includes the headcount (θ=0), the poverty gap (θ=1), and the squared poverty gap (θ=2). If $f(y_t(p)) = \ln\left(\frac{z}{y_t(p)}\right)$ up to the poverty line and zero afterwards, we have the Watts poverty index. Another possibility is a broader social welfare function without a discontinuity at the poverty line, such as Atkinson's (1970) equally-distributed equivalent income (EDEI). In this case $f(y_t(p)) = y_t(p)^\theta$ for all p, and $P_t^{\frac{1}{\theta}}$ is the poverty measure of interest.

Next, we can differentiate this poverty measure with respect to time to get:[4]

[4] Differentiating under the integral sign in Equation (1) requires the application of Leibnitz's rule. Note that the term involving the derivative of the upper limit of integration is zero, since the poverty measures are zero when evaluated at the incomes of those at the poverty line. For EDEI both the upper and lower limits of integration are constant and so the derivative simply passes through the integral sign.

(2) $$\frac{dP_t}{dt} = \int_0^1 \eta_t(p) \cdot g_t(p) \cdot dp$$

Equation (2) tells us that the rate of change in the poverty measure is the average across all percentiles of the income distribution of the growth rate of each percentile multiplied by the sensitivity of the poverty measure to growth in that percentile. In particular, $\eta_t(p) \equiv \frac{df(y_t(p))}{dy_t(p)} \cdot y_t(p)$ is the semi-elasticity of the poverty measure with respect to the income of the p^{th} percentile. This term captures the effect on poverty of a small change in incomes of individuals at the p^{th} percentile of the income distribution. This sensitivity is multiplied by $g_t(p) \equiv \frac{dy_t(p)}{dt} \cdot \frac{1}{y_t(p)}$, which captures the growth rate of incomes at each percentile of the income distribution. Ravallion and Chen (2003) refer to this function as the "growth incidence curve". The overall change in poverty then consists of the average across all percentiles of the product of these two terms.

In order to separate out the effects of growth in average incomes, we can re-write Equation (2) by adding and subtracting average growth to get:

(3) $$\frac{dP_t}{dt} = \left(\frac{d\mu_t}{dt} \cdot \frac{1}{\mu_t}\right) \cdot \int_0^1 \eta_t(p) \cdot dp \; + \; \int_0^1 \eta_t(p) \cdot \left(g_t(p) - \left(\frac{d\mu_t}{dt} \cdot \frac{1}{\mu_t}\right)\right) \cdot dp$$

Equation (3) identifies the three sources of pro-poor growth that we have been discussing: (a) growth in average incomes; (b) the sensitivity of poverty to growth in average incomes; and (c) growth in relative incomes. The first term in Equation (3) captures the first two sources of pro-poor growth. It consists of growth in average incomes, $\left(\frac{d\mu_t}{dt} \cdot \frac{1}{\mu_t}\right)$, multiplied by a term summarizing the sensitivity of the poverty measure to changes in average incomes, $\int_0^1 \eta_t(p) \cdot dp$. This sensitivity is simply the average across all percentiles of the sensitivity of poverty to growth in each percentile of the income distribution. The second term in Equation (3) captures the remaining source of pro-poor growth: changes in relative incomes. In particular, this third source of propooor growth is the average across all percentiles of the income distribution of the product of (a) the growth rate of income in the p^{th} percentile *relative to average income growth*, and (b) the sensitivity of poverty to growth in that percentile. For example, if the poverty measure of interest is very sensitive to growth among the poorest, and if the income of the poorest grows faster than average incomes, then poverty will fall.

Equation (3) is useful for thinking about the various definitions and sources of pro-poor growth. For example, the Kakwani and Pernia (2000) definition of pro-poor growth states that growth is pro-poor if and only if the second term in Equation (3) is negative, i.e. the pattern of growth in relative incomes is such that the poverty measure falls. A broader definition of pro-poor growth suggested by Ravallion and Chen (2003) is that growth is pro-poor if the poverty measure of interest falls. According to this definition, there are three potential sources of pro-poor growth: (a) rapid growth in average incomes; (b) a high sensitivity of poverty to growth in average incomes; and (c) a poverty-reducing pattern of growth in relative incomes.

In the empirical section of this paper, I will use data on income distributions and average incomes for a large sample of developing countries to construct these three sources of pro-poor growth, document their relative importance, and investigate their determinants. Before doing so, however, it is useful to examine the key ingredients in Equation (3) in more detail: the pattern of growth in relative incomes, $g_t(p)-\left(\frac{d\mu_t}{dt}\cdot\frac{1}{\mu_t}\right)$, and the function summarizing the sensitivity of poverty to growth in each percentile, $\eta_t(p)$.

Figure 1 graphs two examples of the pattern of growth in relative incomes, for China over the period 1990-1998, and for Indonesia over the period 1996-1999. In China, according to the household survey average incomes grew at 14 percent per year, and the dollar-a-day headcount measure of poverty fell from 51 percent to 33 percent of the population. However, there was also a sharp increase in inequality during this period, with the Gini coefficient rising from 34 to 40. The pattern of relative income growth rates shown in the relative growth incidence curve highlights this pattern of increased inequality. Growth in the poorest 80 percentiles of the population was below average growth, while the richest 20 percent of the population saw above-average growth. In Indonesia, survey mean income fell dramatically between 1996 and 1999 at nearly 9 percent per year as a result of the East Asian financial crisis. Yet during this period, the pattern of growth in relative incomes was poverty-reducing. Inequality as measured by the Gini coefficient fell from 36.5 to 31.5. The relative growth incidence curve is downward sloping, indicating that incomes of the richer percentiles of the income distribution fell faster than incomes of poorer percentiles. In fact, below-average growth was recorded only for the richest 20 percent of the population. Despite this pro-poor pattern of relative income growth, the headcount measure of poverty increased from 8 percent to 13 percent of the population, driven by the large negative growth effect.

Consider next the sensitivity of the poverty measure to growth in different percentiles of the income distribution. In the case of the Foster-Greer-Thorbecke class, $\eta_t(p) = -\theta \cdot \left(y_t(p)/z\right) \cdot \left(1 - y_t(p)/z\right)^{\theta-1}$ up to the headcount, and zero afterward. For the Watts index, $\eta_t(p) = -1$ up to the headcount, and zero afterward. Finally, for EDEI, we have $\eta_t(p) = -\theta \cdot y_t(p)^{\theta}$. Note that these sensitivies depend not only on the poverty measure of interest, but also on the entire distribution of income as summarized by $y_t(p)$. Figure 2 graphs these sensitivities, using the actual distribution of income in China in 1990 as an example, to show how different poverty measures are sensitive to growth in different percentiles of the income distribution.

In the case of the headcount, this sensitivity is zero everywhere except just below the poverty line where it spikes down to minus infinity. This is because the headcount simply adds up the number of people below the poverty line – small increases in income of inframarginal poor people that do not bring them above the poverty line will not reduce the headcount. The same is true for increases in incomes of those above the poverty line, including the “near-poor” just above the poverty line. The case of the headcount already illustrates the broader point of Figure 2: whether a given pattern of growth is pro-poor or not depends crucially on the poverty measure of interest. In particular, if pro-poor growth in the sense of reducing the headcount measure of poverty is the objective, then a pro-poor growth strategy should focus exclusively on raising the incomes of those just at the poverty line, and should ignore everyone else.

This strong and slightly absurd conclusion is in part driven by the choice of the headcount as the poverty measure of interest. Consider next the poverty gap and the squared poverty gap. The poverty gap is most sensitive to growth in incomes of those at the poverty line, but is also sensitive to growth in incomes of everyone below the poverty line. The intuition for this is the following: the poverty gap reflects a social welfare function which is indifferent to the distribution of income among poor people. In this case a given rate of average growth results in a larger absolute increase in income for a person near the poverty line, and so the poverty measure is most sensitive to those nearest the poverty line, but is non-zero for all poor people.

