Accelerating Poverty Reduction in a Less Poor World: The Roles of Growth and Inequality

Pedro Olinto (World Bank)

Jaime Saavedra (World Bank)

Gabriel Lara-Ibarra (World Bank)

Paper Prepared for the IARIW-IBGE Conference
on Income, Wealth and Well-Being in Latin America

Rio de Janeiro, Brazil, September 11-14, 2013

Session 12: Distribution Dynamics

Time: Friday, September 13, 4:00-5:30

Accelerating Poverty Reduction in a Less Poor World: The Roles of Growth and Inequality

Pedro Olinto[1]

Jaime Saavedra[1]

Gabriel Lara-Ibarra[1]

Keywords: Income growth, inequality, elasticity of poverty, Arellano Bond estimator

JEL Codes: I32, O15

Sector Boards: POV, EPOL

Prepared for presentation at the

IARIW-IBGE Special Conference on Income, Wealth and Well-being in Latin America

September, 2013

[1] World Bank

Abstract

This paper re-examines the roles of changes in income growth and inequality on poverty reduction. The study provides estimates on the relative effects of inequality reduction versus growth promotion in reducing poverty for countries with different levels of initial poverty. Using country panel-data for the 1980-2010 period, the results indicate that, as countries become less poor, inequality-reducing policies are likely to become relatively more effective for poverty reduction than growth promoting policies. In line with other studies, the results indicate that the growth elasticity of poverty reduction (GEPR) either increases or remains constant with the level of initial poverty. Nevertheless, the results also strongly indicate that, as countries become less poor, the inequality elasticity of poverty reduction (IEPR) increases faster than GEPR. Therefore, if the marginal cost of reducing inequality relative to the marginal cost of increasing growth does not increase with lower poverty levels, the results suggest that to accelerate poverty reduction, greater emphasis should be given to equity rather than growth as countries attain higher levels of development.

1. Introduction

The world has become considerably less poor in the past three decades. In 1981, more than half of citizens in the developing world lived on less than \$1.25 a day. This rate has dropped dramatically to 22 percent in 2010. Moreover, despite a 35 percent increase in global population, there are slightly fewer people living on less than \$1.25 a day today (1.3 billion) than there were three decades ago (1.8 billion). Progress is undeniable and most likely the downward trend of poverty has continued after 2010. But 2.5 billion people living in poverty (measured at US\$ 2 dollars a day) and 1.3 in abject poverty are still extremely high figures.

It is widely accepted that economic growth has been the main driver of poverty reduction in the past three decades. In one study, Kraay (2005) finds that growth in average incomes accounts for more than 95 percent of the observed poverty reduction. Other estimates find that two thirds of the drop in poverty is the result of growth, with the other third coming from greater equality[2]. However, despite the past performance of growth in reducing poverty, can we continue to rely mostly on growth to achieve significant poverty reduction in the future? Or, as countries become less poor, should we increasingly shift the focus to inequality reducing policies to further accelerate poverty reduction?

To answer these questions we need to know what happens to the *inequality elasticity of poverty reduction* (IEPR) relative to the *growth elasticity of poverty reduction* (GEPR) as countries become less poor. If relative to IEPR, GEPR increases with the level of development, strategies relying almost exclusively on economic growth are probably justified. But if the IEPR to GEPR ratio increases with lower levels of poverty, faster poverty reduction will likely be obtained with a greater emphasis on policies that reduce inequality.

Several studies have aimed at estimating GEPR solely or jointly with IEPR. For instance, Ravallion and Chen (1997) place the GEPR at around 3, while World Bank (2000) provides estimates closer to 2. Others have recognized the importance of initial conditions on these elasticity. Ravallion (2004) highlights the negative relationship between initial inequality and the (absolute) value of the GEPR, whereas Bourguignon (2003) shows that the GEPR is an increasing function of a country's level of development.

---

[2] The Economist "Not Always with us" June 1st, 2013

After not being able to reject the hypothesis that incomes are distributed log-normally in most countries, Lopez and Serven (2004) relies on this assumption to show that the theoretical values of IEPR are positive and increasing with the level of development and decreasing with the initial level of income inequality. They also show that GEPR increases with decreasing levels of poverty. Fosu (2011) provides empirical estimates for both the GEPR and the IEPR and find evidence in line with the theoretical predictions by income log-normality: the higher the level of development, the higher the estimated GEPR and IEPR; whereas the higher the level of inequality, the lower the IEPR.

This paper aims to contribute to the literature on the potential relative roles of growth-enhancing and inequality-reducing policies for poverty reduction. We focus on providing estimates on the relative importance of inequality and growth in reducing poverty for countries that face different initial poverty rates. In addition to the analyzing more recent data than the previous studies, we focus on estimating and testing what happens with the IEPR to GEPR ratio as poverty declines.

Also, we employ an empirical strategy that does not rely on a priori assumptions about the parametric form of the income distribution. That is, our empirical strategy allows for the fact that the mean income and the Gini coefficient may not completely define the income distribution and the poverty rate in a country. While this would be the case if incomes were log-normally distributed, and there is a strand in the literature that shows the relative good fit of the assumption of log-normality (e.g., Lopez and Serven, 2004 and Bourguignon 2003), we see no reason to rely on this assumption. That is, we allow for situations in which poverty may not decline when growth occurs and the Gini coefficient remains constant. This would be the case if the Gini is not a good statistic to describe the shape of the distribution at the very end of the left tail. Thus, to take into account the potential effect of initial poverty levels on GEPR and IEPR, we explicitly model how initial values of poverty affect the estimated elasticities.

Overall, we find strong evidence supporting the view that, as poverty declines, inequality reduction should increasingly become the focus of policies aimed at accelerating poverty reduction. That is, our results strongly suggest that the IEPR to GEPR ratio is increases when poverty rates fall. In our results, this pattern is mostly due to the positive and decreasing relationship between the IEPR and poverty rates found in the estimation of all different specifications tried. On the other hand, the relationship between GEPR and poverty does not show a clear pattern. While some specifications show the negative relationship between the (absolute) value of GEPR and poverty rates found in the literature, other specifications cannot reject the hypothesis of no relationship between GEPR and different initial poverty levels.

The rest of the paper is structures as follows. Section 2 presents a review of the literature. Section 3 describes our empirical approach and section 4 the data used in the estimations. Section 5 contains the results found and section 6 concludes.

2. A brief review of the literature

There are several studies that aim at estimating the relationship between income growth and poverty reduction, as well as the implications for the focus of policy design and implementation. While the literature on this topic is plentiful, here we present a brief review of studies that are most relevant for our analysis. We refer the reader to Lopez and Serven (2006) for an overview of these and other related literature.

Bourguignon (2003) emphasizes the relevance of the identity relating poverty, inequality and (mean) income growth. By assuming that the income distribution can be fairly described as a log normal, he derives formulae for the theoretical growth elasticity of poverty reduction as well as for the inequality elasticity of poverty reduction. Under this assumption, poverty measures can be described by using two parameters: the level of development[3] and a measure of dispersion such as the standard deviation of the income distribution or the Gini index. He shows that income, and inequality changes, as well as the initial levels of development and inequality have a statistical strong relationship with the evolution of poverty. However, the explanatory power of all these measures is lower than the theoretical income elasticity of poverty based on the log normal assumption. He interprets this finding as evidence of the log normality being a good empirical approximation of the income distribution. Epaulard (2003) also calculates a “neutral elasticity of poverty rate” to test the validity of the log normality assumption. She fails to reject the hypothesis of log normality.

[3] Measured using the ratio of the poverty line ($1/day) and mean income.

