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Abstract

An extensive literature on poverty traps suggests that high levels of poverty deter growth. However, a seemingly basic implication of the underlying theoretical models, namely that countries suffering from higher levels of poverty should grow less rapidly, has remained untested. A parallel literature has suggested a variety of mechanisms through which inequality may affect growth in opposing directions. Because inequality and poverty are different aspects of the income distribution, inequality can affect growth also through poverty, an indirect channel that has not been explicitly analyzed. This paper contributes to fill both gaps. Using a large cross-country panel dataset, we estimate a reduced-form growth equation adding both inequality and poverty to an otherwise standard set of growth determinants. Given inequality, the correlation of growth with poverty is consistently negative. In contrast, given poverty, the correlation of growth with inequality can be positive or negative, depending on the empirical specification and econometric approach used. Yet the indirect effect of inequality on growth through its correlation with poverty is robustly negative. Closer inspection shows that these results are driven by the sample observations featuring high (but not extremely high) poverty rates. Our empirical findings are consistent with the predictions from an analytical framework with learning-by-doing and knowledge spillovers, in which consumers cannot save and invest if their initial endowment is below a minimum consumption level.

Keywords: Growth, Inequality, Poverty.

JEL Classification: O40, O11, O15, E25.

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I. Introduction

Do inequality and poverty affect aggregate income growth? If so, in what direction? These questions have long preoccupied academics and policymakers. Answering them requires taking into account the relation between inequality and poverty, because they are different aspects of the income distribution (Bourguignon, 2003). In this paper, we analyze the inequality-growth and the poverty-growth links from both theoretical and empirical perspectives.[3]

We first present an overlapping-generations model with learning-by-doing and knowledge spillovers in the spirit of Aghion et al. (1999), in which poor people - i.e., those whose initial endowment is below a minimum consumption level - do not save and do not contribute to the economy's aggregate growth. We show that in this setting aggregate income growth depends on the share of people below the poverty threshold and on the distribution of endowments – i.e., poverty and inequality. Inequality affects growth both directly, through the amount and concentration of the savings of the non-poor, and indirectly, through its effect on the extent of poverty for given average income. Moreover, the sign and magnitude of the inequality-growth and the poverty-growth relationships may depend on the prevailing degrees of poverty and inequality in the economy.

In the second part of the paper, we take these theoretical predictions to the data. We specify a reduced-form growth equation with inequality and poverty added to an otherwise standard set of growth determinants. We estimate the resulting equation on a large cross-country panel data set using a GMM approach to control for the potential endogeneity of the regressors (Blundell and Bond, 1998; Roodman, 2009).

Our paper is embedded in several strands of the literature. First, there is an extensive literature analyzing the impact of inequality on growth and reaching conflicting conclusions.[4] The multiplicity of factors affecting both inequality and growth might explain this ambiguity. For example, rising inequality could be the result of growth-enhancing technological change whose returns are captured by talented individuals at the top of the distribution (Goldin and Katz, 2008). In contrast, if rent-

[3] Our paper builds on López and Servén (2009).

[4] For example, Alesina and Rodrik (1994) and Perotti (1996) found a negative relationship between inequality and growth in cross section data, but subsequently Li and Zou (1998) and Forbes (2000) obtained the opposite result using panel data. Barro (2000) found that inequality might affect growth in different directions depending on the country's level of income, while Banerjee and Duflo (2003) concluded that the response of growth to inequality changes has an inverted U- shape. Galor and Moav (2004) argue that the replacement of physical capital accumulation by human capital accumulation as a prime engine of economic growth changed the qualitative impact of inequality on growth. Marrero and Rodríguez (2013) emphasize that the sign of the effect of inequality on growth depends on the type of inequality considered (i.e., inequality of opportunity or of effort). Voitchovsky (2005) and, more recently, van der Weide and Milanovic (2018) argue that the effect of inequality is negative for the income growth of the poor but positive for the income growth of the rich. See also Galor (2011) for a survey of these conflicting results.

seeking is the fundamental force behind growing incomes of the rich, the increase in inequality would come along with declining growth (Stiglitz, 2012). In this vein, an emerging consensus view is that the long-run effect of inequality on growth is significantly negative, and only when looking at short periods of time (or to the within-group variation) the relationship may turn positive (Halter et al., 2014; Dabla-Norris et al., 2015; Berg et al., 2018; Brueckner and Lederman, 2018). Our main contribution to this literature is our analysis of the indirect effect that inequality may have on growth through the generation of poverty, which we find to be negative. We also find that this result is driven by the sample observations featuring high (but not extremely high) poverty rates.

Second, a long-standing theoretical literature has studied a variety of mechanisms through which poverty may deter growth. Its arguments are mostly based on the existence of poverty traps, i.e., mechanisms through which poverty prevents a significant share of the population from helping ignite the growth engine. Under appropriate conditions, those mechanisms may lead to multiple equilibria and make the negative impact of poverty on growth self-reinforcing. Such situation may arise through a variety of channels (see Azariadis and Stachurski, 2005, for a survey). A prominent one involves 'threshold effects', resulting for example from indivisibilities or increasing returns to scale.[5] Coupled with credit constraints, the result is that below a certain level of income or wealth economic agents may be too poor to afford the investments (in human or physical capital) or the technologies necessary to raise their income (Galor and Zeira, 1993; Banerjee and Newman, 1993).[6] Institutional arrangements that place economic opportunities beyond the reach of the poor can also result in reduced income growth (Mokherjee and Ray, 2002; Engerman and Sokoloff, 2006). Another poverty-perpetuating mechanism is related to risk (Banerjee, 2000): because poorer individuals are typically more risk averse, in the absence of well-functioning insurance and credit markets they will skip profitable investment opportunities that they deem too risky.[7]

In spite of the diversity of these analytical models, evidence on their empirical relevance remains largely inconclusive. A few papers (see Durlauf, 2006, for a review) have searched for various empirical regularities consistent with those models, such as aggregate non-convexities (Azariadis and Stachurski, 2005) and convergence clubs (Quah, 1993). A broader empirical review of different mechanisms advanced in the literature finds little evidence that they may be at work, except perhaps

[5] Poverty traps arising from threshold effects have often been offered as a rationale for a 'big push' approach to policy, and in particular for large aid programs, to engineer growth takeoffs. Easterly (2006) finds little support for these views in aggregate cross-country data. Takeoffs are rare and, in general, they are not associated with surges in aid, investment, or educational spending.

[6] See also Dasgupta and Ray (1986), who develop a model focused on investments in health.

[7] The argument that risk aversion leads to underinvestment goes back to Stiglitz (1969). See also Agenor and Aizenman (2011), who argue that aid volatility could induce poverty traps in poor countries through a similar mechanism.

in remote or disadvantaged areas (Kraay and McKenzie, 2014). More recently, large-scale randomized evaluations developed by Bandiera et al. (2015) in Bangladesh yield strong evidence that the poor face imperfections in capital markets that keep them in a low asset-low employment poverty trap. More fundamentally, however, a seemingly basic implication of the theoretical models, namely that countries suffering from higher levels of poverty should grow less rapidly, has not been tested in a systematic way. Our empirical analysis seeks to fill this gap.[8]

The third strand of the literature explores the growth-poverty link focusing on the poverty-reducing effect of growth and the factors that shape it (Bourguignon 2003, Ravallion 2004, and Dollar et al., 2016). This is exactly the reverse of the question pursued in this paper.

Our key finding is that poverty has a robust negative and significant association with subsequent growth. As for inequality, the sign and significance of its direct effect on growth are fragile, while its indirect effect (through poverty) is negative and significant at high (but not extremely high) poverty rates, and insignificant at low poverty rates. These empirical findings are consistent with the predictions of our analytical model.[9]

Our results are robust to a variety of departures from the basic empirical specification, including the use of alternative sets of control variables, alternative sets of instruments in the GMM estimation, alternative poverty lines, and alternative poverty measures. We also find that our preferred GMM specification can address in a satisfactory manner the endogeneity, underidentification and weak instruments problems often encountered in macroeconomic applications of dynamic panel models (Bazzi and Clemens, 2013; Kraay, 2015).

The rest of the paper is structured as follows. In Section II we use a simple model based on Aghion *et al*. (1999) to illustrate how poverty can be a robust growth deterrent while inequality has an ambiguous impact on growth. In Section III, we describe the data and the empirical strategy that we use to test for the effect of poverty and inequality on growth. We also characterize the poverty-inequality nexus, a necessary ingredient to establish the indirect impact of inequality on growth. Section IV assesses the robustness of the poverty-growth and inequality-growth relationships in our

[8] Only a few studies have analyzed empirically the impact of poverty on growth. Exceptions are López and Servén (2009) and Ravallion (2012), both of which conclude that poverty is growth-deterring.