The squared poverty gap is also sensitive to growth in the incomes of all those below the poverty line, but the sensitivity is now U-shaped. Growth in incomes of the richest and poorest of those below the poverty line matters least, and the squared poverty gap is most sensitive to growth in incomes of poor people somewhere in between these two extremes. The intuition for this again depends on the underlying social welfare function, which now values absolute transfers from richer to poorer poor people. This however is offset by the fact that a given average growth rate results in a larger absolute increase in income for richer poor people. This is why the sensitivity of the poverty measure to growth is a non-monotonic function of the income percentile.

The Watts index has the property that it is equally sensitive to growth in all percentiles below the poverty line. This is why Ravallion and Chen (2003) argue that a good measure of pro-poor growth is the average (across all percentiles) growth rate of those below the poverty line, i.e. the average growth rate of incomes of the poor. In this paper I go further and decompose the average growth rate of incomes of the poor into growth in average incomes and the average growth rate of the poor *relative* to growth in average incomes. This allows me to distinguish between the effects of growth in average incomes and growth in relative incomes on the Watts measure, and all the other measures considered here. This distinction is not trivial, as we will see in the empirical section of the paper that there is more evidence for the correlates of growth in average incomes than growth in relative incomes.

Finally, when inequality aversion is positive, i.e. $\theta<1$, the EDEI measure is most sensitive to growth in incomes of the poorest, but is non-zero for all income percentiles.

The key difference with the other poverty measures is that there is no longer a discontinuity at the poverty line – growth in all parts of the income distribution matters for poverty reduction, with growth among the poorest mattering most.

To reiterate, the important point of Figure 2 is that poverty measures differ in their sensitivity to growth in different percentiles of the income distribution. As a result, a given pattern of relative income growth might be pro-poor (in the sense that the poverty measure falls) for some poverty measures, but not for others. Moreover, if we take seriously the objective of pro-poor growth with respect to a particular poverty measure, then this requires a growth strategy focusing on particular parts of the income distribution. For example, pro-poor growth with respect to the headcount requires an emphasis on those just below the headcount, while pro-poor growth with respect to EDEI with strong inequality-aversion requires interventions targetted to reaching the poorest of the poor.

Finally consider the average across all percentiles of the sensitivity $\eta_t(p)$ of poverty to growth in incomes of percentile p. Recall from Equation (3) that this average sensitivity measures the effect of growth in average incomes on the poverty measure. We have been referring to high values of this average sensitivity of poverty to growth in average incomes as one of the three potential sources of pro-poor growth. For the Foster-Greer-Thorbecke class of poverty measures, this average sensitivity can be expressed in terms of the poverty measure itself when θ is not equal to zero, $\int_0^1 \eta_t(p) \cdot dp = -\left(P_t(\theta) - P_t(\theta-1)\right)$, where $P_t(\theta)$ denotes the FGT measure with parameter θ.[5] In the case where θ is zero, the sensitivity of the headcount to growth in average incomes is: $\int_0^1 \eta_t(p) \cdot dp = -\frac{L_t'(H)}{\mu \cdot L_t''(H)}$ which can be expressed as the slope of the density of income at the poverty line. For the Watts measure, the average elasticity is simply minus one times the headcount. For EDEI, the sensitivity to average growth is EDEI itself, implying that the elasticity of EDEI with respect to growth in average incomes is one. While these results are useful for analytically characterizing the sensitivity of the different poverty measures to growth in average incomes, we will see shortly that cross-

[5] This result can be found in Kakwani (1993).

country differences in the sensitivity of poverty to growth in average incomes are not empirically very important, in the sense that they explain little of the cross-country variation in the first term in Equation (3). We therefore do not discuss them further here.

3. Data

The objective of the rest of this paper is to use the analytic framework discussed above to decompose observed changes in poverty into the three terms discussed above: (a) growth in average incomes; (b) the sensitivity of poverty to growth in average incomes; and (c) changes in relative incomes. After constructing these three terms for a large sample of developing countries, I use them to identify the relative importance of, and factors correlated with, these various sources of pro-poor growth.

I use household survey data on average incomes and 10 points on the Lorenz curve for a large number of surveys, as compiled by Martin Ravallion and Shaohua Chen at the World Bank. Their data come directly from primary sources, have been meticulously cleaned, and are available at http://www.worldbank.org/research/povmonitor .[6] Depending on the country, the surveys measure either the distribution of income or the distribution of consumption. Average income or consumption is measured in 1993 dollars and is adjusted for cross-country differences in purchasing power parity. Since I am interested in changes in poverty over time, I take only countries with at least two household surveys. This results in a total of 285 surveys covering 80 developing countries. Most of the survey dates are in the 1990s, with some countries extending back to the 1980s. I use the World Bank's "dollar-a-day" poverty line, which in 1993 dollars is $1.08 per day, or $393 per year.

Using these surveys, I construct two datasets of spells of changes in poverty. In the first dataset, I consider all possible spells for each country, discarding only those few cases where the survey changes from an income to an expenditure survey or vice versa. This results in 205 spells of poverty changes. The length of these spells is quite short, averaging 3.5 years and ranging from one to 13 years. In order to be able to look at changes over longer horizons, I also construct a dataset consisting of one spell per country, where the initial and final years are chosen so as to maximize the length of the spell given available data. This results in a set of 80 spells, with an average length of 8.2 years, and ranging from two to 19 years. Finally I eliminate all spells where the headcount measure of poverty is negligible in either the initial or final period, i.e. below 2

[6] I am grateful to Shaohua Chen for kindly providing key data from all of the household surveys, including some that are not available on the poverty monitoring website.

percent, and I also drop a number of spells where the average annual growth rate in the survey mean is implausibly large, i.e. more than 15 percent in absolute value. This reduces the first dataset to 128 spells covering 58 countries with an average length of 3.5 years, and the second dataset to 42 spells with an average length of 9.6 years.

In order to construct the poverty measures and their decompositions discussed in the previous section, I need the full Lorenz curve and not just the 10 points provided in the Ravallion-Chen data. To obtain this, I assume that the Lorenz curve has the following functional form:

$$L(p) = p^{\alpha} \cdot \left(1-(1-p)^{\beta}\right)^{\gamma}, \alpha \geq 0,\ 0 < \beta \leq 1,\ \gamma \geq 1 \tag{4}$$

This particular parameterization is a member of a family of ordered Lorenz curves proposed by Sarabia, Castillo, and Slottje (1999). I estimate the parameters of this Lorenz curve for each survey using an algorithm suggested by the same authors. This involves selecting all possible combinations of three points on the Lorenz curve, and then for each combination finding values of α, β, and γ such that the Lorenz curve passes through these three points. The final estimates of α, β, and γ are then found by averaging across all the resulting estimates of these parameters, discarding those for which the parameter restrictions indicated in Equation (4) that are required for the Lorenz curve to have positive first and second derivatives do not hold. I then obtain the quantile function by analytically differentiating the Lorenz curve and multiplying by average income. Using this, I can immediately construct $\eta_t(p)$ for each poverty measure of interest, as well as the growth incidence curve over the observed discrete interval, $g_t(p) = \frac{y_t(p)}{y_{t-1}(p)} - 1$.

4. Results

I begin by constructing the poverty measures of interest (the headcount, the poverty gap, the squared poverty gap, the Watts index) for the initial and final years of each spell. I then compute average annual changes in these measures, normalizing each by its initial value so as to get proportionate changes that are more easily comparable across poverty measures. Table 1 reports the simple correlations of the levels and average annual growth rates in these poverty measures with the corresponding log-levels and growth rates of survey mean income. These simple correlations are all negative, and are large in absolute value, especially those in levels and those for the long spells. Figure 3 graphs the proportional change in each poverty measure against the growth rate of average incomes, using the sample of long spells. In each case, there is a strong and highly significant negative relationship between changes in poverty and changes in average incomes. There is somewhat more dispersion around this average relationship for the more bottom-sensitive poverty measures such as the poverty gap and the squared poverty gap, than for the headcount measure. However, this may simply reflect the greater sensitivity of bottom-sensitive poverty measures to measurement error in individual incomes, as I argue in more detail below.