In turn, Lopez and Serven (2006) present an alternative test of the log normality of the income distribution. They calculate the theoretical income share quintiles based on the assumption of log normality and test whether they are good predictors for the empirical quintiles found in the data. Using three different income measures they fail to reject the hypothesis that there is a one to one relationship between the theoretical and empirical quintiles.[4] Relying on the log normality assumption, the authors calculate theoretical values of income elasticity of poverty and inequality elasticity of poverty for a range of possible values of economic development (measured as mean income over the poverty line) and Gini indexes. They show that initial inequality hampers poverty reduction by decreasing both GEPR and IEPR. Initial poverty seems to be a factor in how growth is translated into poverty reduction. For a given poverty line, growth impacts poverty more in richer countries than in poorer ones. Finally, the relationship between inequality and IEPR is nonlinear. In general, inequality lessens the IEPR, but at very low levels of development this relationship is reversed. These findings imply, for example, that for poorer countries, the poverty-reducing effects of growth outweigh the poverty-raising effects of a worsening distribution of income.

Fosu (2011) uses a comprehensive dataset of countries spanning through 30 years to obtain empirical estimates of the GEPR and IEPR. Relying on the assumption of log normality shown in previous studies, the author estimates a fully specified equation to explain changes in poverty. His model includes income growth, inequality growth, as well as their interactions with the lagged Gini coefficient and development (the log of the ratio of the poverty line and mean income). The lagged variables are also included. The study also addresses the panel structure of the data and estimates the parameters in the econometric model via fixed effects, random effects, and, finally, General Method of Moments (GMM) to address the potential endogeneity of the income growth regressors. The author shows strong evidence that the responsiveness of poverty to income changes in larger in countries with higher incomes or lower initial inequality. The IEPR is shown to be positive and increasing with the level of development.

Notwithstanding these results, the assumption of log normality on income (and its implications) may not be guaranteed. Bourguignon (2003) empirically rejects the hypothesized value of log normality for the IEPR, and Lopez and Serven (2006) also reject the hypothesized value for

[4] The test is soundly rejected when consumption measures are used.

GEPR when measures of net income or expenditures (as opposed to mean income over the poverty line?) are used in their empirical estimations. Moreover, the assumption of lognormality implies other testable predictions on the relationship of other poverty measures and income and inequality growth. Bourguinon (2003) rejects these predictions for the poverty gap. Implicitly, Allwine *et al.* (2012) also provide evidence against the predictions of log normality. They simulate the changes in poverty that countries would have experienced should initial conditions of income and inequality would have been the same across all countries. They compare the observed value of a series of poverty reduction measures to the simulated measures to fully quantify the impact of initial conditions (and any underlying nonlinear effects) on poverty changes. Contrary to other studies, they find evidence of a significant negative relationship between initial average income and poverty reduction performance.

To analyze the relative roles of inequality and income growth, we abstract ourselves from the assumption of log normality of income. While this assumption allows the definition of closed-form solutions for poverty measures of interest based only on two parameters, we choose to model the evolution of poverty rate as a function of the growth in income, inequality and lagged values of the poverty. We now turn to our empirical approach.

3. Empirical Model and Estimation Strategy

To estimate the growth and inequality elasticities of poverty reduction, we begin by specifying the headcount rate (*H*) as a function of the country's mean income (*y*), the inequality of the income distribution as expressed by the Gini index (*G*), and disturbance terms. As shown in Bourguignon (2003), if incomes were distributed log-normally, headcount poverty would be a function solely of *y* and *G*. That is, $H = g(y, G)$. However, because we do not assume log-normality, we allow for disturbance terms in *g*(.) to account for the fact that *G* may not describe the shape of the distribution completely, and that we use a linear approximation for *g*(). That is, we specify the following log-linear model for headcount poverty for a given country *i* at year *t*:

$$\ln(\mathrm{H}_{it}) = \beta_1 ln(y_{it}) + \beta_2 ln(G_{it}) + \alpha_i + t \cdot \alpha_i + \varepsilon_{it}. \quad (1)$$

In (1), β_1 is the average GEPR and β_2 is the average IEPR. The disturbance term α_i captures the effects of all the time invariant characteristics of country *i* (e.g., geography, natural resources availability, history, etc.) on its deviations from the conditional mean $E[\ln(\mathrm{H}_{it})|\, ln(y_{it}), ln(G_{it})]$. We also allow for the possibility that these country-specific effects impact poverty trends via $t \cdot \alpha_i$, and that there are other time variant and country specific disturbances around $E[\ln(\mathrm{H}_{it})|\, ln(y_{it}), ln(G_{it})]$ captured by ε_{it} in (1).

As it is conventionally done in the literature, we take first differences to (1) and obtain:

$$\Delta \ln(\mathrm{H}_{it}) = \beta_1 \Delta ln(y_{it}) + \beta_2 \Delta ln(G_{it}) + \alpha_i + \Delta\varepsilon_{it} \tag{2}$$

If we were only interested in estimating average GEPR and IEPR, OLS estimation of the parameters in (2) would be consistent under the identification assumption that $E[\alpha_i + \Delta\varepsilon_{it}|ln(y_{it}), ln(G_{it})] = 0$. But it is reasonable to expect that country unobserved characteristics (i.e. system of laws and other institutions, geography, history, etc.) may affect its easiness to conduct business and promote growth; at the same time, such laws may provide a good environment for economic upward mobility and opportunities to escape poverty. In that case the assumption that $E[\alpha_i + \Delta\varepsilon_{it}|ln(y_{it}), ln(G_{it})] = 0$ is too strong.

A weaker assumption is that $E[\Delta\varepsilon_{it}|ln(y_{it}), ln(G_{it})] = 0$, but $E[\alpha_i|ln(y_{it}), ln(G_{it})]$ is allowed to be non-zero. This takes into account the effects of time-invariant country characteristics as described above. Under this weaker identification assumption, fixed-effects estimation would be consistent.

However, as it has been recognized in the literature, GEPR and IEPR may be functions of past levels of poverty (Bourguignon, 2003; Fosu 2011; Lopez and Serven, 2004). For instance, under log-normally distributed incomes, GEPR and IEPR are by definition functions of a country's level of initial poverty.[5]

To allow for these relationships between GEPR and IEPR and initial (or lag) poverty we specify the following model for the disturbance term $\Delta\varepsilon_{it}$:

$$\Delta\varepsilon_{it} = \delta_0 \ln\,(H_{i,t-1}) + \delta_1 \Delta ln(y_{it}) \cdot \ln\big(H_{i,t-1}\big) + \delta_2 \Delta ln(G_{it}) \cdot \ln\big(H_{i,t-1}\big) + \mu_{it} \tag{3}$$

Thus, we rewrite equation (2) as:

[5] In this context, initial poverty is typically specified as a linear projection of lag Gini and the lag of the ratio of average income to the poverty line. Under log-normality these two statistics are completely define lag poverty.

$$\Delta\ln(\mathrm{H}_{it}) = \beta_1\Delta ln(y_{it}) + \beta_2\Delta ln(G_{it}) + \delta_1 \ln\left(H_{i,t-1}\right) + \delta_1\Delta ln(y_{it}) \cdot \ln\left(H_{i,t-1}\right) + \delta_2\Delta ln(G_{it}) \cdot \ln\left(H_{i,t-1}\right) + \alpha_i + \mu_{it} \quad (5)$$

Given the parameters in (5), the growth elasticity of poverty reduction and the inequality elasticity of poverty reduction now depend on the past level of poverty and are given by:

$$GEPR = \beta_1 + \delta_1 \cdot \ln\left(H_{i,t-1}\right) \quad (6)$$

$$IEPR = \beta_2 + \delta_2 \cdot \ln\left(H_{i,t-1}\right) \quad (7)$$

While equation (6) is expected to be negative for all values of $H_{i,t-1}$, the sign of (7) may vary with the initial level of poverty. To see this, consider a country in which 90 percent of its citizens are poor ($H_{i,t-1} = .9$) and the few non-poor are just above the poverty line. In this case, a decrease in inequality is likely to be obtained by redistributing income from (taxing) the few non-poor, and throwing then into poverty, while not lifting anyone above the poverty line. In this case, IEPR would be negative.