[9] In an application to the U.S., Marrero et al. (2016) find that the negative relationship between overall inequality and the future income growth of the poor can be traced to inequality of opportunity. As the opportunities of more disadvantage people tend to worsen with higher poverty rates, our finding that inequality affects growth through its impact on poverty is consistent with the inequality of opportunity view (see also Roemer and Trannoy, 2016, or Marrero and Rodriguez, 2013).

dataset. Section V analyzes how these relationships might depend on the prevailing degrees of poverty and/or inequality, and gauges the direct and indirect effects of inequality on growth. Finally, Section VI concludes.

II. An illustrative model

To illustrate the effects of poverty and inequality on growth, we sketch a model in the spirit of Aghion *et al*. (1999), who introduce learning-by-doing and knowledge spillovers in a simple overlapping-generations framework. We modify their basic setup by adding a minimum consumption requirement in the model. Poor consumers are defined as those whose initial endowment is below the minimum consumption level. In the absence of capital markets, they cannot invest, and do not contribute to the economy's aggregate growth.[10]

There is a continuum of non-altruistic overlapping-generations individuals, indexed by $i \in [0,1]$, who live for at most two periods. Individuals born at time t have a random endowment w_{it}. Survival into the second period entails a minimum consumption requirement $\bar{c}$ (possibly reflecting nutritional needs), which can exceed the original endowment. We denote by λ the share of population with initial endowment below survival needs, to whom we shall refer as the poor (i.e., λ is the headcount poverty rate),

$$\lambda = p(w_{it} \leq \bar{c}) = \int_{0}^{\bar{c}} f(w_{it})dw_{it}, \tag{1}$$

where $f(.)$ is the probability density function of individual endowments w_{it}, with mean $\bar{w}$ and standard deviation σ.

The utility of the *i-th* individual of generation t is given by:

$$\begin{aligned} U_{it} &= c_{it} && \text{if} \quad c_{it} \leq \bar{c} \\ &= \bar{c} + \ln(c_{it} - \bar{c}) + \rho \ln c_{it+1} && \text{if} \quad c_{it} > \bar{c}, \end{aligned} \tag{2}$$

[10] We do not need to rule out capital markets altogether. It would suffice to assume that lenders impose on borrowers a collateral requirement, which individuals below the minimum consumption level would be unable to meet.

where c_{it} and c_{it+1} denote consumption when young and old, respectively, of generation t.[11] Thus, young poor individuals do not survive to the second period and they do not save.

Non-poor individual i uses her saving to purchase physical capital k_{it}, which fully depreciates within the period. Individual production takes place according to the technology:

$$y_{it} = A_t \cdot k_{it}^{\theta}, \tag{3}$$

where A_t is the level of technical knowledge available to all individuals at time t, and $0<\theta<1$. As in Aghion *et al*. (1999), we assume that there are learning-by-doing spillovers, so that $A_t = e^{a_0} y_{t-1}$, where a_0 denotes the state of technology, and y_{t-1} is lagged level of aggregate income. Thus an increase in the production of individual i raises the level of knowledge available to all individuals in the next period. Therefore, aggregate growth Γ in period t is given by:

$$\Gamma_t = \ln(y_t / y_{t-1}) = a_0 + \ln \int k_{it}^{\theta} \cdot di = a_0 + \ln E[k_t^{\theta}]. \tag{4}$$

It is apparent that aggregate growth depends on the distribution of investment across individuals. To sharpen the argument, we assume that capital markets do not exist. Hence, the equilibrium levels of consumption and saving vary across individuals depending on their initial endowments. In particular, for non-poor individuals (i.e., those with $w_{it} > \bar{c}$) we have,

$$c_{it} = \bar{c} + (1+\theta\rho)^{-1}(w_{it} - \bar{c}), \tag{5}$$

$$k_{it} = \theta\rho(1+\theta\rho)^{-1}(w_{it} - \bar{c}) = s(w_{it} - \bar{c}), \tag{6}$$

where s is the saving rate. Hence, saving and investment of the non-poor is just proportional to their initial wealth (net of their minimum consumption requirement). In turn, poor individuals (i.e., those with $w_{it} \leq \bar{c}$) do not save and simply consume all their endowment:[12]

$$c_{it} = w_{it}, \tag{7}$$

$$k_{it} = 0. \tag{8}$$

[11] Strictly speaking, we should add a constant in the second line of (2) to prevent the utility level from declining when first-period consumption rises marginally above the subsistence level. We ignore this technical issue for simplicity. See Gollin et al. (2002) for a similar approach.

[12] Atkeson and Ogaki (1996), López et al. (2000) and Dynan et al. (2004) offer empirical evidence supportive of the differing saving behavior of rich and poor individuals.

Aggregate investment is then given by:

$$k_t = E[k_{it}] = (1-\lambda)E[k_{it} \mid w_{it} > \bar{c}] = (1-\lambda)E[s(w_{it} - \bar{c}) \mid w_{it} > \bar{c}], \tag{9}$$

which reflects the fact that only a fraction (1-λ) of the population invests. Using (4) and (9), we easily obtain the expression for the growth rate:

$$\Gamma_t = a_0 + \ln(1-\lambda) + \ln(s^{\theta} E[(w_{it} - \bar{c})^{\theta} \mid w_{it} > \bar{c})]) . \tag{10}$$

As in neoclassical models, growth is directly affected by the state of the technology, a_0, and also by θ and ρ, through the average per capita investment of the non-poor (the third term on the right-hand side of (10)). However, two additional elements arise in this setup.

First, poverty deters growth, as shown by the second term on the right-hand side of (10). For given average per capita investment of the non-poor, a higher λ unambiguously leads to lower growth, as it raises the number of poor individuals who cannot contribute to the growth process through the creation of physical capital. The ingredient responsible for this result is the minimum consumption threshold, which is the cause of the differential saving and investing behavior of poor and non-poor individuals.[13] Moreover, the negative effect of poverty on growth increases with the level of poverty.

Second, given θ and ρ, the output generated by the investment of the non-poor depends not only on their initial endowments relative to the minimum consumption requirement, but also on the distribution of endowments among the non-poor. In addition, changes in inequality also have an effect on poverty. Thus, while the impact of poverty on growth is unambiguously negative, the effect of inequality on growth depends on how inequality affects the different terms in (10). To clarify this issue, take the derivative of (10) with respect to σ:

$$\frac{\partial \Gamma}{\partial \sigma} = -\frac{\partial \lambda / \partial \sigma}{(1-\lambda)} + \frac{\partial E[(w_{it} - \bar{c})^{\theta} \mid w_{it} > \bar{c}] / \partial \sigma}{E[(w_{it} - \bar{c})^{\theta} \mid w_{it} > \bar{c}]} . \tag{11}$$

The first term represents the indirect impact of inequality on growth channeled through poverty, while the second term reflects the direct impact of inequality on growth due to changes in the investment of the non-poor.

[13] Similar results would be obtained in the presence of threshold effects arising instead from some other source – e.g., investment indivisibilities (as in Azariadis and Drazen, 1990, for example) or increasing returns to scale, so that below a certain level of income or wealth individuals are too poor to acquire growth-enhancing assets (human or physical capital) or technologies. See Azariadis and Stachursky (2005) for a variety of examples.

Regarding the first term, for $\overline{w} < \overline{c}$, a perfectly egalitarian distribution (i.e., with $\sigma=0$) would bring everybody below the poverty line, thus investment would fall to zero. As inequality increases and an unchanged aggregate endowment is concentrated among fewer and fewer individuals, some of them might move above the poverty threshold $\overline{c}$ and become able to invest and generate some growth. Thus, inequality may reduce poverty when poverty is initially very high and inequality is very low. Otherwise, increased inequality leads to higher poverty and, through this channel, reduces growth.

As for the second term in (11), the sign of $\partial E[(w_{it} - \overline{c})^{\theta} \mid w_{it} > \overline{c}] / \partial\sigma$ depends on two factors. First, decreasing returns in the production function imply that, for given aggregate capital, a higher concentration of its ownership among fewer people (higher σ) lowers growth. Second, as long as the increase in σ represents a mean-preserving spread, the average capital stock of the non-poor rises, and this tends to affect growth in the opposite (i.e., positive) direction. Thus, in general, the sign of the second term in (11) is ambiguous, and depends on the concavity of the production function as measured by θ.