Table 1 and Figure 3 confirm the widely-understood empirical regularity that poverty measures tend to fall as average incomes increase. The rest of this section documents the relative importance of the different sources of pro-poor growth discussed above, and some evidence on the correlates of growth in average and relative incomes.

Relative Importance of Sources of Pro-Poor Growth

I now document the relative importance of the three sources of pro-poor growth that we have been discussing. I do this in two steps. I first decompose the change in poverty in each spell into a "growth component" and a "distribution component" using the decomposition suggested by Datt and Ravallion (1992), which is the discrete-time analog of Equation (3). Let $P(\mu_t, L_t)$ denote a poverty measure based on mean income at time t, μ_t, and the Lorenz curve at time t, L_t. I then write the proportional change in the poverty measure over the discrete interval between time t and t-1 as:

(5) $$\frac{P(\mu_t, L_t) - P(\mu_{t-1}, L_{t-1})}{P(\mu_{t-1}, L_{t-1})} = \frac{P(\mu_t, L_{t-1}) - P(\mu_{t-1}, L_{t-1})}{P(\mu_{t-1}, L_{t-1})} + \frac{P(\mu_{t-1}, L_t) - P(\mu_{t-1}, L_{t-1})}{P(\mu_{t-1}, L_{t-1})} + \varepsilon_t$$

The first term on the right-had side is the growth component of the change in poverty, and is constructed as the proportional difference between the initial poverty measure and a hypothetical poverty measure computed using the second period mean but the first period Lorenz curve. The second term is the distribution component which is computed as the proportional difference between the initial poverty measure and a hypothetical poverty measure constructed using the first period mean but the second period Lorenz curve. These two components are the discrete-time analogs of the two terms in Equation (3). Unlike Equation (3), however, there is also a residual term because the decomposition is done over a discrete and not an infinitesmal interval. I measure the proportional changes on the left- and right-hand side of Equation (5) as log differences and normalize by the length of the interval to get average annual percent changes in poverty and its growth and distribution components for each spell.

Tables 2 and 3 report the results of applying this decomposition to the two datasets of spells. Throughout these two tables, I use the following variance decomposition to summarize the relative importance of the various components. If X and Y are two correlated random variables, then I define the share of the variance of X+Y due to variation in X as $\frac{VAR(X) + COV(X,Y)}{VAR(X) + VAR(Y) + 2 \cdot COV(X,Y)}$.[7] The top panel of each table documents the importance of the residual relative to the sum of the growth and distribution components of the change in poverty. The first column shows the variance of the sum of the growth and distribution components, the second column the variance of the residual, and the third the covariance between the two. The final column reports the share of the variance of changes in poverty due to the growth and distribution components, which is virtually one for all poverty measures. This simply reflects the fact that the variance of the residual term is tiny relative to the variance in measured changes in poverty. This can also be verified visually from the top panel of Figure 4, which

[7] When X and Y are normally distributed, this variance decomposition has a very natural interpretation. It tells us how much the conditional expectation of X increases for each unit that we observe the sum (X+Y) to be above its mean value.

graphs the change in poverty on the horizontal axis, and the sum of the growth and distribution components on the vertical axis, using the dataset of long spells. The slope of the OLS regression line is the share of the variance in poverty changes due to the growth and distribution components, and one minus the slope is the share due to the residual term. It is clear from this graph that changes in poverty are largely accounted for by the sum of the growth and distribution components, with very little of the variation due to the residual.

The middle panel of Tables 2 and 3 does the same variance decomposition, but now to assess the importance of the growth component relative to the distribution component of changes in poverty. For the sample of all spells, between one-third and one-half of the variation in changes in poverty is due to the growth component, with the remainder due to changes in distribution. The story is quite different for the long spells, where the growth component of changes in poverty dominates, accounting for between 65 and 90 percent of changes in poverty. In both tables, the growth component is relatively less important for bottom-sensitive poverty measures such as the poverty gap and the squared poverty gap. The middle panel in Figure 4 graphically summarizes this second decomposition for the long spells sample, plotting the growth component of changes in poverty on the vertical axis, and the sum of the growth and distribution components on the horizontal axis. Again, the slope of the OLS regression line can be interpreted as the share of the variation on the horizontal axis due to the growth component. Visually inspecting this graph, it is clear that if poverty reduction is large, it is mostly because the growth component of poverty reduction is large.

The bottom panel of Tables 2 and 3 further disentangles the growth component into growth in average incomes, and the sensitivity of poverty to growth in average incomes, i.e. it separates the first term in Equation (3) into its two components. Since the decomposition we have been using applies to sums of random variables, I take the logarithm of the absolute value of the growth component, which then becomes the sum of the logarithm of the absolute value of growth, and the logarithm of the absolute value of the average sensitivity of poverty to growth, and apply the decomposition to this sum. Tables 2 and 3 show that over 80 percent of the cross-country variation in the growth component of changes in poverty is due to cross-country differences in average income growth, and very little is due to cross-country differences in the sensitivity of poverty to average income growth. The bottom panel of Figure 4 illustrates this, but without the log transform required to do the variance decomposition. On the horizontal axis I graph the growth component of the change in poverty, while on the vertical axis I graph growth in average incomes. While the slope of this regression cannot be interpreted as a variance share, it nevertheless is very clear that cross-country differences in the growth component of poverty are overwhelmingly accounted for by cross-country differences in growth. Put differently, it is clear from this graph that if the growth component of poverty reduction is large, it is most likely that growth itself was large, rather than that the sensitivity of poverty to growth was large.[8]

Two striking features of Tables 2 and 3 merit further discussion: (a) the share of the variance due to growth is smaller over the short horizons represented in the dataset of all spells, and is larger in the dataset of long spells; and (b) in both datasets, the share of the variation in poverty measures due to growth declines as the poverty measures become more bottom-sensitive, for example when we move from the headcount to the poverty gap to the squared poverty gap. We can understand these properties better with the help of a simple example using the EDEI poverty measure. We can write the discrete proportional change in EDEI as:

$$\text{(6)} \qquad \Delta \ln EDEI_t(\theta) = \Delta \ln EDEI_t(1) + \left(\Delta \ln EDEI_t(\theta) - \Delta \ln EDEI_t(1)\right)$$

Recall that EDEI(1) is just average income, and that the sensitivity of EDEI to growth in average incomes is one. As a result, Equation (6) is a way of writing the Datt-Ravallion decomposition for this measure, with the first term corresponding to the growth component and the second to the distribution component. Moreover, the distributional change component of the change in this poverty measure corresponds to the change in

[8] At first glance this result seems inconsistent with Ravallion (1997), who documents that the sensitivity of poverty to growth varies significantly with initial inequality. However, using either sample of spells I can replicate the result that the interaction of growth with the initial Gini coefficient is significantly correlated with the change in headcount measures of poverty. Intuitively, the difference between the results here and those in Ravallion (1997) can be understood as follows: although the interaction of growth with initial inequality is significant in explaining changes in poverty, it does not add much to the explanatory power of the regression in my samples. Put differently, although there are cross-country differences in the sensitivity of poverty to growth which are significantly correlated with initial inequality, in the data these differences are dominated by the much larger cross-country differences in growth itself.

a particular inequality measure: it is simply the proportional change in one minus the Atkinson inequality measure.[9]

For the purpose of this example, assume that the logarithm of household incomes is distributed normally with mean μ_t and standard deviation σ_t. As the number of households in each country becomes large, it is straightforward to see that lnEDEI(θ) converges in probability to $\mu + \frac{\theta}{2} \cdot \sigma^2$.[10] Using this result, we can write the Datt-Ravallion decomposition for EDEI as:

$$(7) \qquad \Delta \ln EDEI_t(\theta) \xrightarrow{p} \Delta\mu_t + \left(\frac{\theta - 1}{2}\right) \cdot \Delta\sigma_t^2$$

Equation (7) is helpful for understanding the two key features of Tables 2 and 3 mentioned above. Suppose that $\Delta\mu_t$ and $\Delta\sigma_t^2$ are independent across countries. Then the share of variance of changes in poverty due to growth with be $V[\Delta\mu_t] / \left(V[\Delta\mu_t] + \left(\frac{\theta - 1}{2}\right)^2 \cdot V[\Delta\sigma_t^2] \right)$. The further θ is from one, i.e. the more EDEI weights incomes of the poor (for θ<1) or the rich (for θ>1), the smaller is the share of the variance of change in poverty due to growth and the larger is the share due to the distribution component. In other words, the more bottom-sensitive (or for that matter, top-sensitive), the poverty measure, the larger will be the contribution of changes in relative incomes to changes in the poverty measure. This suggests an explaination why the share of the variance of changes in poverty due to growth declines as the poverty measures become more bottom-sensitive.