The signs for δ_1 and δ_2 cannot be unambiguously determined, unless one is willing to assume a parametric form for the distribution of income. For instance, under the assumption that incomes are distributed log-normally, lower poverty levels imply in larger GEPR in absolute value. Therefore, $\delta_1 > 0$. For δ_2, log-normality implies that its sign will change depending on whether poverty is above or below a threshold level.

But while the assumption of log-normal incomes is commonly not rejected by many empirical studies, observers might entertain the hypothesis that δ_1 is negative for low enough levels of poverty. For instance, growth may not have any impact on poverty in a country with low levels of poverty and in which the poor are concentrated in isolated pockets of the population such as hard-to-reach rural areas[6]. That is, changes in average incomes may not have an impact on poverty if most of the poor are concentrated in areas that are disconnected from markets and isolated form public services networks.

[6] For example, Dorosh and Malik (2006) study the case of Pakistan and Gakuru and Mathenge (2012) run a simulation model for Kenya showing that sectoral growth mainly benefit the richest households.

Likewise, in such situations of low poverty levels and where poverty is concentrated in a few pockets, it is reasonable to expect that targeted interventions that reduce the disparities between the poor and the rest of society would increasingly become more effective than overall growth in reducing poverty. Therefore, under such scenario we would expect that $\delta_2 > 0$ and that the ratio IEPR/(-GEPR) would increase, indicating the increasingly greater impact of reducing inequality relative to increasing growth in poverty reduction.[7]

Under the assumption that $E\left[\alpha_i + \mu_{it} \middle| ln(y_{it}), ln(G_{it}), \ln\left(H_{i,t-1}\right)\right] = 0$ OLS estimation of the parameters in (5) will be consistent. However, under the weaker assumption that $E\left[\mu_{it} \middle| ln(y_{it}), ln(G_{it}), \ln\left(H_{i,t-1}\right)\right] = 0$, such that $E\left[\alpha_i \middle| ln(y_{it}), ln(G_{it}), \ln\left(H_{i,t-1}\right)\right]$ is allowed to be non-zero, fixed-effect estimation will not be consistent as in the case of estimation of (2). This is because $\ln\left(H_{i,t-1}\right)$ is correlated with μ_{it-1} by definition, which makes it correlated with the within transformation μ_{it} by construction.

We therefore estimate equation (5) using the Arellano-Bond (AB, 1991) estimator to control for country fixed effects. The estimator uses an instrumental variables approach where second (and further) lags are used as instruments for the covariates of the differenced version of equation (5) [8]. Making the (testable) assumption that the errors μ_{it} are serially uncorrelated[9], the AB estimator for dynamic models is consistent.

4. Data

We use the comprehensive dataset available at PovCalNet from the World Bank as of January 2013.[10] The unit of observation is country-year. This dataset contains information on poverty measures, inequality (as measured by the Gini coefficient), and mean income for over 100 countries. Poverty and inequality measures are based on comparable household surveys and mostly based on consumption rather than income. We include in our analysis countries that have

[7] We write IEPR/(-GEPR) because GEPR is usually negative but we would like to focus on the relative magnitudes of the impacts of growth and inequality in poverty reduction.
[8] In our estimations we also present results using only one lag as instrument. This approach was proposed by Anderson and Hsiao (1981).
[9] This assumption implies that $\Delta\mu_{it}$ are correlated with $\Delta\mu_{i,t-1}$. At the same time $\Delta\mu_{it}$ will not be correlated with $\Delta\mu_{i,t-s}$ for $s \geq 2$ and thus subsequent lags of the dependent variable are valid instruments (Cameron and Trivedi, 2009).
[10] http://iresearch.worldbank.org/PovcalNet/index.htm

data available for at least two surveys. The data spans from 1980 to 2011.[11]. The mean income measure refers to the average monthly income in 2005 prices and at Purchasing Power Parity (PPP) following World Bank (2008). Given data availability, our dataset is an unbalanced panel with "spells" (i.e. time gap between two observations for the same country) ranging from one to 15 years.. The growth rate of country *i* between time period *t* and time period *t - d* for measure *x* is calculated as $gr(x_{it}) = ln\ (x_{it} / x_{it-d}\ )$. While we focus on one measure of poverty, the headcount index (H), we will estimate equation (5) for three poverty lines as they help answer different questions. One analysis is performed using the updated $1 / day poverty line, that is, a $1.25 /day at 2005 PPP. A second set of results are obtained for the $2 / day poverty line. This line is a better representation of poverty standards in developing and transition countries.[12] Finally, we present results for headcount rates for a $4/day poverty line, closer to moderate poverty lines in middle income countries. . Summary statistics for the spells and for all regions included in the regressions are presented in Table 1.

As noted in Ravallion (2012), we are cautious about the inclusion of countries in the Eastern Europe and Central Asia (EECA) region. These countries "started their transitions from socialist command economies to market economies with very low poverty rates, but poverty measures then rose sharply in the transition." Their experience is clearly not typical of the developing world. We take a conservative approach and present results both including and excluding countries from this region.

5. Results

Table 2 presents the results from the estimation of the model of interest. The left panel presents the results for the headcount rate based on a poverty line of $1.25 a day. The middle and right panels present the results for the $2 and $4 a day poverty lines, respectively. In each panel, the first two columns present results using all the countries in our dataset, whereas the last two

[11] Appendix table A1 presents the distribution of observations by region and data availability. In our analysis, we include all countries with mean income, headcount rate and Gini coefficient data available. The total number of countries available is 102. Our preferred measure of welfare is consumption. Thus, if a country had headcount rates data available for both income and consumption we keep only the consumption-based measure. These countries include Mexico, Jamaica, Nicaragua, and Peru. An Excel version of our dataset is available from the authors upon request.

[12] This line is the median poverty line found in Ravallion *et al.* (2009).

columns present results excluding countries from the EECA region. Finally, we present results using either all available lags of the endogenous variables or one lag.

As expected, the growth in income is found to have a negative effect on poverty in all specifications. This effect is statistically significant in most cases. Also as expected, increased inequality seems to have a positive and significant effect on the poverty across all specifications.

The results indicate that the relationship between GEPR and the initial level of poverty (captured by $\hat{\delta}_1$) depends on the poverty line used. For a headcount rate based on a $1.25/day poverty line, there is no evidence that GEPR varies with the level of poverty. That is, growth seems to have the same impact on poverty reduction in countries with high and low (extreme) poverty rates as defined by the conventional $1.25/day poverty line.

Using a $2/day poverty line, we find that there is a negative relationship between GEPR and the level of poverty only when EECA region countries are excluded from the estimation sample. Similarly, for the $4/day poverty line, there seems to be negative relationship between GEPR and poverty rates in both samples. Therefore, for these higher poverty lines, the results indicate that the relationship between GEPR and initial poverty is consistent with the log-normality assumption. That is, other things equal, growth seems to have a larger impact on poverty reduction in the countries with lower poverty rates.

For all poverty lines and all estimation samples, the results indicate that IEPR decreases with the level of poverty (i.e.$\hat{\delta}_2 < 0$). That is, a one percent reduction in the Gini index will have a larger impact on poverty reduction in countries with less poverty.

We now turn the analysis of the relative roles of inequality and income growth and how these vary at different levels of poverty. We illustrate these relationships by calculating the estimated ratio of IEPR to GEPR at different poverty rates in figures 1 and 2. Figure 1 presents the estimated IEPR, GEPR[13] and associated ratio based on the results obtained using the full sample of countries available and one lag as the instrument set. Figure 2 presents the corresponding results when countries from the EECA region are excluded from the regressions. Given the

[13] For a simple interpretation we present the negative of the growth elasticity of poverty reduction.

potential problems with the data from the EECA region countries, our preferred estimates are those shown in figure 2.