We can illustrate the ambiguous relationship between inequality, poverty and growth through numerical simulation. For this purpose, we assume that the initial endowment follows a lognormal distribution, and consider the effects of a mean-preserving spread,[14] achieved by changing the variance (and hence the Gini coefficient) of the distribution under alternative values of the mean, while holding constant the remaining parameters of the model.[15]

Figure 1 shows simulation results for four scenarios respectively featuring levels of poverty in ranges that, for ease of reference, we shall label 'extremely high', 'high', 'moderate', and 'low'. They are characterized by different values of $\overline{w}$ with a given $\overline{c}=1$. In each case, the graphs depict the poverty rate, the growth rate, and the direct effect of inequality on growth, given by the last term on the right-hand side of (10), as functions of the Gini coefficient.

As already argued, higher inequality reduces poverty and raises growth (i.e., both terms in (11) are positive) only in economies with extremely high poverty rates, such as the situation shown in the

[14] Specifically, as in Benabou (1996), we assume that w follows a log normal distribution such that $\ln w \sim N\left(\ln \overline{w} - \sigma^2/2 ; \sigma^2\right)$. In this manner, w has a constant mean $\overline{w}$ invariant to changes in σ.

[15] For the simulation, we use standard values for the preference and technology parameters: θ=0.35 and ρ=0.98, which together imply a saving rate of 0.25 and a real interest rate of 2%. We fix $\overline{c}=1$ and consider different values of $\overline{w}$ to generate economies with alternative poverty rates. In each case, a_0 is set so as to achieve growth rates of 2.5% on average, which is the mean of our sample (see Table 1 in Section III).

top-left graph. Such configuration is rare in our sample, as we shall further discuss in Section V.[16] At the other extreme, in economies with very low poverty rates (bottom-right graph), the effect of raising inequality on poverty is virtually negligible, and its impact on growth, which is shown to be slightly negative, occurs only through the decreasing returns to scale in the production function.

In the intermediate case of poor (but not extremely poor) economies shown in the top-right and bottom-left graphs, the impact of inequality on poverty is always positive, and hence its indirect contribution to growth is negative, more so the higher the prevailing poverty rate. In turn, the direct effect of inequality on growth (i.e., the second term in (11)) is almost zero, due to the mutually opposing effects discussed above. As a consequence, the overall impact of inequality on growth is negative, due to the indirect effect of inequality that accrues through poverty. Finally, it is worth noting that these conclusions hold regardless of the prevailing level of inequality, at least for values of the Gini coefficient in the range between 0.2 and 0.8 – which covers 99% of our empirical sample, as shown in Section III.

III.- Growth, inequality and poverty: empirical implementation

We turn to the empirical strategy for analyzing the relationship between growth, inequality and poverty. First, we describe the data we use. Second, we present the baseline growth equation and examine the correlation between the key variables in the model.

III.1. Data

We use an extended version of the poverty database constructed by López and Servén (2009). Details are given in the Appendix. In brief, given the limited availability of survey-based poverty data, we construct the headcount ratio, P0, the poverty gap, P1, and the squared poverty gap, P2, using a lognormal approximation on the basis of the observed per capita income levels and Gini coefficients, which are available much more widely (López and Servén, 2006). Similar approaches have been used by Dollar and Kraay (2002), Sala-i-Martín (2006) or Pinkovsky and Sala-i-Martin (2013; 2014). We experiment with alternative and widely-used poverty lines: US$ 1.25, US$ 2 and US$ 4 per person and per day, in 2005 PPP US$.

Our final database is an unbalanced panel of non-overlapping five-year periods, containing 804 observations covering 158 countries and spanning the years 1960-2010. This sample is fairly large

[16] Our sample mainly contains economies with headcount poverty rates between 0.10 and 0.60, as well as rich economies with negligible poverty, as discussed in the next section.

in both the time and the cross-country dimension.[17] Indeed, as far as we are aware, it is the largest sample used to study the impact of both poverty and inequality on growth.[18] Estimation samples are somewhat smaller due to the unavailability of data on other regressors included in the empirical specifications.

For our benchmark sample, Table 1 presents summary statistics on annual growth, mean income, inequality and the constructed poverty measures for the common sample of these variables in the unbalanced 1960-2010 panel. The table shows the wide range of per capita income levels (expressed in 2005 US dollars in PPP terms) in the sample – from just over $200 (the Democratic Republic of Congo in the mid-2000s) to about $73,000 (Luxembourg in 2005). The median observation corresponds to Brazil in the mid-1970s, with per capita income about $5,500. The overall sample mean is about $9,800, much larger than the median, which reflects a world income distribution skewed to the right.

Regarding inequality, both the median and the mean of the Gini coefficient equal 0.4, which matches the values found for the US (in 2000), Burkina Faso (in 1995), Turkey (in 2010) or Singapore (in 1970). The maximum value (above 0.74) corresponds to Zimbabwe in 1995, and the minimum (below 0.16) corresponds to Bulgaria in 1975. Around 80 percent of the observations fall in the range between 0.28, a value found among Western European countries, and 0.54, a value found among Latin American and Sub-Saharan African countries.

Regarding poverty, it rises by construction with the poverty line and declines as the poverty measure changes from P0 to P2 (i.e., as one considers more bottom-sensitive measures). The table shows that median headcount poverty P0 is 0.6% using US$ 1.25 per day as poverty line, but it raises to 2.3% with a US$ 2 poverty line, and to 13% with US$ 4. Likewise, the median poverty gap P1 ranges from less than 0.1% for US$ 1.25 to about 4% for US$ 4, while the median squared poverty gap P2 ranges from less than 0.1% for US$ 1.25 to almost 2% for US$ 4. Although the mean and the median of these poverty measures are relatively small, the heterogeneity in the sample is quite

[17] In terms of the World Bank income classification, our 804 observations comprise a total of 121 data points (32 countries) corresponding to low-income countries, 180 (41 countries) to lower-middle, 240 (44 countries) to upper-middle, 57 (11 countries) to high-income non-OECD countries, and 206 (30 countries) to high-income OCDE countries. According to geographic location, the sample includes 18 observations (2 countries) from North America, 248 (48 countries) from Europe and Central Asia, 159 (28 countries) from Latin American and the Caribbean, 53 (12 countries) from Middle East and North Africa, 144 (40 countries) from Sub-Sahara Africa, 56 (9 countries) from South Asia and 126 (19 countries) from East Asia and Pacific.

[18] The sample in López and Servén (2009) comprises 325 observations from 85 countries over the period 1960 to 2000, excluding many developing countries. In contrast, Ravallion (2012) uses a version of POVCAL covering a maximum of 97 developing countries over 1981-2005, in a majority of cases with data available only from 1990 on.

high, since the ranges of the various poverty measures run from a minimum of zero (reflecting the presence of high-income countries in the sample) to a maximum whose value depends on the particular poverty measure and poverty line under consideration. For example, it goes from 90% to 99% for P0, from 60% to 86% for P1 and from 50% to 75% for P2. The maximum corresponds in all cases to Tanzania. Still, extreme values of the headcount poverty rate (e.g., P0 above 90%) are rare in the data: using poverty lines of US$ 1.25, 2.0 and 4.0 per day, just 0.1%, 1% and 7.5% of the sample, respectively, show a headcount poverty rate above 90%.

We use headcount poverty P0 (with a poverty line of US$2 per day) as our baseline poverty measure for the rest of the paper. However, in Section IV we perform a sensitivity analysis of the main results to alternative poverty measures P1, P2 and alternative poverty lines.

Figure 2 shows the sample correlation between annual per capita growth, our baseline poverty rate, and the Gini coefficient as an overall measure of inequality. Poverty and inequality are measured at the beginning of the corresponding 5-year period, while the growth rate is the average annual growth rate over the period. The top graphs plot growth against poverty, and the bottom graphs plot growth against the Gini coefficient. The leftmost graphs show the unconditional correlation, while the center graphs control for lagged income and the rightmost graphs add also regional dummies (by geographic location, see footnote 17).

The top left scatter, which shows the unconditional correlation between growth and poverty, highlights the degree of heterogeneity in the sample. For instance, there is a wide range of observations with very small poverty rates and very large variation in growth rates (from -5% to +10%). At high poverty rates (above 80%, say) the range of variation of growth rates is fairly wide as well. However, once we control for real per capita GDP (top center graph), the relationship between growth and poverty turns negative and significant. The result is robust to the addition of regional dummies. Results are different for the growth-inequality scatter plots in the bottom graphs of Figure 2. The ambiguous relation shown in the leftmost graph turns negative when we control for real per capita GDP. However, it becomes slightly positive (but remains insignificant) when adding regional dummies to control for region effects.