Equation (7) is also helpful for thinking about why the share of the variance of changes in all poverty measures due to growth is smaller in the short run than in the long run. One possible explanation is that measurement error in changes in inequality is

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[9] The Atkinson class of inequality measures is 1-EDEI(θ)/EDEI(1).

[10] This is because EDEI(θ)$^{1/\theta}$ is the sample average of incomes raised to the power θ. As the number of households becomes large, this converges to the expectation of income raised to the power θ. If incomes are lognormally distributed, we can use the moment generating function of the lognormal distribution to evaluate this expectation to obtain the result in the text.

relatively more important than measurement error in changes in average incomes when the period under consideration is short. It is not clear how one might directly document that this is the case. However, it is worth noting that this pattern of relative importance of measurement error seems quite plausible. Suppose for example that in every period, log household income is measured with an additive zero-mean measurement error, which is independent of true incomes and is i.i.d. normal across households. If the number of households is large, this zero-mean measurement error will not be reflected in average income. However, the variance of measured log incomes will now be $\sigma_t^2 + \xi_t^2$, where ξ_t^2 is the variance of measurement error. Suppose further that the variance of measurement error fluctuates randomly over time. As long as the the variance of measurement error does not trend up or down too fast, the average annual change in the distribution component of changes in poverty, $\frac{\theta-1}{2}\cdot\left(\frac{\sigma_t^2-\sigma_{t-k}^2}{k}+\frac{\xi_t^2-\xi_{t-k}^2}{k}\right)$ will be smaller the longer is the time interval, k. While this is not conclusive, it does suggest that part of the reason for the relatively smaller importance of the growth component of changes in poverty over shorter horizons might simply be measurement error in household incomes.

In summary, the results in this subsection tell us that, over longer horizons, between 65 and 90 percent of cross-country differences in poverty changes can be accounted for by growth in average incomes. Over shorter horizons the share of the variance of changes in poverty due to changes in growth is somewhat smaller, and changes in income distribution are relatively more important. However, this may in part be an artifact of measurement error in individual incomes. While there are of course cross-country differences in the sensitivity of poverty changes to average income growth, reflecting cross-country differences in the initial distribution of income, empirically these are relatively unimportant in understanding changes in poverty. Finally, although these calculations are done based on a discrete-time decomposition with unavoidable residuals, empirically these residuals are also small and do not detract from the main conclusions.

What Drives the Sources of Pro-Poor Growth?

I now turn to the question of what drives the various sources of pro-poor growth. In light of the results of the previous section that cross-country differences in the sensitivity of poverty to growth in average incomes are relatively unimportant, I focus primarily on the first and third sources of pro-poor growth: growth in average incomes, and changes in relative incomes. I measure growth in average incomes as the average annual growth rate over the spell of household average income or consumption. I use five different measures of changes in relative incomes. The first is simply the average annual change in the Gini index, for comparability with existing results on the determinants of changes in inequality. The next four measures are the discrete-time distribution components of the change in each of the four poverty measures I have been considering. Recall that, for infinitesmal changes, the distribution component of the change in the headcount measures the growth rate of incomes of those at the poverty line relative to average growth. For the poverty gap and the squared poverty gap, the distribution component measures a weighted average of relative growth rates of those below the poverty line, with the poverty gap giving most weight to those at the poverty line. For the Watts index, the distribution component measures the average growth rate of those below the poverty line relative to overall growth.

There are many limitations to this dataset which make it very difficult to use it to identify causal determinants of growth or change in relative incomes. The sample of countries is quite small, especially when we consider the long spells dataset where the determinants of longer-term growth and distributional change are more likely to be apparent. There is also substantial measurement error in the data on growth in survey means, and for measures of distributional change. While classical measurement error in these dependent variables will not necessarily lead to biases in coefficient estimates, it will inflate standard errors and reduce the significance of estimated coefficients. Because we have relatively few spells per country in the dataset consisting of all spells, and only one per country in the long spells dataset, we cannot meaningfully base identification on the within-country variation in the data. This raises the possibility that any partial correlations we uncover may be driven by unobserved country-specific characteristics excluded from the regressions. The small number of spells per country also means that we will not be able to rely on internal instruments to achieve identification.[11]

In light of these difficulties, my more modest objective here is to simply document the partial correlations between these sources of pro-poor growth and a number of right-hand-side variables of interest, and to interpret them with an appropriate abundance of caution. I consider the same list of right-hand-side variables as in Dollar and Kraay (2002). In that paper, we considered a small number of variables that are frequently found to be robustly correlated with real GDP growth in the cross-country growth literature: institutional quality as proxied by a measure of property rights protection (the "rule of law" indicator from Kaufmann, Kraay and Mastruzzi (2003)) as well as the World Bank's Country Policy and Institutional Assessment (CPIA) indicator; openness to international trade (the constant-price local currency ratio of exports plus imports to GDP); inflation as a proxy for stable monetary policy (measured as the logarithm of one plus the CPI inflation rate); the size of government (measured as the share of government consumption in GDP in local currency units); and a measure of financial development (the ratio of M2 to GDP in local currency units).

We also considered a number of variables that are generally less robustly correlated with growth, but that some studies have found to be correlated with inequality, either in levels or in differences. These include a measure of democracy (the "voice and accountability" indicator from Kaufmann, Kraay and Mastruzzi (2003)); relative productivity in agriculture (measured as the ratio of value added per worker in agriculture relative to overall value added per worker, both in current local currency units); and primary educational attainment.

This list of variables is clearly not an exhaustive list of the potential determinants of growth in average incomes or changes in relative incomes. However, it does provide us with a useful place to begin looking for the correlates of growth and distributional change that matter for poverty reduction. I begin by estimating a number of very

[11] This is of course especially problematic for the regressions below that involve a lagged dependent variable, which, together with unobserved country-specific effects, will make estimates of the coefficient on the lagged dependent variable inconsistent, and can bias the coefficients on the other variables in different directions depending on their correlation with the lagged dependent variable.

parsimonious regressions for each of the dependent variables of interest. I regress growth in average incomes on the log-level of initial period income (to pick up convergence effects) plus each of the control variables described above, one at a time. I do the same for the change in the Gini coefficient, instead including the initial level of the Gini coefficient to pick up convergence in this variable. For the remaining four distribution components of changes in poverty, I simply estimate univariate regressions of each one on each of the right-hand-side variables. [12]

Table 4 shows the results using the sample of all spells, and Table 5 shows the same information but using only the smaller sample of long spells. Each entry in these two tables corresponds to a different regression. The rows correspond to each of the indicated right-hand-side variables. The columns correspond to the different dependent variables. The first two columns report regressions for growth and for the change in the Gini. Both these regressions also include either initial log income or the initial Gini. I do not report the coefficients on these variables to save space, but they generally enter negatively and usually significantly in all specificiations, consistent with available evidence on convergence in both of these variables. The remaining columns report results for the distribution component of the change in each of the four poverty measures. Recall that these measures are oriented such that a reduction corresponds to a reduction in poverty.