As shown in figure 2, for all three poverty lines, as poverty levels decrease the ratio of IEPR to GEPR increases with the level of initial poverty. Note also that the estimated IEPR and the ratio are negative for poverty rates above 80 percent. Also, for poverty rates below 50 percent the ratio is above 1 indicating that IEPR is larger than the estimated GEPR. The elasticity of inequality increases at a faster rate when poverty rates are based on the $1.25/day and $2/day poverty line than for the $4/day line. That is, the ratio appears flatter across different poverty levels for the $4 poverty line.

5.1 Elasticities based on a bootstrap

To check if our results are driven by specific countries or time spells, we re-estimate our models using bootstrapped samples. We do not rely on an arbitrary choice of time periods for the sample used in the estimations. Instead we randomly draw 300 three-year-per-country bootstrap samples and re-estimate equation (5). Table 3 presents the results from these estimations via OLS (shown in panel A), fixed effects (panel B) or the Arellano-Bond estimator (panel C). As in our previous estimates, we provide results for the three poverty lines of interest ($1.25, $2, and $4). Finally, we also present results where we include the full sample of countries available and results not including countries from the EECA region.

We find extremely similar patterns across all estimations methods and the results are in line with our previous findings using all available data. Both GEPR (in absolute terms) and IEPR seem to increase with lower levels of poverty.

5.2 Are these findings in line with previous studies?

Our results on the IEPR/GEPR ratio suggest that as countries succeed in reducing poverty, further poverty reduction will likely need to rely less and less on growth and more on inequality reduction. But what have previous studies suggest in terms of the relationship between the IEPR/GEPR ratio and poverty?

Figure 3 depicts the simulated inequality and income elasticities of poverty reduction if we would use the data from Bourguignon (2003). The patterns found are similar to the ones found in our analysis. There are two main differences, however. First, the estimated values of the elasticities seem to increase at a faster pace as poverty rates change. The estimated value of GEPR goes from approximately 1 to close to 4 when poverty rates are close to 50 and zero, respectively. Increases in the IEPR are more prominent.

To complement our results, we rerun Bourguignon (2003) specification using our data. Specifications are run via Ordinary Least Squares and Fixed Effects for $1.25 and $/day poverty lines. The results are presented in the appendix (tables A2-A5). We find similar results across all specifications. Income (Gini) growth has a negative (positive) effect on poverty growth. We also find that both IEPR and (absolute) GEPR are decreasing with poverty, albeit the slopes of the estimated elasticities are more modest. A second difference is that under log normality the IEPR is defined to be negative for all poverty rates above 50 percent. In our results we find that this is not the case for a non-negligible range of poverty rates: 50 – 80 percent. While we recognize that our estimations are not intended to be a formal test of the log normality assumption, it is worth pointing out that such an assumption may be too restrictive in the analysis of elasticities of poverty.

6. Conclusions

Growth has been the main driver of poverty reduction in the past three decades. Will growth continue to deliver poverty reduction in the future as it has in the past? Our results indicate that the impact of growth in reducing poverty will continue to be important and likely to increase.

However, relative to inequality reduction, the role of growth may be diminished in the future. Our results indicate that as poverty declines, the inequality elasticity of poverty reduction increases faster than the growth elasticity. That is, the IEPR/GEPR ratio increases with lower levels of poverty.

As poverty has been declining on a sustained basis for many more countries, one can expect that to further accelerate poverty reduction, increased emphasis should be given to inequality reducing policies versus growth promoting policies.

This is not to say that direct income re-distribution should have an increasing role, as, depending on their magnitude, and specific characteristics such policies may be even harmful for growth and eventually for sustained poverty reduction. Nevertheless, few would disagree that policies that are consistent with less inequality through equalizing opportunities and promoting social inclusion should be emphasized and will be key in significantly accelerating poverty reduction.

References

Allwine, M., Rigolini, J., and Lopez-Calva, L.F. (2012) "The Unfairness of (Poverty) Targets" Mimeograph

Arellano, Manuel and Bond, Stephen (1991) "Some Tests of Specification for Panel Data: Mone Carlo Evidence and an Application to Employment Equations" *The Review of Economic Studies,* 58 (2): 277-97.

Bourguignon, François (2003) "The growth elasticity of poverty reduction: explaining heterogeneity across countries and time periods", Chapter in Inequality and Growth Theory and Policy Implications, Theo S. Eicher and Stephen J. Turnovsky (Eds.) MIT Press

Cameron, Colin A. and Trivedi, Pravin (2005) "Microeconometrics. Methods and Applications" Cambridge University Press.

Cameron, Colin A. and Trivedi , Pravin (2009) "Microeconometrics using Stata" STATA Press.

Dorosh, Paul A. and Malik, Sohail L. (2006) "Transitions Out of Poverty: Drivers or Real Income Growth for the Poor in Rural Pakistan" Annual Meeting of International Association of Agricultural Economists http://purl.umn.edu/25387 (accessed 06/14/13)

Epoulard, Anne (2003) "Macroeconomic Performance and Poverty Reduction" IMF Working Paper 03/72

Fosu, Augustin Kwasi (2011) "Growth, Inequality, and Poverty Reduction in Developing Countries" UNU-WIDER Working Paper No. 2011/01

Gakuru, Rhoda and Mathenge, Naomi (2012) "Poverty, Growth, and Income Distribution in Kenya: A SAM Perspective", AGRODEP Working Paper 0001, June.

Lopez, J. Humberto "Pro-poor growth: a Review of What We Know (and of What We Don't)" Mimeograph.

Lopez, J. Humberto and Servén, Luis (2006) "A Normal Relationship? Poverty, Growth, and Inequality" World Bank Policy Research Working Paper 3814.

Ravallion, Martin (2012) "Why Don't We See Poverty Convergence?", *American Economic Review,* 102 (1): 504- 23.

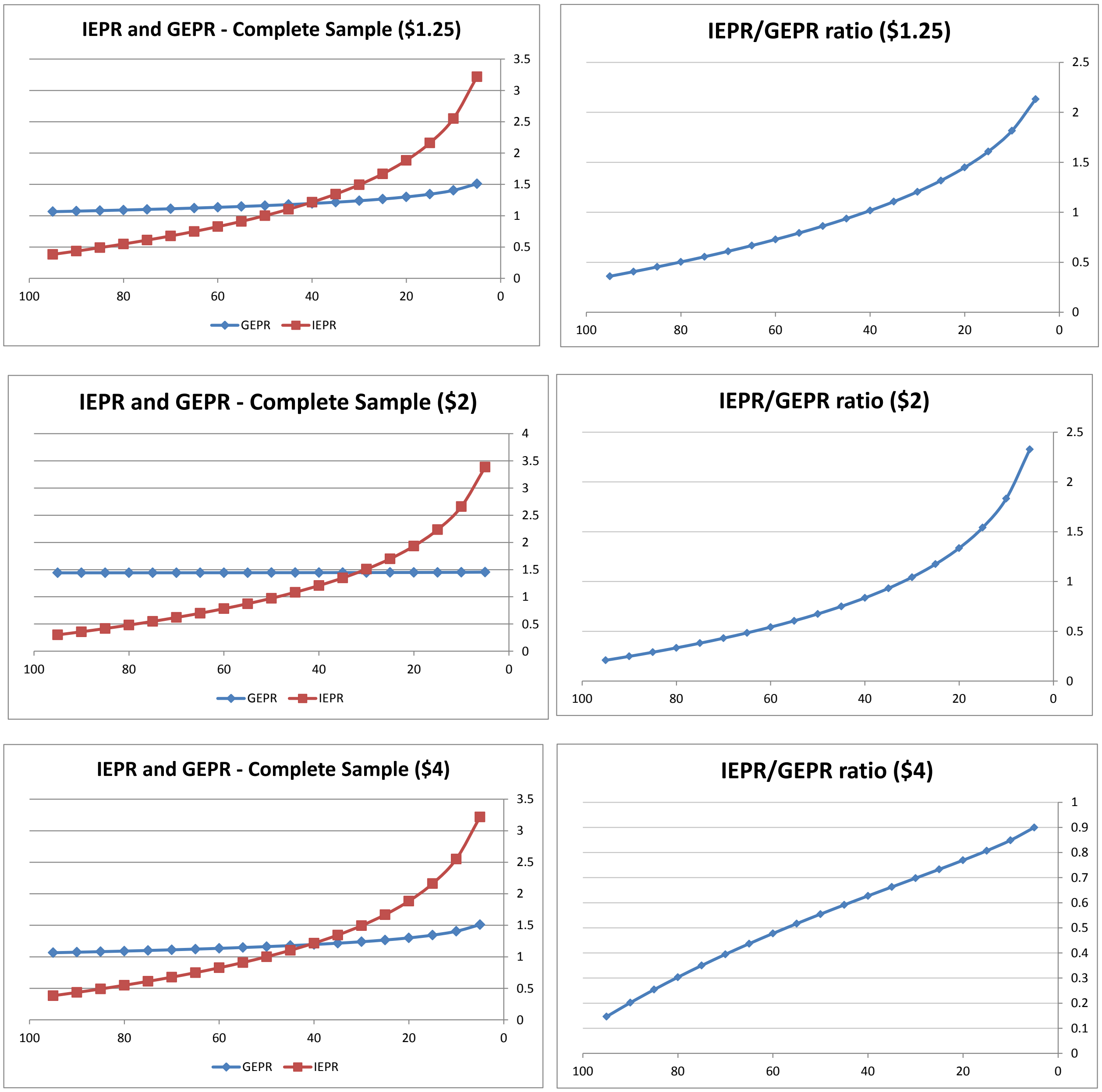
Ravallion M., and Chen, S. (1997) "What can new survey data tell us about recent changes in distribution and poverty?" The World Bank Economic Review" 11:357-382