III.2. The empirical growth model

To explore the links between growth, inequality and poverty, our empirical strategy generalizes the standard specification used in the literature concerned with the impact of inequality on growth.[19] Building on the illustrative model presented in Section II, we use a specification adding suitable measures of inequality and poverty to an otherwise standard empirical growth regression:

$$(y_{it} - y_{it-1}) = \alpha_i + \gamma_t + \beta y_{it-1} + \delta p_{it-1} + \varphi g_{it-1} + \omega' x_{it} + \upsilon_{it}, \tag{12}$$

where y is the log of per capita income, α_i and γ_t are country- and time-specific effects, p is a measure of poverty, g is the Gini coefficient, x represents a set of control variables, which we shall discuss shortly, and υ is an i.i.d error term.

The parameter δ in (12) captures the impact of poverty on growth. Thus, if poverty is a growth deterrent, as predicted by the model in Section II (eq. 10), we should find δ<0. In turn, the coefficient φ in (12) reflects the direct effect of inequality on growth, for given poverty and per capita income levels. However, the overall impact of inequality on growth also depends on how inequality affects poverty - the indirect effect examined in eq. (11). The reason is that, from theory, as well as the very construction of our poverty data (see the Appendix), poverty is a (nonlinear) function of (log) average income (y) and inequality (g), i.e., $p=p(g, y)$. Thus,

$$\partial(y_{it} - y_{it-1}) / \partial g_{it-1} = \varphi + \delta(\partial p_{it-1} / \partial g_{it-1}), \tag{13}$$

which means that, even if the direct effect of inequality on growth is nil (i.e., φ=0), its overall effect on growth could still be nonzero through its correlation with poverty.

Identifiability of β, δ and φ in (12) hinges on the relationship between poverty, income and inequality. If poverty were close to an exact linear function of (log) per capita income and the Gini coefficient, the estimating equation would feature perfect collinearity. In such scenario, we could drop poverty from (12) and estimate a model including only lagged per capita income and lagged inequality – as done in earlier literature. However, if poverty is not well approximated by a linear combination of y and g, then δ is identifiable (as are β and φ), and it captures the effect of poverty on economic growth holding inequality and average per capita income constant.

To assess this issue, we run a linear regression of the headcount poverty rate (using a poverty line of US$2) on (log) average income and the Gini coefficient. The non-linear effect of the regressors

[19] See Forbes (2000), Barro (2000) and, more recently, Halter et al. (2014), Dabla-Norris et al. (2015), Kraay (2015), Brueckner and Lederman (2018) or Berg et al. (2018), among many others.

is then included in the residual term. Consistent with the empirical model (12), we include fixed effects in the specification and run Within-Group (WG) regressions. The estimated equation is (robust *t* statistics in parentheses):

$$p_{it} = \underset{(4.83)}{1.278^{***}} - \underset{(-5.13)}{0.148^{***}} \cdot \ln(y_{it}) + \underset{(3.40)}{0.368^{***}} \cdot g_{it} + \hat{\varepsilon}_{it}, \ \mathrm{R}^2 = 0.421. \tag{14}$$

***: significant at 1%.

Thus, poverty is negatively correlated with (log) average per capita income, and positively correlated with inequality.[20] The coefficient estimates are strongly significant. However, the linear specification accounts for just 42% of the sample variation of poverty.[21] Put differently, the non-linear effects of income and/or inequality could account for up to 58% of the variation of poverty. Thus, we conclude that collinearity does not prevent identification of δ in (12), because poverty is far from being a linear function of average income and inequality.[22]

To conclude this section, we turn to the set of controls included in x. Rather than adding to the already huge variety of growth models contributing yet another idiosyncratic set of regressors, we opt for considering alternative growth specifications found in the literature, in order to explore the sensitivity of our results to the specific choice of control variables.

First, we consider a skeleton model of growth (M1), which includes only lagged income, poverty and the Gini coefficient as regressors in (12) (i.e., x=0). In this parsimonious setting, the estimated parameters capture the direct impacts of poverty and inequality on growth, as well as potential indirect effects due to other variables excluded from the model (Galor, 2009). Our second model (M2) is taken from the empirical literature on inequality and growth.[23] It comprises a measure of market distortions, given by the domestic price of investment goods relative to that of the U.S., and a measure of human capital, which includes the average years of secondary education of the male population and the average years of secondary education of the female population. Our third model (M3) focuses on standard policy indicators (Barro, 2000). It includes the inflation rate (GDP

[20] However, the simulations in Figure 1 suggest that the correlation between poverty and inequality may depend on the prevailing level of poverty: it may turn negative at very high levels of poverty, and vanish at very low levels of poverty. We return to the role of the prevailing level of poverty in Section V.

[21] Using alternative poverty lines (US\$1.25 and US\$ 4.00) or definitions (*P1* and *P2*, as defined in the Appendix), estimation results are qualitatively similar: positive and significant coefficients for per capita income, negative and significant for the Gini coefficient. Quantitatively, the parameter estimates differ as expected: for per capita income, they range from -0.021 for *P2* (US\$ 1.25) to -0.211 for *P0* (US\$ 4); for the Gini coefficient, they range from 0.1929 for *P2* (US\$ 1.25) to 0.390 for *P0* (US\$ 1.25). The regression R^2 ranges from 0.255 for *P2* (US\$ 1.25) to 0.575 for *P0* (US\$ 4).

[22] This of course follows from the construction of the poverty data. See footnote 38 in the Appendix for details.

[23] See Perotti (1996), Forbes (2000), Knowles (2005), López and Servén (2009), and Berg et al. (2018), among others.

deflator) as an indicator of macroeconomic stability, the adjusted ratio of the country's volume of trade to its GDP as an indicator of the degree of openness of the economy, and the ratio of public consumption to GDP as an indicator of the burden imposed by the government on the economy.[24] Lastly, the fourth model (M4) is taken from López and Servén (2009). It includes the inflation rate, the average years of secondary female education, and a lagged composite index of public infrastructure.[25]

IV. Growth, poverty and inequality: estimation results

We turn to the estimation of (12) under alternative model specifications and using different econometric approaches. As summarized above, the GMM estimators of Arellano and Bover (1995) and Blundell and Bond (1998) attempt to deal with the endogeneity of regressors typical of dynamic panel data models like (12) using internal instruments. However, when the cross-sectional dimension of the sample is not large relative to its time dimension -- a common situation with macroeconomic panel data -- these GMM estimators can behave poorly (Bun and Sarafidis, 2015). In this setting, it is not obvious that GMM should be preferred to more conventional estimation methods, such as OLS with time and/or country dummies. For this reason, we report both sets of estimates, which helps also assess the robustness of the results.

IV.1. Pooled-OLS and Within-Group estimates

Table 2 presents robust pooled-OLS and within-group (WG) estimates of the four models considered (M1, M2, M3 and M4). Time dummies are included in all models. As noted above, we use the headcount poverty rate (with poverty line of US$ 2) as our baseline measure of poverty.[26] For ease of comparison with the existing literature, we also report estimates of (12) omitting the poverty rate and including only inequality. For each model, we can then assess the contribution of poverty by comparing the estimates including only inequality (first column of each block in the table) with those including both poverty and inequality (second column).

[24] We use the residuals of a regression of the openness index on country size and two dummies indicating whether the country is landlocked and whether it is an oil exporter (Loayza et al., 2005).

[25] The infrastructure index is an updated version of that used by Calderón et al. (2015).

[26] Following López and Servén (2009), we drop Nigeria and Swaziland from the sample because of the poor quality of their PWT7.1 GDP data. Moreover, for models M2, M3 and M4, we found several big outliers for the investment price and inflation times series. For instance, there are 3 observations above 4 and even 5 standard deviations for the domestic investment price, and 6 big outliers for inflation. These anomalous observations affect mainly the specification tests of system GMM (the Hansen and m2 tests), bringing them closer to rejection in some cases, but have only minor incidence on the estimation results.

A quick look at Table 2 shows that the coefficient on poverty is negative and significant for both pooled-OLS and WG estimates, and for all the sets of controls considered. The magnitude of the poverty coefficient is larger in absolute value in the within-group regressions than in the pooled-OLS regressions, but it is in all cases economically significant. Other things equal, a one-standard deviation decline in poverty (24.6 p.p. according to Table 1) is associated with an increase of income growth between 0.7% (model M2, pooled-OLS) and 2.1% (model M3, WG estimates) per annum.