A first glance at Tables 4 and 5 show that very few of the explanatory variables of interest are significantly correlated with the dependent variable of interest at conventional significance levels. In fact, in the 108 regressions in these two tables, there is only one coefficient that is significant at the 5 percent level, and only three that are significant at the 10 percent level. One possible explanation for the lack of significant results is that the measures of growth and distributional change on the right-hand-side are contaminated by substantial measurement error. It is difficult to judge however by how much standard errors should be adjusted to reflect this measurement

[12] Ravallion (2001) documents the empirical importance of inequality convergence using the Gini coefficient. I have experimented with alternative initial inequality measures in the regressions involving the distributional change components of the various poverty measures, but I find that none are robustly significant.

error.[13] Rather than try to assess the statistical significance of the partial correlations documented in Tables 4 and 5, I simply describe some of the qualitative patterns that emerge.

Consider first *institutional quality*, as proxied by the rule of law indicator. This tends to be positively correlated with growth, but also positively correlated with each of the measures of distributional change, suggesting that distributional change tends to raise poverty in countries with good institutional quality. However, the strength of the correlation with growth is much larger than the correlations with distributional change: the t-statistic from the growth regression is about twice the average t-statistic for the different measures of distributional change. The *voice and accountability* measure follows the same pattern, likely because it is quite highly correlated with rule of law in this sample.

In the case of *openess to international trade*, the correlation with growth is generally stronger than the correlations with distributional change. Moreover, the sign of the correlation with each of the measures of distributional change is negative, indicating that distributional change tends to be poverty-reducing in countries that trade more. *Inflation* tends to be extremely weakly correlated with growth in this sample, and tends to be positively correlated with distributional change, but again the correlation is very weak. *Government consumption* is negatively correlated with growth, but interestingly is also negatively correlated with each of the measures of distributional change, suggesting that distributional change tends to be pro-poor in countries with larger governments. *Financial development* also appears to be very weakly correlated with either growth or distributional change in these regressions.

Relative productivity in agriculture is essentially uncorrelated with growth, but tends to be positively correlated with distributional change measures. Somewhat surprisingly the sign of the correlation suggests that countries with higher relative productivity in agriculture are more likely to experience poverty-increasing changes in relative incomes. Finally, *primary education* is also virtually uncorrelated with growth,

[13] In Table 4, there is an additional factor which likely biases standard errors upward. For countries with multiple spells of growth or distributional change, there is likely to be by construction a negative correlation between the errors of successive spells. Correcting for this will likely reduce standard errors somewhat.

and also is essentially uncorrelated with most of the distributional change measures, with the exception of the Gini in the long spells regression.

Overall, while most of the partial correlations documented in Tables 4 and 5 are not statistically significant, the qualitative pattern suggests that there may be some tradeoffs. Rule of law is positively correlated with growth but also with poverty-increasing shifts in relative incomes. The opposite is true for government consumption. In contrast trade is positively correlated with growth and with poverty-reducing shifts in relative incomes. In Table 6 we examine these possible tradeoffs in a slightly richer empirical specification, using the dataset of long spells. We begin by estimating a more fully-specified growth regression with initial income, and initial values of institutional quality, trade openness, and size of government as right-hand-side variables. Despite the likely noisiness of the data, it is possible to find plausible specifications in which some of the determinants of growth from the growth literature are also significantly correlated with growth in the household survey mean. The first column of Table 6 illustrates one such regression, which includes initial income, institutional quality, trade openness, and government consumption on the right-hand-side. Each of these variables enters with signs consistent with the broader growth literature. Initial income enters negatively, picking up convergence effects. Institutional quality and trade are both positively correlated with growth, and larger government size is associated with slower growth. I do not want to claim that these results are a robust feature of this particular dataset. However, the results are broadly consistent with the findings of the empirical growth literature, which uses per capita GDP growth rates for a much larger sample of countries, and so it seems reasonable to focus on this particular specification.

In the second column of Table 6, I show the same regression, but instead using the change in the Gini coefficient as the dependent variable. None of the correlates of growth are significantly correlated with changes in this summary statistic of inequality. It is however difficult to move from the results in these first two columns to conclusions about the effects on poverty, without making restrictive assumptions on the shape of income distributions. Since I have already constructed the growth and distribution components of changes in poverty, I can simply use these as dependent variables to investigate how these correlates of growth matter for changes in poverty. The remaining four columns of Table 6 do this for the headcount and for the Watts index. Given the high correlation between the growth components of poverty changes and average income growth documented above, it is not surprising that the regressions for the growth components of poverty are very similar to the growth regression in the first column. Institutional quality, trade, and government size are significantly correlated with the growth components of changes in these two poverty measures, although the significance is slightly less than before. In contrast, I find very little evidence that any of these three variables are significantly correlated with the distribution component of changes in poverty. The only exception is institutional quality, which is significant at the 10 percent level in the headcount distribution component regression. The sign indicates that poverty-increasing distributional change is more likely to occur in countries with better institutional quality.

Despite the general insignificance of the distributional change regressions, it is interesting to quantify the relative magnitudes of the estimated coefficients as well. Since the observed change in poverty is essentially equal to the sum of the growth and distribution components (with a relatively unimportant residual as we have seen), the overall effect on poverty of each of these variables is just the sum of the two coefficients. Figure 5 graphically illustrates the growth and distribution effects of these variables on poverty as measured by the headcount. For Rule of Law, the growth effect lowers poverty, while the distribution effect raises it. The overall net effect is negative, however, since the growth effect is larger in absolute value than the distribution effect. For trade, both the growth and distribution effects reduce poverty, with a much larger growth effect. Finally, the growth and distribution effects work in opposite directions for government size, again with the adverse growth effect dominating the smaller poverty-reducing distribution effect.

Conclusions

What do we learn from all of this? I have used standard decomposition techniques to identify three potential sources of pro-poor growth: (a) a high rate of growth of average incomes; (b) a high sensitivity of poverty to growth in average incomes; and (c) a poverty-reducing pattern of growth in relative incomes. Empirically implementing these decompositions for a large sample of changes in poverty, we have seen that only the first and third sources of pro-poor growth are empirically relevant. Moreover, in the medium to long run, cross-country differences in growth in average incomes are the dominant factor explaining changes in poverty. Together, these decomposition results indicate that the search for pro-poor growth should begin by focusing on determinants of growth in average incomes. At some level, this is an encouraging conclusion, because we have by now a large body of empirical results on the policies and institutions that drive growth in average incomes.

Nevertheless, the empirical results shown here on the correlates of growth and distributional change are rather unsatisfactory. Most of the simple correlations between these dependent variables and a number of right-hand-side variables of interest are quite far from significant at conventional levels, although the balance of the evidence seems to suggest that the correlations with growth are on average somewhat more significant than the correlations with distributional change. It is possible to find multivariate specifications for growth in survey means over longer horizons that yield sensible results consistent with the empirical growth literature. At most, this provides some comfort that the results on partial correlates of growth in survey mean income documented here are more broadly robust and may even have causal interpretations. However, there is much more to be learned about why per capita GDP growth, whose determinants are well-documented, translates so imperfectly into growth in survey means.[14]

In contrast, in this sample it is difficult to find significant correlates of either changes in summary statistics of inequality such as the Gini, or distributional shifts that matter for a variety of poverty measures of interest such as the ones I have constructed here. Moreover, some of the partial correlations with distributional change documented

[14] See for example Deaton (2003) for a discussion of some of the relevant issues.

here do not appear to be consistent with those uncovered in other papers. For example, a number of papers have found that increased openness increases summary measures of inequality, at least in low-income countries (Barro (2000), Lundberg and Squire (2003), Milanovic (2003)). In contrast Dollar and Kraay (2002) find no correlation at all between several measures of openness and income distribution, with and without several interactions. The results here, although not very significant, consistently show that more open countries are more likely to see poverty-reducing shifts in income distribution. This wide range of signs and significance of results from the cross-country literature should caution us against drawing particularly strong conclusions about the determinants of pro-poor changes in relative incomes from any one cross-country study.