Ravallion, M., Chen, S. and Sangraula, P. (2009) "Dollar a Day Revisited" *World Bank Economic Review,* 23 (2) : 163-184.

World Bank (2000) “Attacking Poverty, World Development Report 2000/2001” Oxford: Oxford University Press.

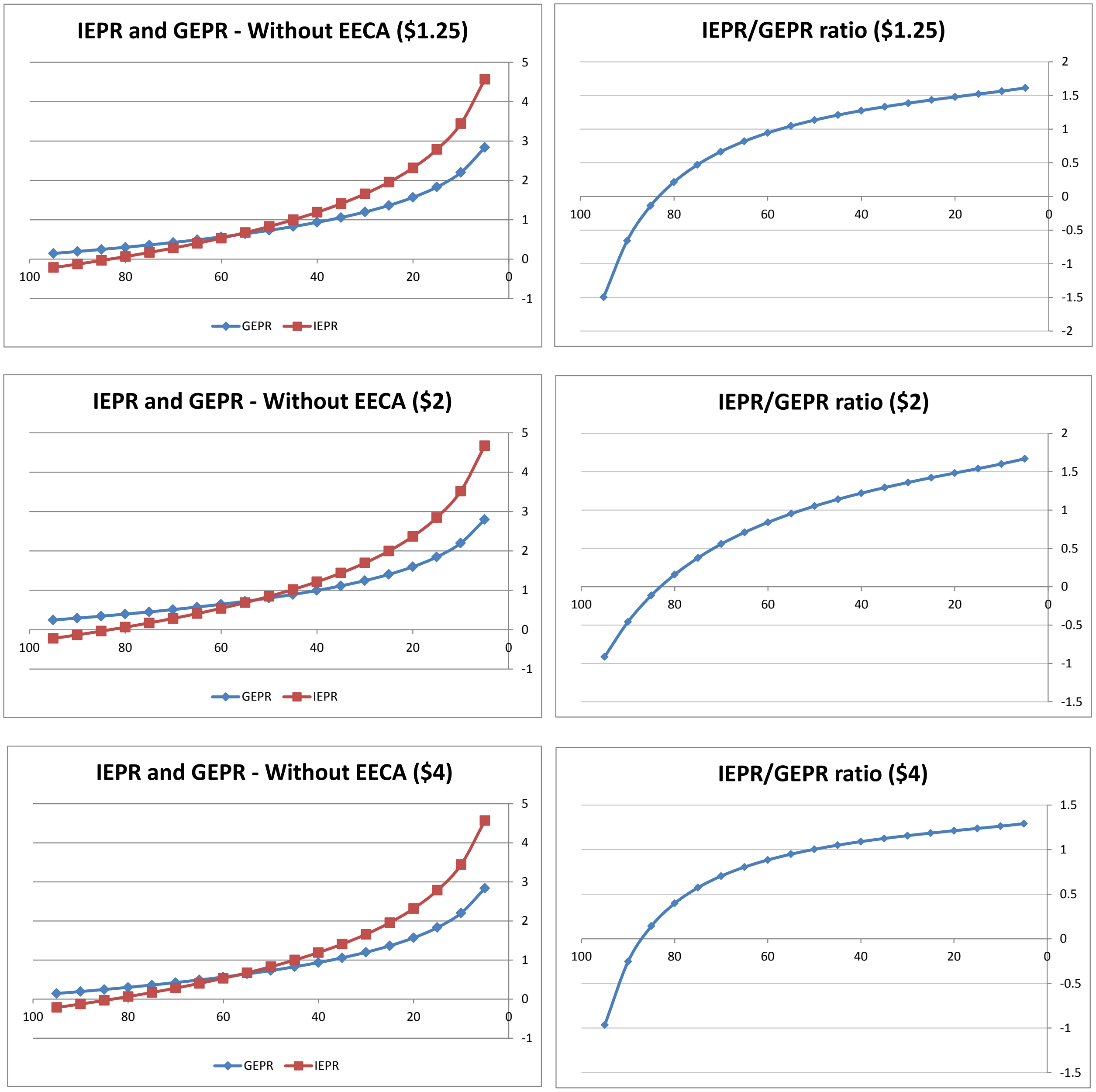
World Bank (2008) “Global Purchasing Power Parities and Real Expenditures. 2005 International Comparison Program.” Washington, DC: World Bank.

Figure 1. Simulated elasticities using estimates from the full sample, by poverty line



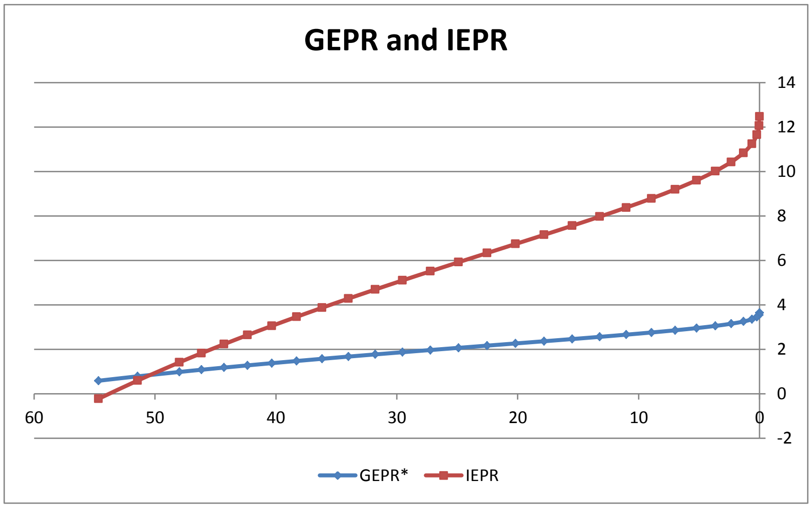
Notes: Graphical representation of Arellano Bond estimates using 1 lag as instrument. IEPR stands for Inequality Elasticity of Poverty Rate, GEPR refers to the Income Elasticity of Poverty Rate. Headcount rate is depicted in the horizontal axis.