In contrast, results are not robust regarding the inequality-growth relationship. The estimated coefficients on the Gini index are uniformly negative and significant when using pooled OLS, but uniformly positive in the WG estimation, and significantly so when poverty is also included in the regression.

The coefficients of the other controls are generally consistent across estimation methods. Lagged income carries negative and significant coefficients in all cases (except for the OLS estimates of model M1 when poverty is excluded). The market distortions proxy (in model M2) and inflation (M2 and M3) both carry significant negative coefficients, as expected. In turn, trade openness (in model M3) and the infrastructure index (in model M4) carry positive and significant coefficients, as suggested by theory and, for the latter variable, other applications, such as Calderón et al. (2015).

In contrast, the effects of male and female secondary education depend on model specification. Female education carries a positive and significant coefficient in model M4, but turns insignificant (even negative) in model M2. In turn, the coefficient of male education is generally positive, but its significance depends on the estimation method. Similarly, among the policy variables the coefficient of government size is generally negative, but it is significant only for the WG estimates.

The results in Table 2 are in line with the analytical model outlined in Section II, which predicts a negative effect of poverty on growth along with an ambiguous impact of inequality. However, these estimates may be subject to endogeneity issues typical of dynamic panel data. To address them, we next turn to GMM estimation.

IV.2. GMM estimates

Our empirical strategy poses several endogeneity concerns. On the one hand, the joint determination of income, poverty and inequality could result in biased estimates. The fact that poverty and inequality are pre-determined in (12) should help alleviate this concern, at least in part. On the other hand, estimation of (12) still has to overcome the presence of country-specific unobservables potentially correlated with the regressors.

To do this in the absence of suitable external instruments (a standard problem with empirical growth models), we opt for using internal instruments. Taking first differences in (9) removes α_i. For the resulting set of equations in first-differences, we employ the levels of the regressors lagged three or more periods (i.e., y_{it-s}, p_{it-s}, g_{it-s} and x_{it-s}, for $s \geq 3$) as instruments.[27]

However, working only with the model in first differences may lead to major finite sample biases if the variables are highly persistent (Blundell and Bond, 1998), as is likely to be the case for income, inequality and poverty. An alternative is to consider the system GMM approach (Blundell and Bond, 1998), which imposes further restrictions to generate additional moment conditions to be used in a supplementary set of equations in levels, with the instruments for the regressors in levels given by suitable lags of their own first differences (i.e., Δy_{it-1}, Δp_{it-1}, Δg_{it-1} and Δx_{it-1}).

For each of these two alternatives, the validity of the instruments can be tested using Hansen's J-test of overidentification. We also report results for the Difference-in-Hansen statistic, which tests the validity of the subset of instruments employed in the level equation of the system GMM estimation. In many applications of system GMM, the excessive proliferation of instruments, relative to the number of cross-sectional units, biases downward the estimated standard errors and weakens the power of the overidentification tests (Bowsher, 2002).[28] To remedy this, we apply the Windmeijer (2005) correction to the variance-covariance matrix, and also reduce the number of instruments employed in the estimation (Roodman, 2009). Specifically, we limit the number of lags in the matrix of instruments, and/or collapse the matrix of instruments and create one instrument for each variable and lag distance, rather than one instrument for each lag distance, time period and variable as commonly done in the system GMM approach.

Taking into account all these issues, Table 3 shows estimation results for first difference GMM (top-left panel), and system GMM under alternative methods of reducing the dimension of the instrument set: limiting the instrument matrix to a single lag (top-right panel), collapsing the matrix of

[27] We initially constructed the instrument matrices using the second and higher lags of the variables ($s \geq 2$), which is the standard. However, the test for second-order serial correlation in the first differences of the errors (the *m2* test, Arellano and Bond, 1991) rejected the null in most of these specifications. Hence, we opted for lagging the instruments one more period, so that they are valid even in the presence of second (but no higher) order serial correlation of the residuals. To check this, in the tables we add an AR(3) test on the first differences of the residuals.

[28] The general principle is that, to minimize the overfitting problem caused by too many instruments, the number of instruments should not exceed the number of cross-section units (countries in our case) in the sample (Roodman, 2009).

instruments (bottom-left), and limiting and collapsing the instruments at the same time (bottom-right).[29] For first difference GMM, we use two lags in the matrix of instruments so as to have the same number of orthogonality conditions as in the system GMM estimation in the top-right panel, thus making the results more easily comparable.[30]

The p-values of the Hansen tests shown in Table 3 suggest that in virtually every case the null of joint validity of all instruments cannot be rejected. Moreover, the Difference-in-Hansen test results, whose p-values always exceed 0.10 (in most cases by a large amount) point towards the superiority of system GMM over first difference GMM.

The parameter estimates of the variables of interest follow the pattern found earlier. The coefficient on the poverty headcount is consistently negative and highly significant, regardless of the model and specification estimated. In contrast, the coefficient of the inequality variable varies in sign and significance depending on the GMM approach and the controls used in the estimation. It is positive and, in most cases, significant for first difference GMM, consistent with our results for the within-group estimates in Table 3 and part of the earlier literature (e.g., Forbes, 2000). However, it is negative and, in some cases, significant for system GMM, consistent with our results for pooled-OLS and another strand of the literature (e.g., Berg et al., 2018, and references therein).[31]

The tentative conclusion is that the negative effect of poverty on growth is robust to changes in model specification and estimation method, while the effect of inequality on growth, which has been the focus of a massive literature, is not.

IV.3. Weak instruments analysis

System GMM relies on lagged levels and differences of the regressors as internal instruments. Bazzi and Clemens (2013) and Kraay (2015) have recently raised the potential problem of weak instruments when using system GMM estimation in growth regressions. Weak identification arises

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[29] The conclusions do not change if we take orthogonal deviations instead of first differences to remove the fixed effects in (12). The results are available upon request.

[30] Data for the infrastructure index included in Model M4 is available for only 88 countries under the system GMM specification and 79 under the first difference GMM specification. Thus, the estimates of this model shown in the top panel feature a number of instruments exceeding the cross-section dimension of the data. However, reducing the number of instruments by collapsing the matrix of instruments (as in the bottom panel) or erasing instruments manually from the matrix of instruments (for example, using instruments for lagged income, Gini and poverty only) leads to results (available upon request) very similar to those shown in the table.

[31] Since the coefficient estimates on the controls themselves are of no direct interest here, they are omitted from the table to save space. However, it is worth noting that in most cases they are not significant. The main exception is lagged income, as well as lagged infrastructure and lagged female education in model M4.

when the instruments are only weakly correlated with the endogenous regressors, and its consequence is that estimators perform poorly (Nelson and Startz, 1990).

To assess the strength of the instruments employed in our system GMM estimations – in particular, the identification of the poverty and inequality parameters – we use tools designed for settings featuring multiple endogenous regressors.[32] Thus, we follow the approach of Sanderson and Windmeijer (2016) (SW hereafter), who propose a conditional *F* statistic based on Angrist and Pischke (2009) to test whether, in a multivariate setting, a particular endogenous regressor alone is weakly instrumented. Each conditional test is constructed by "partialing-out" linear projections of the remaining endogenous regressors.[33] SW show that the conditional *F* statistic can be assessed against the Stock and Yogo critical values, and the weakness can then be expressed in terms of the size of the bias of the IV (or 2SLS) estimator relative to that of the OLS estimator. The null hypothesis is that the instruments are weak, where weakness is defined in terms of a maximum bias of the 2SLS relative to the OLS estimates. The null hypothesis is rejected if the conditional *F* statistic exceeds the corresponding critical value. In the exercises below, we use a critical value allowing for a 30 percent maximal relative bias.

Additionally, using the conditional regressions, we can also perform a Chi-square under-identification test separately for each regressor. Here, the null hypothesis is that the matrix of coefficients from the first-stage conditional regressions is not full rank, signaling a complete failure of identification (i.e., the excluded instruments are uncorrelated with the endogenous regressors). Thus, rejection of the null supports identification, although not necessarily the absence of weak identification (Kleibergen and Paap, 2006).

These tests have been originally designed for use with external instruments in IV or 2SLS settings; no alternatives exist for system GMM at present. Thus, to apply the tests to our system GMM setting, we follow Bun and Windmeijer (2010) and construct the exact instrument matrix for the difference

[32] Standard first-stage *F* statistics used to test for weak instruments (Stock and Yogo, 2005) may lead to misleading conclusions in settings featuring multiple endogenous regressors, as is our case. In such settings, the null hypothesis is defined in terms of a weighted average of the relative biases in all the coefficients, and it could conceal the fact that some variables may be more strongly identified than others.