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Table 1: Correlations of Poverty Measures and Survey Mean Income or Consumption

	Levels	Growth Rates
All Spells (128 Observations)		
Headcount	-0.842	-0.590
Poverty Gap	-0.727	-0.519
Squared Poverty Gap	-0.615	-0.472
Watts	-0.647	-0.489
Long Spells (42 Observations)		
Headcount	-0.935	-0.717
Poverty Gap	-0.722	-0.672
Squared Poverty Gap	-0.630	-0.635
Watts	-0.651	-0.640

Table 2: Decomposing Changes in Poverty: All Spells

Growth, Distribution and Residual Components of Change in Poverty: dP = G + D + R

Growth and Distribution Components vs Residual (G+D vs R)

	V(G+D)	V(R)	COV(G+D,R)	Share of Variance Due to G+D
Headcount	0.0284	0.0008	-0.0004	0.9859
Poverty Gap	0.0485	0.0010	-0.0004	0.9877
Squared Poverty Gap	0.0702	0.0013	-0.0007	0.9914
Watts	0.0599	0.0010	-0.0005	0.9917

Growth vs Distribution Components (G vs D)

	V(G)	V(D)	COV(G,D)	Share of Variance Due to G
Headcount	0.0168	0.0173	-0.0029	0.4912
Poverty Gap	0.0216	0.0334	-0.0033	0.3781
Squared Poverty Gap	0.0255	0.0517	-0.0035	0.3134
Watts	0.0231	0.0435	-0.0033	0.3300

Average Growth and Sensitivity to Average Growth in Growth Component: $\ln|G| = \ln|d\ln\mu| + \ln|\eta|$

	V(|dlnμ|)	V(|η|)	COV(|dlnμ|,|η|)	Share of Variance Due to |dlnμ|
Headcount	1.1290	0.1577	0.1436	0.8086
Poverty Gap	1.1089	0.1311	0.1202	0.8302
Squared Poverty Gap	1.1073	0.1369	0.1224	0.8259
Watts	1.1021	0.1243	0.1135	0.8364

Table 3: Decomposing Changes in Poverty: Long Spells

Growth, Distribution and Residual Components of Change in Poverty: dP = G + D + R

Growth and Distribution Components vs Residual (G+D vs R)

	V(G+D)	V(R)	COV(G+D,R)	Share of Variance Due to G+D
Headcount	0.0064	0.0005	-0.0004	0.9836
Poverty Gap	0.0120	0.0008	-0.0010	1.0185
Squared Poverty Gap	0.0181	0.0011	-0.0017	1.0380
Watts	0.0148	0.0009	-0.0011	1.0148

Growth vs Distribution Components (G vs D)

	V(G)	V(D)	COV(G,D)	Share of Variance Due to G
Headcount	0.0077	0.0024	-0.0018	0.9077
Poverty Gap	0.0106	0.0046	-0.0016	0.7500
Squared Poverty Gap	0.0129	0.0073	-0.0010	0.6538
Watts	0.0116	0.0063	-0.0015	0.6779

Average Growth and Sensitivity to Average Growth in Growth Component: $\ln|G| = \ln|d\ln\mu| + \ln|\eta|$

	$V(\|d\ln\mu\|)$	$V(\|\eta\|)$	$COV(\|d\ln\mu\|,\|\eta\|)$	Share of Variance Due to $\|d\ln\mu\|$
Headcount	1.3228	0.1642	0.1402	0.8278
Poverty Gap	1.2836	0.1492	0.1131	0.8419
Squared Poverty Gap	1.2765	0.1527	0.1114	0.8401
Watts	1.2702	0.1414	0.1025	0.8491

Table 4: Correlates of Pro-Poor Growth: All Spells

	Dependent Variable Is:		Distribution Component of Change in:				
	Growth	Change in Gini	P0	P1	P2	Watts	# Obs
RHS Variable is:							
CPIA	0.006	-0.001	-0.007	-0.007	-0.008	-0.009	121
	0.920	0.160	0.477	0.354	0.310	0.360	
KK Rule of Law	0.012	0.002	0.016	0.019	0.023	0.019	128
	1.339	0.292	0.766	0.674	0.633	0.568	
Trade/GDP	0.017	-0.017	-0.034	-0.038	-0.041	-0.041	126
	1.120	1.431	0.990	0.805	0.692	0.757	
ln(1+Inflation)	0.001	0.006	0.039	0.039	0.039	0.037	116
	0.059	0.323	0.790	0.566	0.449	0.474	
Government	-0.154	-0.053	-0.421	-0.488	-0.507	-0.532	125
Consumption/GDP	1.206	0.515	1.539	1.250	1.041	1.192	
M2/GDP	0.015	-0.008	-0.024	-0.013	-0.002	-0.010	124
	0.638	0.431	0.475	0.182	0.028	0.130	
KK Voice and	0.002	0.006	0.003	0.004	0.004	0.002	128
Accountability	0.294	0.891	0.194	0.150	0.153	0.086	
Relative Productivity	-0.005	0.017	0.053	0.060	0.065	0.061	126
in Agriculture	0.271	1.200	1.324	1.106	0.969	0.994	
Average Years of	0.003	0.002	-0.006	-0.007	-0.008	-0.010	101
Primary Education	0.538	0.649	0.534	0.477	0.410	0.576	

Note: Heteroskedasticity-consistent t-statistics reported below coefficient estimates.

Table 5: Correlates of Pro-Poor Growth: Long Spells

	Dependent Variable Is:		Distribution Component of Change in:				
	Growth	Change in Gini	P0	P1	P2	Watts	# Obs
RHS Variable is:							
CPIA	0.005	0.001	0.001	0.004	0.006	0.005	40
	0.555	0.267	0.143	0.282	0.336	0.315	
KK Rule of Law	0.024	0.007	0.022	0.022	0.021	0.020	42
	1.726	0.950	1.583	1.100	0.861	0.864	
Trade/GDP	0.035	-0.006	-0.008	-0.014	-0.019	-0.015	42
	1.656	0.497	0.364	0.441	0.482	0.423	
ln(1+Inflation)	-0.002	0.003	-0.005	-0.023	-0.038	-0.031	39
	0.073	0.258	0.196	0.681	0.896	0.778	
Government	-0.110	-0.033	-0.225	-0.278	-0.327	-0.327	42
Consumption/GDP	0.742	0.421	1.526	1.350	1.256	1.357	
M2/GDP	-0.028	-0.016	-0.053	-0.048	-0.045	-0.045	42
	0.663	0.722	1.205	0.783	0.572	0.618	
KK Voice and	0.021	0.008	0.013	0.011	0.101	0.009	42
Accountability	1.659	1.231	1.049	0.646	0.462	0.438	
Relative Productivity	0.013	0.021	0.044	0.050	0.054	0.056	42
in Agriculture	0.543	1.388	1.513	1.277	1.105	1.217	
Average Years of	-0.001	0.008	0.004	0.006	0.008	0.006	32
Primary Education	0.063	2.601	0.638	0.521	0.558	0.475	

Note: Heteroskedasticity-consistent t-statistics reported below coefficient estimates.

Table 6: Multivariate Growth and Distributional Change Regressions

	Annual Percent Change in: Survey Mean	Annual Percent Change in: Gini	Annual Percent Change in Headcount: Growth Component	Annual Percent Change in Headcount: Distribution Component	Annual Percent Change in Watts Index: Growth Component	Annual Percent Change in Watts Index: Distribution Component
Initial Income	-0.017	-0.008	0.037	-0.018	0.040	-0.023
	1.978	1.470	1.769	1.409	1.577	1.284
KK Rule of Law	0.022	0.009	-0.046	0.029	-0.049	0.029
	2.050	0.919	2.188	1.785	2.108	1.221
Trade/GDP	0.045	-0.011	-0.060	-0.007	-0.077	-0.011
	1.978	0.911	1.659	0.361	1.667	0.310
Government	-0.280	-0.048	0.600	-0.244	0.667	-0.330
Consumption	2.229	0.425	2.114	1.010	2.124	1.175
R-Squared	0.239	0.095	0.263	0.182	0.222	0.103
# Observations	42	42	42	42	42	42

Note: Heteroskedasticity-consistent t-statistics reported below coefficient estimates.