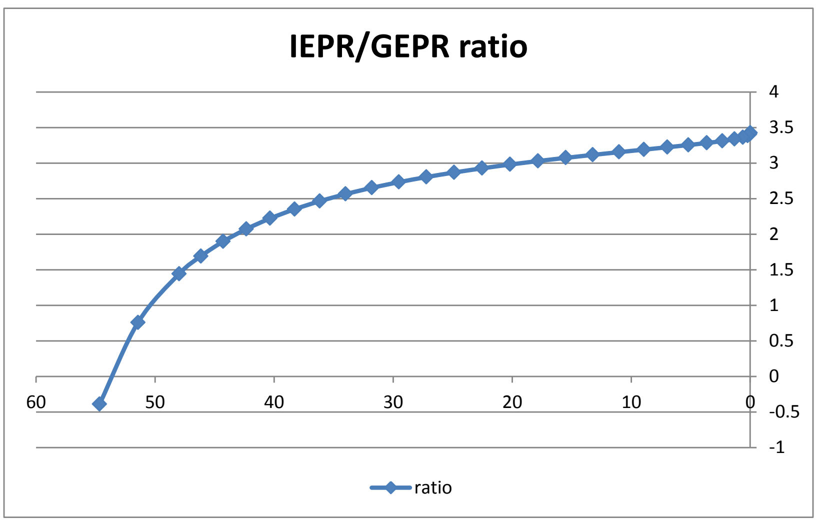
Figure 2. Simulated elasticities using estimates from sample without EECA countries, by poverty line



Notes: Graphical representation of Arellano Bond estimates using 1 lag as instrument. IEPR stands for Inequality Elasticity of Poverty Rate. GEPR refers to the Income Elasticity of Poverty Rate. Headcount rate is depicted in the horizontal axis.

Figure 3. Simulated elasticities using Bourguignon (2003) results





Notes: IEPR stands for Inequality Elasticity of Poverty Rate, GEPR refers to the Income Elasticity of Poverty Rate. A $1.25 /day poverty rate is depicted in the horizontal axis. The simulations assume a Gini index equal to the median in the estimations' sample (42.62).

Table 1. Summary Statistics

Region	*Variable*	*Mean*	*Std Dev*
East Asia and Pacific (N=68)	HC ($4)	74.97	23.41
	HC ($2)	49.11	28.21
	HC ($1.25)	27.54	21.57
	Mean Income	114.18	82.82
	GDP p/capita	3638.51	2788.54
	Gini	39.91	6.72
Eastern Europe and Central Asia (N=226)	HC ($4)	32.3	29.08
	HC ($2)	11.31	17.17
	HC ($1.25)	4.21	8.72
	Mean Income	247.66	135.57
	GDP p/capita	8310.5	4726.18
	Gini	33.15	5.5
Latin American and Caribbean (N=289)	HC ($4)	42.68	16.53
	HC ($2)	19.69	12.42
	HC ($1.25)	10.6	8.74
	Mean Income	253.28	97.2
	GDP p/capita	6974.57	2740.14
	Gini	51.89	5.57
Middle East and North Africa (N=34)	HC ($4)	55.41	17.63
	HC ($2)	17.89	10.7
	HC ($1.25)	4.47	4.64
	Mean Income	156.04	48.23
	GDP p/capita	4507.6	1695.83
	Gini	38.12	4.38
South Asia (N=31)	HC ($4)	92.76	8.02
	HC ($2)	71.29	19.18
	HC ($1.25)	42.24	20.89
	Mean Income	58.48	23.37
	GDP p/capita	1701.13	946.59
	Gini	33.22	4.67
Sub Saharan Africa (N=129)	HC ($4)	88.68	13.88
	HC ($2)	70.26	21.2
	HC ($1.25)	50.6	22.72
	Mean Income	70.82	64.56
	GDP p/capita	2017.37	2998.4
	Gini	45.31	8.69

Source: Authors' calculations using data from PovCalNet and WDI. HC refers to the Headcount rate based on $1.25, $2, or $4 a day. Mean Income is the average monthly income obtained from survey data. Mean income and GDP per capita are expressed in 2005 PPP US dollars.

Table 2. Estimates of Elasticity of Poverty

	Dependent Variable: Change in Log Headcount Rate											
	Poverty Rate based on $1.25/day				Poverty Rate based on $2/day				Poverty Rate based on $4/day			
VARIABLES	Complete Sample [1]	No EECA countries [2]	Complete Sample [3]	No EECA countries [4]	Complete Sample [5]	No EECA countries [6]	Complete Sample [7]	No EECA countries [8]	Complete Sample [9]	No EECA countries [10]	Complete Sample [11]	No EECA countries [12]
Change in Log(Mean Income)	-1.611***	-1.753***	-3.623	-4.306***	-1.357***	-1.461**	-4.030***	-4.193***	-3.506***	-3.671***	-4.722	-5.039***
	(0.523)	(0.450)	(2.717)	(0.571)	(0.524)	(0.673)	(0.810)	(0.283)	(0.353)	(0.384)	(3.971)	(0.491)
Change in Log(Mean Income) *times* Lagged Log HC Rate	0.0850	0.151	0.724	0.914***	0.00068	0.0045	0.840***	0.867***	0.640***	0.672***	1.005	1.077***
	(0.179)	(0.162)	(0.655)	(0.154)	(0.161)	(0.198)	(0.191)	(0.0680)	(0.0856)	(0.103)	(0.982)	(0.107)
Change in Log(Gini)	4.861***	4.769***	6.695	7.185***	4.880***	5.069***	6.322	7.345***	2.702*	3.555***	5.790	6.669***
	(1.530)	(1.106)	(4.210)	(1.404)	(1.402)	(1.316)	(4.544)	(1.533)	(1.415)	(1.116)	(3.871)	(1.065)
Change in Log(Gini) *times* Lagged Log HC Rate	-1.027***	-0.963***	-1.514	-1.625***	-1.047***	-1.047***	-1.402	-1.662***	-0.546	-0.761***	-1.282	-1.493***
	(0.343)	(0.296)	(1.030)	(0.354)	(0.362)	(0.346)	(1.166)	(0.402)	(0.376)	(0.279)	(0.888)	(0.250)
Lag Log Headcount Rate	-0.211	-0.240**	-0.167	-0.134	-0.0672	0.0233	-0.0746	-0.0223	-0.0274	0.00626	-0.0363	-0.0297
	(0.183)	(0.119)	(0.130)	(0.0870)	(0.114)	(0.0926)	(0.215)	(0.0412)	(0.0812)	(0.0443)	(0.535)	(0.0506)
Constant	0.305	0.380*	0.391	0.303	0.163	-0.0764	0.223	0.0548	0.103	-0.0246	0.136	0.108
	(0.325)	(0.214)	(0.355)	(0.221)	(0.300)	(0.245)	(0.703)	(0.140)	(0.298)	(0.160)	(2.092)	(0.204)
Observations	630	630	449	449	653	653	454	454	662	662	456	456
Number of countries	100	100	73	73	101	101	73	73	102	102	74	74
Number of lags used as IV	All available	1 lag	All available	1 lag	All available	1 lag	All available	1 lag	All available	1 lag	All available	1 lag
Test of zero autocorrelation in errors (p-value):												
Order (1)	0.003	0.0007	0.0205	0.0086	0.0021	0.0013	0.009	0.003	0.038	0.03	0.1288	0.0094
Order(2)	0.943	0.998	0.276	0.254	0.726	0.702	0.67	0.4437	0.526	0.55	0.461	0.1174
Sargan test (p-value)	1.00	0.813	1.00	0.97	1.00	0.99	1.00	0.99	1.00	0.97	1.00	0.98

Notes: Results based on author's calculations using the two-step GMM Arellano Bond estimator. Covariates interacted with the lag of log headcount rate and the lag of log headcount rate are instrumented. Column headers indicate the dependent variable. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0. HC stands for Headcount. The next to last row presents the p-value of the test of zero autocorrelation in the first-differenced errors. The null hypothesis of the test for order (k) is that $Cov(\Delta\mu_{it}, \Delta\mu_{i,t-k}) = 0$. Sargan test row shows the p-value of a test of overidentifying restrictions where the null hypothesis is that the overidentifying restrictions are valid.