[33] For example, for the case of two endogenous regressors (x1 and x2), three instruments (z1, z2 and z3) and one exogenous regressor (w1), the conditional *F* statistic F1/2 is computed as follows (the conditional F2/1 is analogous). First, regress (using 2SLS) x1 over x2, instrumenting x2 with z1, z2, z3 and w1; second, regress the residual (the part of x1 not explained by x2) of the previous regression against z1, z2, z3 and w1. The partial F1/2 test is then given by the *F* statistic of this latter regression corrected by *k*/*k-2*, where *k* is the number of observations minus the number of parameters estimated.

and level equations of each system GMM estimator, and then apply the standard 2SLS regressions and tests to each case.[34]

In our case, we focus on the growth effects of both inequality and poverty. Table 4 reports the results of the SW tests for our two preferred system GMM specifications (shown in the right panel of Table 3). The left panel of Table 4 uses only one lag of the instruments, and the right panel in addition collapses the matrix of instruments. For each of our two key variables, lagged poverty and lagged inequality, we present two tests: the Chi-2 under-identification test, and the weak instruments *F* statistic.

The Chi-squared tests indicate that underidentification of the poverty coefficient is not a major problem in any of the models and specifications considered, neither for the levels equation nor for the differences equation. In contrast, the inequality parameter does exhibit symptoms of underidentification in the specification shown in the right panel (reduce and collapse) of Table 4, for both the equations in levels and in first differences.

As for the SW weak instruments *F* test, for the system GMM estimates including one lag in the matrix of instruments (shown in the left panel of the table) the null hypothesis that lagged poverty is weakly instrumented is rejected, as the conditional *F* statistic exceeds the Stock and Yogo critical value for both the first-difference and the level equations of models M1, M3 and M4, while it is not rejected for model M2. For lagged inequality and for all models considered, the null is rejected for the level equation but not for the first-difference equation.

In turn, for the reduce-and-collapse GMM specification in the right panel of Table 4, the weak instrument problem appears to be a minor issue for lagged poverty, as we find that the SW conditional *F* statistic exceeds the Stock and Yogo critical value in six out of eight cases considered (for M1, M3 and M4 for the first-difference equation, and for M1, M2 and M4 for the level equation). In contrast, it is a major concern for lagged inequality, since the SW *F* statistic is below the Stock and Yogo critical value in all cases.

Overall, the results of these tests reveal two facts. First, including the level equation in the estimation helps alleviate potential problems of underidentification and weak instruments. This points to system GMM as the preferred estimation approach. Second, the system GMM specification using

[34] Using these tools, Kraay (2015) finds pervasive evidence of weak internal instruments in the system GMM estimators employed by the literature on the growth effects of inequality. He concludes that the data used in papers such as Halter et al. (2014), Dabla-Norris et al. (2015) or Berg et al. (2018) are consistent with a wide range of both positive and negative values of the causal effect of inequality on growth.

only one lag to construct the instruments yields better results in the weak instruments and under-identification tests than collapsing the instrument matrix. Thus, for the remaining exercises we use the system GMM specification including only one lag in the matrix of instruments. Moreover, this is the only specification in which the inequality estimate does not appear to suffer from underidentification and weak instruments problems.

IV.4.- Further robustness checks

The empirical exercises reported so far take headcount poverty (P0) for a US$ 2 poverty line as the benchmark measure of poverty. However, it can be argued that the headcount is just one among many possible poverty measures, just as US$ 2 is just an arbitrary poverty line. To assess the robustness of our results to the use of alternative poverty measures, we re-estimate the empirical growth equation (12) using the poverty gap (P1) and the squared poverty gap (P2) instead of the poverty headcount, and considering alternative poverty lines: US$ 1.25, $2 and $4 per person per day. We do this for the four alternative models considered (M1, M2, M3 and M4).

Table 5 reports system GMM estimates of the 36 specifications that this strategy yields, with the matrix of instruments defined in all cases as in the top-right panel in Table 3. The results are easily summarized. Regarding the estimates of the poverty coefficient, 36 out of 36 are negative and significant -- regardless of the poverty measure, the poverty line, and the set of control variables employed. In general, the absolute value of the poverty coefficient rises as we move from P0 to P2. In turn, while all 36 estimates of the inequality coefficient are negative (recall that the positive estimates arise from the within-country dimension of the data), only 15 of them are significant at the 10 percent level or better. Finally, the Hansen tests in Table 5 do not show evidence against the validity of the instruments: 35 out of the 36 tests show a p-value higher than 0.1, and all p-values of the Hansen-difference test exceed 0.1.

We also performed a number of other robustness checks concerning the empirical specification and estimation approach. To save space we just provide a brief summary here; the full results are available upon request.

Among the robustness exercises, we modified the system GMM estimation employing different lag structures – e.g., lagging all instruments by one more period – and using 1-step instead of 2-step estimates. We also experimented with a modified version of the basic empirical equation including a quadratic term in the Gini coefficient. The main conclusion is that the significantly negative effect of poverty on growth is quite robust to all these variations in specification and estimation approach, while the inequality-growth relationship is highly fragile. Moreover, the magnitudes of the estimated poverty coefficients are very similar to those shown in Table 3.

Finally, we also re-estimated the four models (M1 to M4) in a pure cross-section of countries, using sample averages (over the entire sample period) of all the variables – likely capturing what could be viewed as the long-run relationships. The estimated poverty coefficient remains uniformly negative and significant, although its precision declines somewhat relative to the panel estimates. In turn, inequality tends to show a negative and significant coefficient, more frequently than in the panel estimates.

V. Poverty regimes

In the analytical model sketched in Section II, the effects of poverty and inequality on growth both depend on the prevailing level of poverty – a fact illustrated also in Figure 1. Also, inequality can affect growth directly, but also indirectly through its impact on poverty. In this section we assess how these predictions hold up empirically in our sample.

V.1. Poverty regimes and the effect of poverty on growth

To explore the role of the level of poverty, we start by estimating alternative versions of equation (12) allowing for different coefficients on lagged poverty and lagged inequality depending on whether the lagged value of P0 lies above or below the sample median (2.7% for our baseline US$ 2 poverty line, see Table 1). As a robustness check, we follow the same strategy conditioning instead on the lagged level of inequality, and estimate equation (12) allowing for different coefficients on poverty and inequality depending on whether the lagged Gini coefficient lies above or below its sample median (39.8%, see Table 1).

Table 6 shows the estimation results under the baseline system GMM approach. The top half of the table reports estimates distinguishing whether poverty is above or below the median – what we shall label the 'high poverty regime' and 'low poverty regime', respectively. The bottom half of Table 6 reports the estimates distinguishing whether inequality is above or below the median –the 'high inequality regime' and 'low inequality regime', respectively. The top half of the table shows that, under the low poverty regime -- i.e., poverty levels below the sample median -- the impact of poverty on growth is negative but statistically insignificant, consistent with the simulation results in the bottom-right graph in Figure 1. However, it is consistently negative and highly significant under the high poverty regime, consistent with the top-right graph in Figure 1. In turn, the estimated coefficient on the Gini index is in most cases negative, but it turns significant only for high poverty rates and for the M1 and M3 model specifications. Thus, like with the unconditional estimates, while the result for poverty is robust, the result for inequality is not.[35]

In contrast, the bottom half of Table 6 shows that when we condition on the lagged level of inequality, the estimated coefficients on poverty and inequality exhibit very little variation across inequality regimes. In effect, they are very similar to the unconditional estimates from Table 3. Regardless of whether the level of lagged inequality is above or below the median, the estimated coefficients of poverty are always negative and highly significant, while those for inequality can have either sign and are never significant. In other words, while the effects of poverty and inequality on growth depend on the prevailing level of poverty, they do not depend on the prevailing level of inequality, at least for the range of values in our sample.