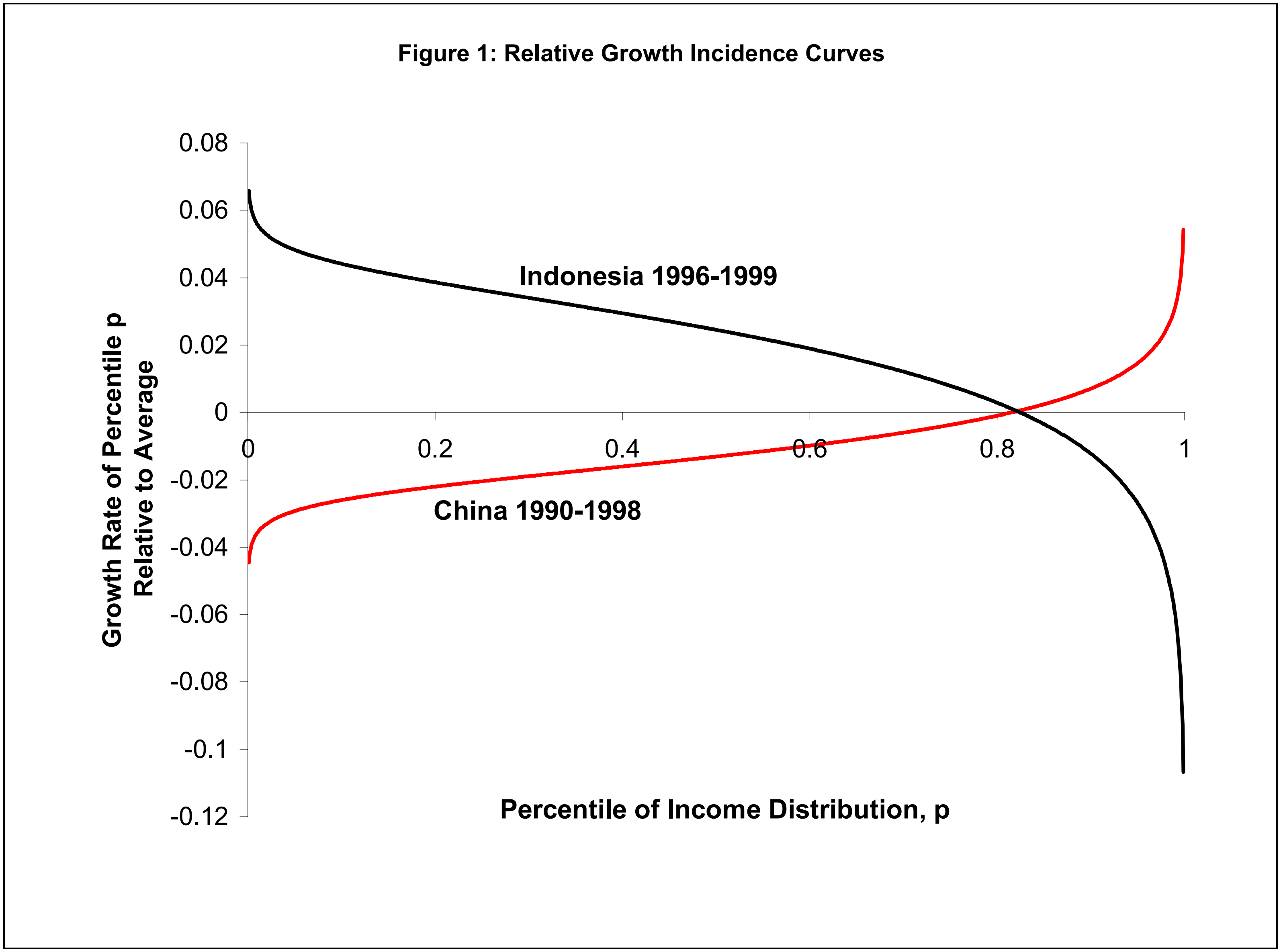
Figure 1: Relative Growth Incidence Curves
0.08
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
0
0.2
0.4
0.6
0.8
1
Indonesia 1996-1999
China 1990-1998
Growth Rate of Percentile p Relative to Average
Percentile of Income Distribution, p