Table 3. Bootstrapped coefficients using 3-year-per-country random samples

A. OLS estimations

	$1.25		$2.00		$4.00	
VARIABLES	Full	No EECA	Full	No EECA	Full	No EECA
Change in Log(Mean Income)	-2.43***	-4.06***	-2.82***	-4.33***	-4.01***	-5.05***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Change in Log(Mean Income) *times*Lagged Log Headcount Rate	0.26***	0.76***	0.42***	0.87***	0.78***	1.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Change in Log(Gini)	4.11***	6.56***	4.22***	7.38***	3.66***	5.98***
	(0.06)	(0.09)	(0.07)	(0.07)	(0.08)	(0.06)
Change in Log(Gini) *times* Lagged Log Headcount Rate	-0.80***	-1.47***	-0.87***	-1.65***	-0.79***	-1.32***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Lagged Log Headcount Rate	0.02***	0.04***	0.02***	0.03***	0.01***	0.05***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Countries	88	61	88	61	88	61

B. FE estimations

	$1.25		$2.00		$4.00	
VARIABLES	Full	No EECA	Full	No EECA	Full	No EECA
Change in Log(Mean Income)	-1.69***	-3.24***	-1.92***	-3.79***	-3.41***	-4.75***
	(0.03)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Change in Log(Mean Income) *times*Lagged Log Headcount Rate	0.18***	0.64***	0.28***	0.77***	0.67***	1.00***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Change in Log(Gini)	2.95***	4.82***	2.69***	6.21***	2.50***	5.38***
	(0.07)	(0.11)	(0.08)	(0.09)	(0.1)	(0.08)
Change in Log(Gini) *times* Lagged Log Headcount Rate	-0.56***	-1.05***	-0.53***	-1.38***	-0.52***	-1.18***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Lagged Log Headcount Rate	-0.52***	-0.38***	-0.54***	-0.24***	-0.28***	-0.12***
	(0.009)	(0.011)	(0.01)	(0.01)	(0.012)	(0.008)
Countries	88	61	88	61	88	61

Table 3 (continued). Bootstrapped coefficients using 3-year-per-country random samples
C. AB estimations

	$1.25		$2.00		$4.00	
VARIABLES	Full	No EECA	Full	No EECA	Full	No EECA
Change in Log(Mean Income)	-2.76***	-4.42***	-3.15***	-4.94***	-4.47***	-5.53***
	(0.05)	(0.07)	(0.06)	(0.28)	(0.13)	(0.95)
Change in Log(Mean Income) *times*Lagged Log Headcount Rate	0.34***	0.89***	0.48***	1.02***	0.88***	1.19***
	(0.02)	(0.02)	(0.02)	(0.08)	(0.03)	(0.23)
Change in Log(Gini)	4.53***	5.68***	5.97***	8.09***	6.35***	9.80***
	(0.11)	(0.17)	(0.13)	(0.92)	(0.3)	(4.65)
Change in Log(Gini) *times* Lagged Log Headcount Rate	-0.92***	-1.22***	-1.34***	-1.82***	-1.43***	-2.18***
	(0.03)	(0.04)	(0.03)	(0.22)	(0.07)	(1.06)
Lagged Log Headcount Rate	0.20***	0.04***	0.30***	0.09***	0.26***	-0.01
	(0.016)	(0.012)	(0.019)	(0.03)	(0.022)	(0.119)
Countries	88	61	88	61	88	61

Source: Authors' calculations using PovCalNet data. Each column presents the mean and standard deviation (in parenthesis) of coefficients obtained from 300 regressions using 3-year per country draws of available data. Panel A results are obtained via OLS regressions. Panel B results are obtained via Fixed Effects (FE) and Panel C results are obtained using the Arellano-Bond (AB) estimator. Each regression also contained a constant. Column headers describe the poverty line used to calculate the poverty rate and the sample of countries used. Standard deviations in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix

Table A1. Countries in PovCalNet by region and years with complete data

Years Available	*EAP*	*EECA*	*LAC*	*MENA*	*SAS*	*SSA*	Countries
2	2	1	2	2	1	6	14
3	0	3	0	0	0	6	9
4	2	1	1	0	2	9	15
5	0	3	0	4	1	3	11
6	1	1	0	0	0	2	4
7	0	2	2	1	0	2	7
8	1	3	1	0	2	0	7
9	3	2	0	0	0	1	6
10	0	4	2	0	0	0	6
11	0	2	1	0	0	0	3
12	0	2	0	0	0	0	2
13	1	1	3	0	0	0	5
14	0	2	2	0	0	0	4
15	0	1	0	0	0	0	1
16	0	0	3	0	0	0	3
18	0	0	1	0	0	0	1
21	0	0	1	0	0	0	1
22	0	0	1	0	0	0	1
23	0	0	1	0	0	0	1
26	0	0	1	0	0	0	1
Countries	10	28	22	7	6	29	102

Source: Authors' calculations based on PovCalNet data. EAP: East Asia and Pacific, EECA: East Europe and Central Asia, LAC: Latin America and the Caribbean, MENA: Middle East and North Africa, SAS: South Asia, SSA: Sub Saharan Africa. Years available refer to the total number of years with information for all variables of interest (headcount rates, GDP and Gini index data available).

Table A2. Comparison of Bourguignon model with current data via Least Squares Estimation ($1.25 / day poverty line)

VARIABLES	Bourguignon (2003) specifications Dep variable: Change in Log(Headcount Rate)				Complete Sample Dep variable: Change in Log(Headcount Rate)				Sample without EECA region countries Dep variable: Change in Log(Headcount Rate)			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Change in Log(Mean Income)	-1.65***	-2.01***	-6.35***	-7.87***	-1.479***	-1.696***	-3.050***	-2.634**	-1.199***	-1.352***	-4.704***	-4.327***
	(0.258)	(0.222)	(1.245)	(1.131)	(0.215)	(0.217)	(1.102)	(1.151)	(0.138)	(0.151)	(0.749)	(0.729)
Change in Log(Mean Income) *times* Lag(z/y)			3.97***	3.95***			0.836***	0.602***			1.035***	0.849***
			(1.166)	(1.028)			(0.187)	(0.158)			(0.258)	(0.199)
Change in Log(Gini)		4.72***	5.24***	21.56***		2.655***	2.787***	7.964***		1.763***	2.166***	6.138***
		(0.673)	(0.652)	(4.120)		(0.477)	(0.476)	(2.054)		(0.416)	(0.423)	(2.018)
Change in Log(Gini) *times* times Lag(z/y)				-16.39***				-4.416***				-3.763***
				(2.825)				(0.776)				(0.824)
Change in Log(Gini) *times* Lagged Gini			7.004***	9.69***			2.220	1.199			5.413***	4.416***
			(2.4586)	(2.210)			(2.117)	(2.249)			(1.280)	(1.322)
Change in Log(Gini) *times* Lagged Gini				-20.36***				-7.115*				-3.652
				(7.438)				(3.711)				(3.319)
Constant	0.0826**	0.097***	0.084***	0.098***	-0.037	-0.029	-0.036	-0.049**	-0.044**	-0.028	-0.018	-0.011
	(0.0434)	(0.036)	(0.034)	(.032)	(0.025)	(0.023)	(0.023)	(0.020)	(0.018)	(0.017)	(0.017)	(0.015)
Observations					630	630	630	630	449	449	449	449
R-squared	0.2666	0.4916	0.555	0.6651	0.198	0.347	0.377	0.459	0.224	0.368	0.458	0.564