V.2. Poverty regimes and the direct and indirect effects of inequality on growth

As a final exercise, we compute the indirect and the total effect of inequality on growth, as defined in equation (13). To allow for the role of poverty regimes in this calculation, we take the values of φ and δ from the estimates shown in the top panel of Table 6.[36] In the same spirit, to evaluate $\partial p / \partial g$ in (13), we re-estimate (14) dividing the sample in two depending on whether poverty is above or below the median. In addition, for illustrative purposes, we also estimate the equation separately for an 'extreme poverty' sample in which P0 lies above its 95th sample percentile (74% for the US$ 2 poverty line). This yields the following results:

$$p_{it} = 0.0286^{***} - 0.0038^{***}\ln(y_{it}) + 0.0293^{***} g_{it} + \hat{v}_{it}\text{, for P0} \leq \text{Median}, \tag{15}$$

$$p_{it} = 2.398^{***} - 0.3336^{***}\ln(y_{it}) + 0.9529^{***} g_{it} + \hat{v}_{it}\text{, for P0} > \text{Median}, \tag{16}$$

$$p_{it} = 2.2152^{***} - 0.2185^{***}\ln(y_{it}) - 0.0818^{**} g_{it} + \hat{v}_{it}\text{, for P0} > 95^{th}\text{ percentile}. \tag{17}$$

Consistent with the predictions from the analytical model in Section II – as well as the simulations in Figure 1 – the poverty-inequality slope is positive but relatively flat for low poverty rates (i.e.,

[35] Moreover, alternative estimation approaches, whether system GMM with 2 lags and collapsing the matrix of instruments, first difference GMM, pooled OLS with regional and time dummies, or within-group estimation, all yield a robust negative coefficient for poverty, but not for inequality.

[36] In assessing the role of alternative regimes, we only consider poverty regimes (the top panel of Table 6) because, as the bottom panel shows, conditioning on high and low inequality yields estimates very similar to the unconditional ones.

P0 below the median) and strongly positive for high poverty rates (P0 above the median). However, in extremely poor economies – i.e., those where poverty lies above the 95th sample percentile – the relation turns negative, in line with the model predictions as illustrated in the simulation results in the top left corner of Figure 1.

Combining these estimates of $\partial p / \partial g$ with the estimates of φ and δ shown in Table 6, we can obtain point estimates of the indirect and total effects on inequality on growth under different poverty regimes. However, when poverty is low (P0 below the median), Table 6 shows that the direct and indirect effects of inequality on growth are both negligible (i.e., φ and δ are statistically insignificant); this also is consistent with the predictions of the analytical model (illustrated in the simulation in the bottom-right graph in Figure 1). Thus, in the remainder of the section, we focus on the high-poverty subsample (P0 above the median) and, as an illustration, on the extreme poverty subsample.

Figure 3 shows the estimated direct, indirect and total effect of inequality on growth (expressed in percent per year). Specifically, the figure illustrates the consequences of a one-standard deviation increase of the Gini coefficient (i.e., by 0.10 according to Table 1). We report the calculation for the different estimated models (M1, M2, M3 and M4) and three alternative sets of estimates: the unconditional estimates, ignoring the prevailing poverty regime (top graph); the estimates obtained when poverty is above the median (middle graph); and the estimates for the case of extreme poverty (bottom graph). In all cases, we control for initial real per capita GDP and poverty, and include also the additional controls characterizing each model.

For the top panel, we combine the estimated $\partial p / \partial g$ from (14) (equal to 0.368) with the unconditional estimates of φ and δ in (13) from the baseline system GMM (top-right panel in Table 3), setting to zero any estimates that are not significant. The direct effect of inequality on growth is significantly negative only for models M1 and M3. However, the indirect effect of inequality (through poverty) on growth is always negative, and so is the overall impact. Specifically, a 10-point increase in the Gini coefficient generates, through the indirect effect, a decrease in annual growth by about 0.30 percentage points in all models. When in addition the direct effect is significant (in models M1 and M3), the total impact of a 10-point increase in the Gini coefficient is to reduce growth by about 1.5 percentage points for model M1, and about 1.3 percentage points for model M3.

For the case of poverty above the median, we employ the estimates of φ and δ applicable to that regime from Table 6, and the estimated $\partial p/\partial g$ of 0.9529 from (16). In this scenario, the indirect impact of inequality on growth is uniformly negative, and larger than the unconditional one, i.e., a 10-point increase in inequality reduces growth on average by 0.7 percentage points (model M3) or 1.2 percentage points (model M1) per year. Since the direct impact is only significant for models M1 and M3, the overall effect of inequality on growth is negative and larger in absolute value than that obtained from the unconditional estimates. Specifically, when poverty is above the median, a 10-point increase in the Gini coefficient has an overall negative impact on growth of about 2.2 and 1.8 percentage points in model M1 and M3, respectively, and about 0.9 percentage points in models M2 and M4, in which the direct effect is insignificant and therefore the total impact is just equal to the indirect effect.

Finally, with extremely high poverty (bottom graph in Figure 3), the theoretical model in Section II predicts that the effect of poverty on growth remains negative, but the indirect effect of inequality on growth becomes positive. To illustrate this scenario, we use the estimated $\partial p/\partial g$ from (17), which equals -0.0818, along with the estimates of φ and δ from Table 6 conditional on high poverty.[37] Through the indirect effect, a 10-point increase in the Gini coefficient now raises growth by about 0.10 percentage points per year. The sign of the overall effect of inequality on growth now varies across models. When the direct effect is zero (models M2 and M4), the overall effect is positive but small. In turn, when the direct effect is negative and significant (models M1 and M3), the overall effect is negative, although smaller in absolute value than in the unconditional or the high-poverty estimates.

To summarize, we find that the effect of poverty on growth is negative. Closer inspection reveals that this result is driven by the sample observations featuring high poverty rates (i.e., above the sample median); indeed, when poverty is below the median it does not have a material effect on growth.

In contrast, the overall effect of inequality on growth is less clear cut. On the one hand, the sign of the direct effect (i.e., at given poverty levels) is not robust. Indeed, we find both negative and positive estimates depending on the econometric approach employed. On the other hand, the indirect effect of inequality on growth accruing through poverty is negative. However, closer analysis again

[37] Alternatively, we could attempt to estimate a growth equation using GMM and allowing for different coefficients when poverty is in the 'extreme' region. Since such region comprises only 36 observations, however, the resulting estimates would be highly unreliable.

shows that such negative impact arises from the observations with above-median (but not extreme) poverty rates. Indeed, the indirect impact is negligible when poverty is below the median, and it even turns positive at extremely high levels of poverty. Importantly, these empirical findings are fully consistent with the analytical model sketched in Section II.

VI. Conclusions

This paper has examined two issues that have received limited attention in the otherwise extensive empirical literature of growth, inequality and poverty. First, the paper provides an empirical assessment of the impact of poverty on growth, building on the earlier work by López and Servén (2009). Second, as a byproduct, the paper also highlights the indirect effect of inequality on growth accruing through poverty.

To guide its empirical work, the paper uses a simple analytical model in which growth is driven by aggregate investment, but poor consumers lack the resources to save and invest. In the model, the impact of poverty on growth is unambiguously negative, and its magnitude increases with the extent of poverty. In contrast, the impact of inequality on growth can go either way, as it combines two different effects that may be mutually opposing. The first one is the indirect impact of inequality on growth accruing through poverty, which is uniformly negative except when extremely high poverty is coupled with very low levels of inequality. The second is due to the impact of inequality on the aggregate investment of non-poor individuals, which is also shown to be ambiguous.

To test these predictions, the paper uses a large panel dataset including 804 observations covering 158 countries and spanning the years 1960-2010. The empirical strategy involves including inequality and poverty indicators among the explanatory variables in an otherwise standard empirical growth equation.

On the whole, the results reveal a consistently negative and strongly significant correlation of poverty with subsequent growth. Its magnitude is economically significant too: a 10 percentage-point decrease in the headcount poverty rate is associated with a rise in annual per capita real growth of 0.5% to 1.8%, depending on the precise specification of the empirical model. However, further analysis reveals that the magnitude and significance of the effect depends on the prevailing level of poverty. Specifically, when the level of poverty is low (below the sample median), the growth effect of poverty is not statistically significant. In contrast, when the level of poverty is high, changes in the poverty headcount rate show a significantly negative association with subsequent growth – i.e., a 10 percentage-point decrease in the headcount poverty rate is associated with an increase in growth ranging between 1% and as much as 2%.

In contrast, we find that, holding poverty constant, the link between inequality and growth is fragile. It can take either sign depending on the particular model and econometric approach employed. Consistent with previous results in the literature, we find a positive (significant in some specifications) sign when using the within dimension of the data, and a negative one (also significant at times) when using the cross-country dimension. Still, the indirect effect of inequality (through poverty) on growth is found to be robustly negative, especially when the level of poverty is high. Its magnitude is also economically significant, e.g., a 10-percentage point decrease in the Gini coefficient is associated with an increase of per capita growth of 0.3% in the full sample, and between 0.7% and 1.1% in the above-median poverty subsample. In contrast, under extremely high poverty, the sign of the correlation turns positive, and a 10-percentage point increase in the Gini coefficient is associated with an increase in per capita growth of about 0.1%. Importantly, these empirical results agree qualitatively with the predictions of the analytical model.