Figure 2: Sensitivity of Poverty to Growth in Percentile p

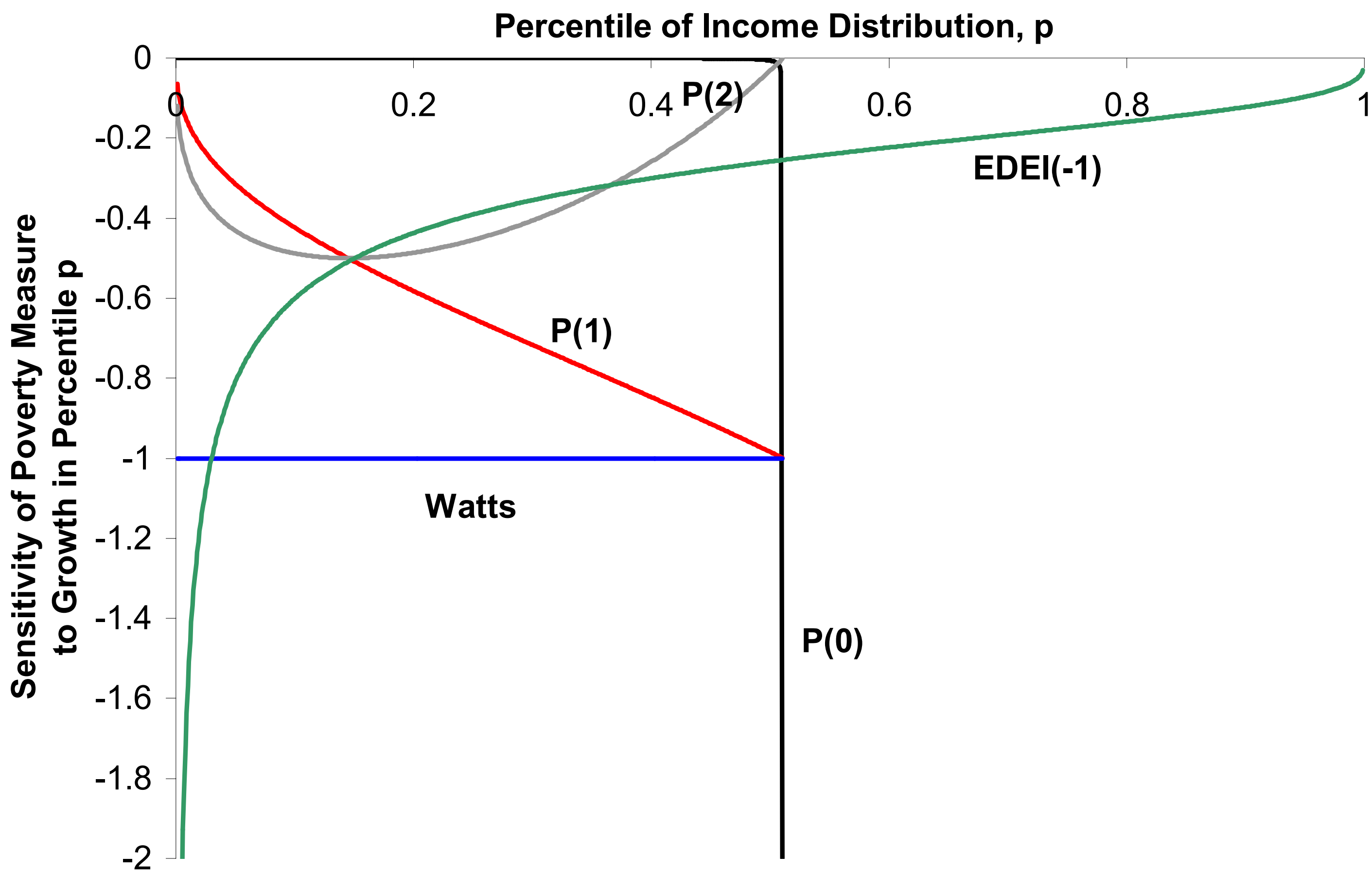

Figure 3: Growth and Poverty Reduction: Long Spells

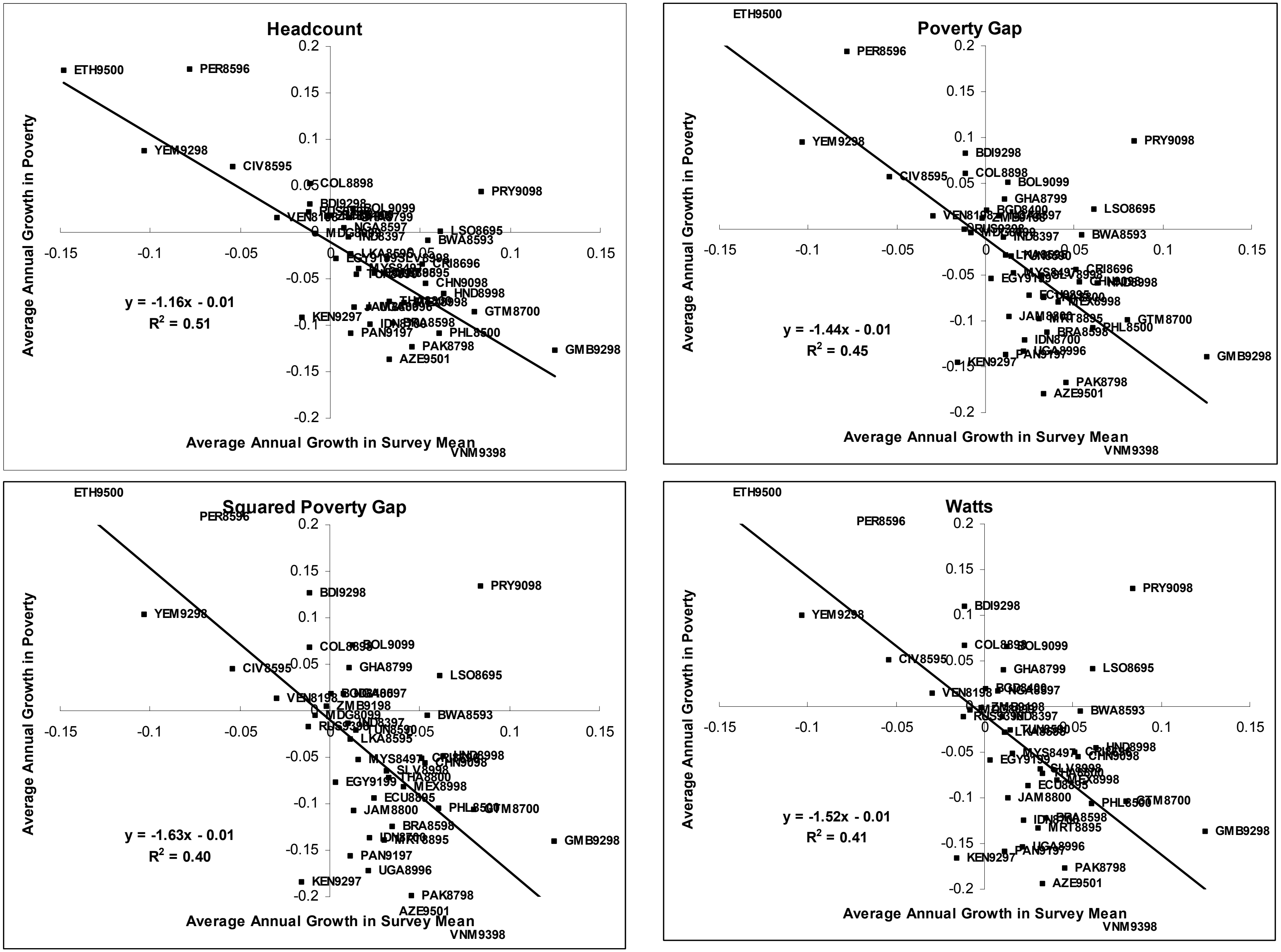

Figure 4: Decomposing Changes in the Headcount

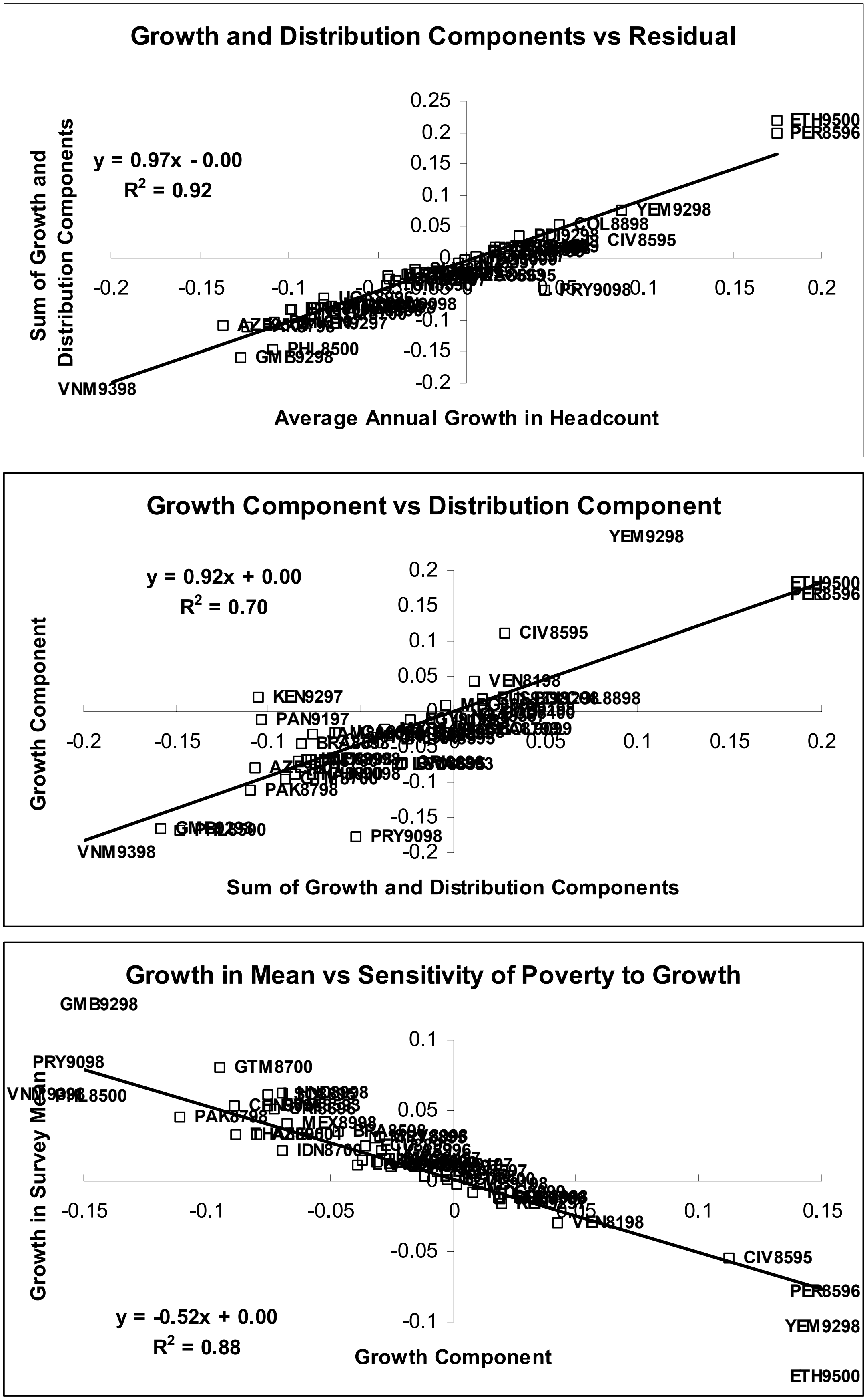

Figure 5: Policies and the Growth and Distribution Components of Changes in Policy