Notes: Left panel presents a replication of selected results presented in table 1.1 of Bourguignon (2003). Middle and right panels show authors' results using data from PovCalNet. Robust standard errors shown in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table A3. Comparison of Bourguignon model with current data via Least Squares Estimation ($2 / day poverty line)

VARIABLES	Bourguignon (2003) specifications Dep variable: Change in Log(Headcount Rate)				Complete Sample Dep variable: Change in Log(Headcount Rate)				Sample without EECA region countries Dep variable: Change in Log(Headcount Rate)			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Change in Log(Mean Income)	-1.65***	-2.01***	-6.35***	-7.87***	-1.339***	-1.452***	-2.730***	-2.335***	-0.909***	-0.996***	-3.454***	-3.159***
	(0.258)	(0.222)	(1.245)	(1.131)	(0.161)	(0.164)	(0.720)	(0.746)	(0.114)	(0.128)	(0.642)	(0.595)
Change in Log(Mean Income) *times* Lag(z/y)			3.97***	3.95***			0.581***	0.483***			0.552***	0.481***
			(1.166)	(1.028)			(0.137)	(0.116)			(0.158)	(0.133)
Change in Log(Gini)		4.72***	5.24***	21.56***		1.680***	1.778***	5.015***		1.010***	1.324***	3.350***
		(0.673)	(0.652)	(4.120)		(0.307)	(0.305)	(1.480)		(0.245)	(0.267)	(1.011)
Change in Log(Gini) *times* times Lag(z/y)				-16.39***				-1.970***				-1.594***
				(2.825)				(0.337)				(0.276)
Change in Log(Gini) *times* Lagged Gini			7.004***	9.69***			2.040	1.080			3.851***	3.082***
			(2.4586)	(2.210)			(1.364)	(1.448)			(1.029)	(0.988)
Change in Log(Gini) *times* Lagged Gini				-20.36***				-3.935				-1.000
				(7.438)				(2.729)				(1.700)
Constant	0.0826**	0.097***	0.084***	0.098***	-0.002	0.002	-0.009	-0.015	-0.009	-0.001	0.005	0.012
	(0.0434)	(0.036)	(0.034)	(.032)	(0.018)	(0.017)	(0.017)	(0.015)	(0.014)	(0.014)	(0.014)	(0.013)
Observations					653	653	653	653	454	454	454	454
R-squared	0.2666	0.4916	0.555	0.6651	0.268	0.360	0.418	0.476	0.280	0.381	0.518	0.624

Notes:Left panel presents a replication of selected results presented in table 1.1 of Bourguignon (2003). Middle and right panels show authors' results using data from PovCalNet. Robust standard errors shown in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table A4. Comparison of Bourguignon model with current data via Fixed Effects ($1.25 / day poverty line)

VARIABLES	Bourguignon (2003) specifications Dep variable: Change in Log(Headcount Rate)				Complete Sample Dep variable: Change in Log(Headcount Rate)				Sample without EECA region countries Dep variable: Change in Log(Headcount Rate)			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Change in Log(Mean Income)	-1.65***	-2.01***	-6.35***	-7.87***	-1.457***	-1.757***	-2.731*	-2.424	-1.192***	-1.433***	-4.520***	-4.499***
	(0.258)	(0.222)	(1.245)	(1.131)	(0.304)	(0.307)	(1.565)	(1.561)	(0.172)	(0.185)	(0.954)	(1.065)
Change in Log(Mean Income) *times* Lag(z/y)			3.97***	3.95***			0.677***	0.474*			0.936***	0.782***
			(1.166)	(1.028)			(0.241)	(0.244)			(0.275)	(0.243)
Change in Log(Gini)		4.72***	5.24***	21.56***		2.971***	3.033***	8.690***		1.987***	2.318***	6.701**
		(0.673)	(0.652)	(4.120)		(0.625)	(0.620)	(2.393)		(0.613)	(0.610)	(2.698)
Change in Log(Gini) *times* times Lag(z/y)				-16.39***				-4.607***				-3.921***
				(2.825)				(0.917)				(1.096)
Change in Log(Gini) *times* Lagged Gini			7.004***	9.69***			1.652	0.925			5.140***	4.860**
			(2.4586)	(2.210)			(3.008)	(3.076)			(1.696)	(1.950)
Change in Log(Gini) *times* Lagged Gini				-20.36***				-8.401*				-4.553
				(7.438)				(4.434)				(4.220)
Constant	0.0826**	0.097***	0.084***	0.098***	-0.038**	-0.026*	-0.035***	-0.054***	-0.045***	-0.023**	-0.016	-0.011
	(0.0434)	(0.036)	(0.034)	(.032)	(0.015)	(0.015)	(0.013)	(0.015)	(0.009)	(0.011)	(0.011)	(0.011)
Observations					630	630	630	630	449	449	449	449
R-squared	0.2666	0.4916	0.555	0.6651	0.179	0.348	0.363	0.446	0.199	0.373	0.435	0.545
Number of countries					100	100	100	100	73	73	73	73

Notes:Left panel presents a replication of selected results presented in table 1.1 of Bourguignon (2003). Middle and right panels show authors' results using data from PovCalNet. Robust standard errors shown in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table A5. Comparison of Bourguignon model with current data via Fixed Effects Estimation ($2 / day poverty line)

VARIABLES	Bourguignon (2003) specifications Dep variable: Change in Log(Headcount Rate)				Complete Sample Dep variable: Change in Log(Headcount Rate)				Sample without EECA region countries Dep variable: Change in Log(Headcount Rate)			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Change in Log(Mean Income)	-1.65***	-2.01***	-6.35***	-7.87***	-1.409***	-1.571***	-2.612***	-2.284**	-0.986***	-1.136***	-3.954***	-3.825***
	(0.258)	(0.222)	(1.245)	(1.131)	(0.215)	(0.223)	(0.968)	(1.005)	(0.152)	(0.174)	(0.918)	(0.925)
Change in Log(Mean Income) *times* Lag(z/y)			3.97***	3.95***			0.549***	0.458***			0.553***	0.487***
			(1.166)	(1.028)			(0.167)	(0.159)			(0.192)	(0.167)
Change in Log(Gini)		4.72***	5.24***	21.56***		1.954***	1.992***	5.510***		1.233***	1.532***	3.795***
		(0.673)	(0.652)	(4.120)		(0.439)	(0.428)	(2.014)		(0.340)	(0.368)	(1.352)
Change in Log(Gini) *times* times Lag(z/y)				-16.39***				-2.057***				-1.709***
				(2.825)				(0.444)				(0.335)
Change in Log(Gini) *times* Lagged Gini			7.004***	9.69***			1.712	0.947			4.741***	4.309***
			(2.4586)	(2.210)			(1.885)	(2.005)			(1.530)	(1.614)
Change in Log(Gini) *times* Lagged Gini				-20.36***				-4.705				-1.443
				(7.438)				(3.729)				(2.299)
Constant	0.0826**	0.097***	0.084***	0.098***	0.001	0.007	-0.007	-0.016	-0.005	0.007	0.011	0.018*
	(0.0434)	(0.036)	(0.034)	(.032)	(0.010)	(0.010)	(0.009)	(0.012)	(0.008)	(0.010)	(0.011)	(0.010)
Observations					653	653	653	653	454	454	454	454
R-squared	0.2666	0.4916	0.555	0.6651	0.282	0.398	0.436	0.495	0.278	0.412	0.528	0.637
Number of countries					101	101	101	101	73	73	73	73

Notes:Left panel presents a replication of selected results presented in table 1.1 of Bourguignon (2003). Middle and right panels show authors' results using data from PovCalNet. Robust standard errors shown in parenthesis. *** p<0.01, ** p<0.05, * p<0.1