The paper also reports a battery of additional experiments showing that the empirical results are robust to the use of alternative sets of control variables, estimation procedures, poverty lines and poverty measures.

The conclusion that poverty tends to deter growth has potentially major implications for the choice of growth-oriented policies. Specifically, our findings suggest that the biggest growth payoff is likely to result from policies that not only promote growth, but also exert an independent, direct impact on poverty – hence reducing the drag of poverty on growth.

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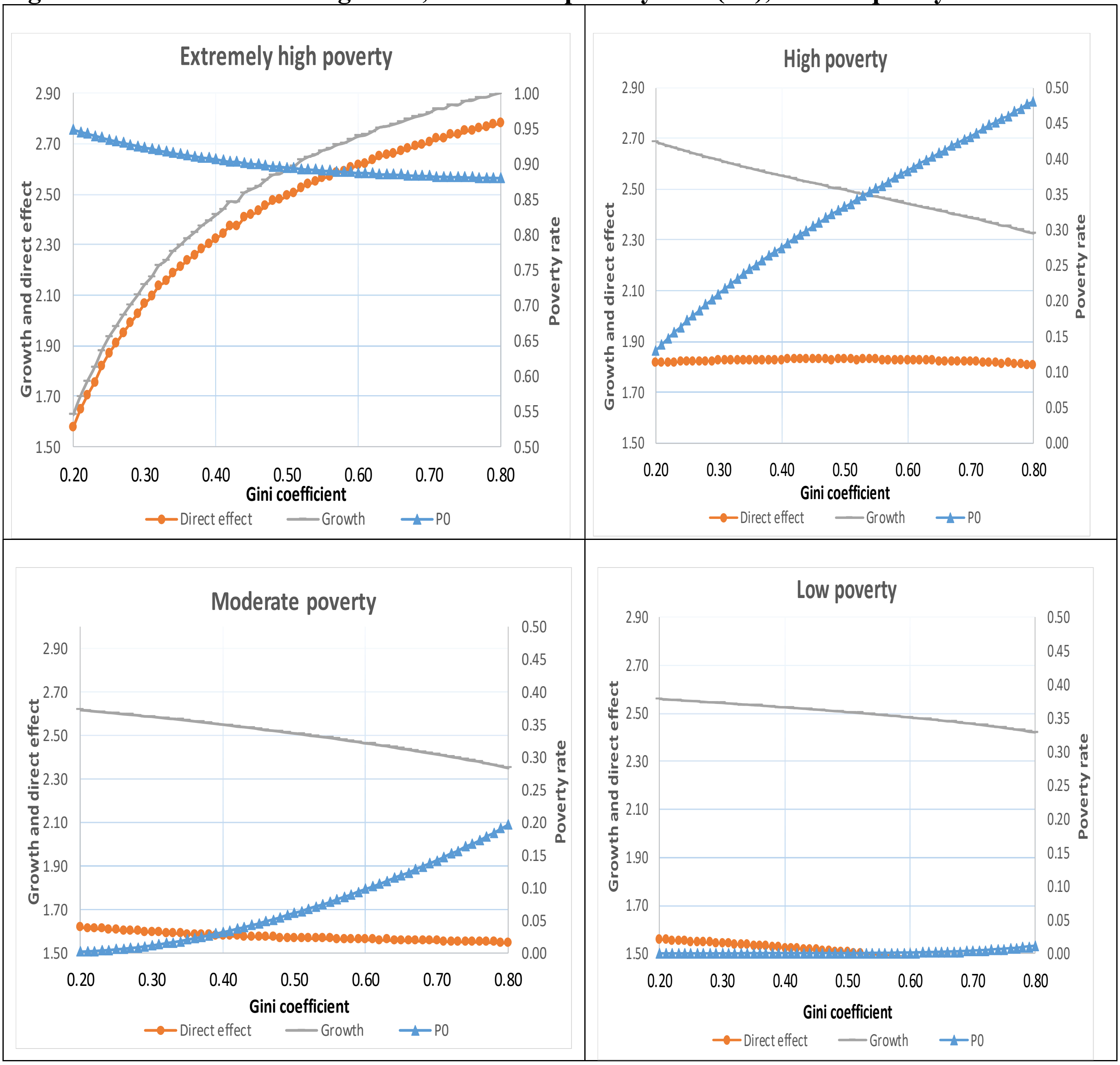
Figure 1. Model simulation: growth, headcount poverty rate (P0), and inequality



Note: For the simulation, we use standard values for the preference and technology parameters: θ=0.35 and ρ=0.98, which together imply a saving rate of 0.25 and a real interest rate of 2%. We fix $\overline{c}$ =1 and consider alternative values of $\overline{w}$ to generate economies with different poverty rates, assuming that income follows a lognormal distribution. In each case, a_0 is set so as to achieve a growth rate of 2.5% on average, which is the mean of our sample (see Table 1, Section III). The growth rate is calculated from (10), while the direct effect is the third term in (10), and the headcount poverty rate P0 refers to expression (1).

Figure 2. Growth, poverty and inequality: preliminary cross-section evidence

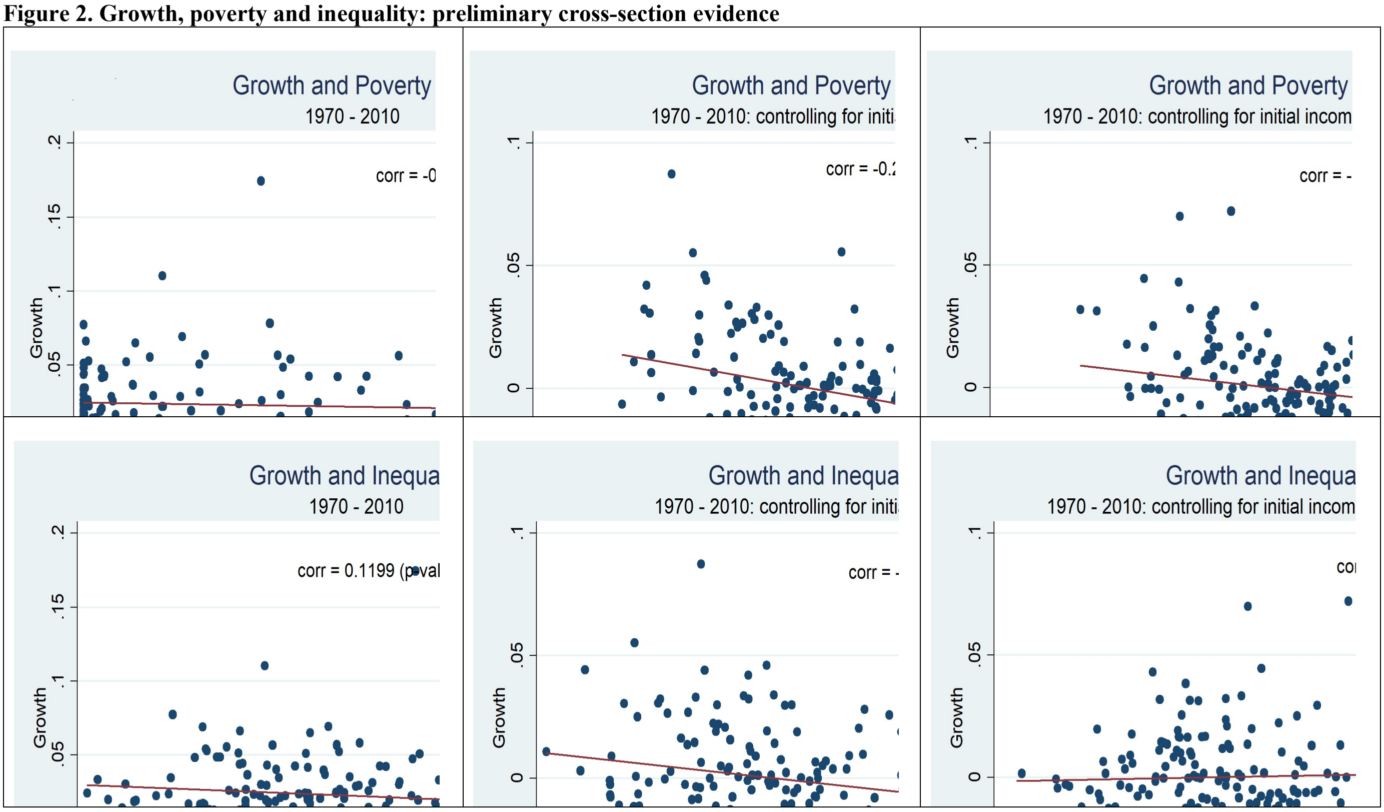
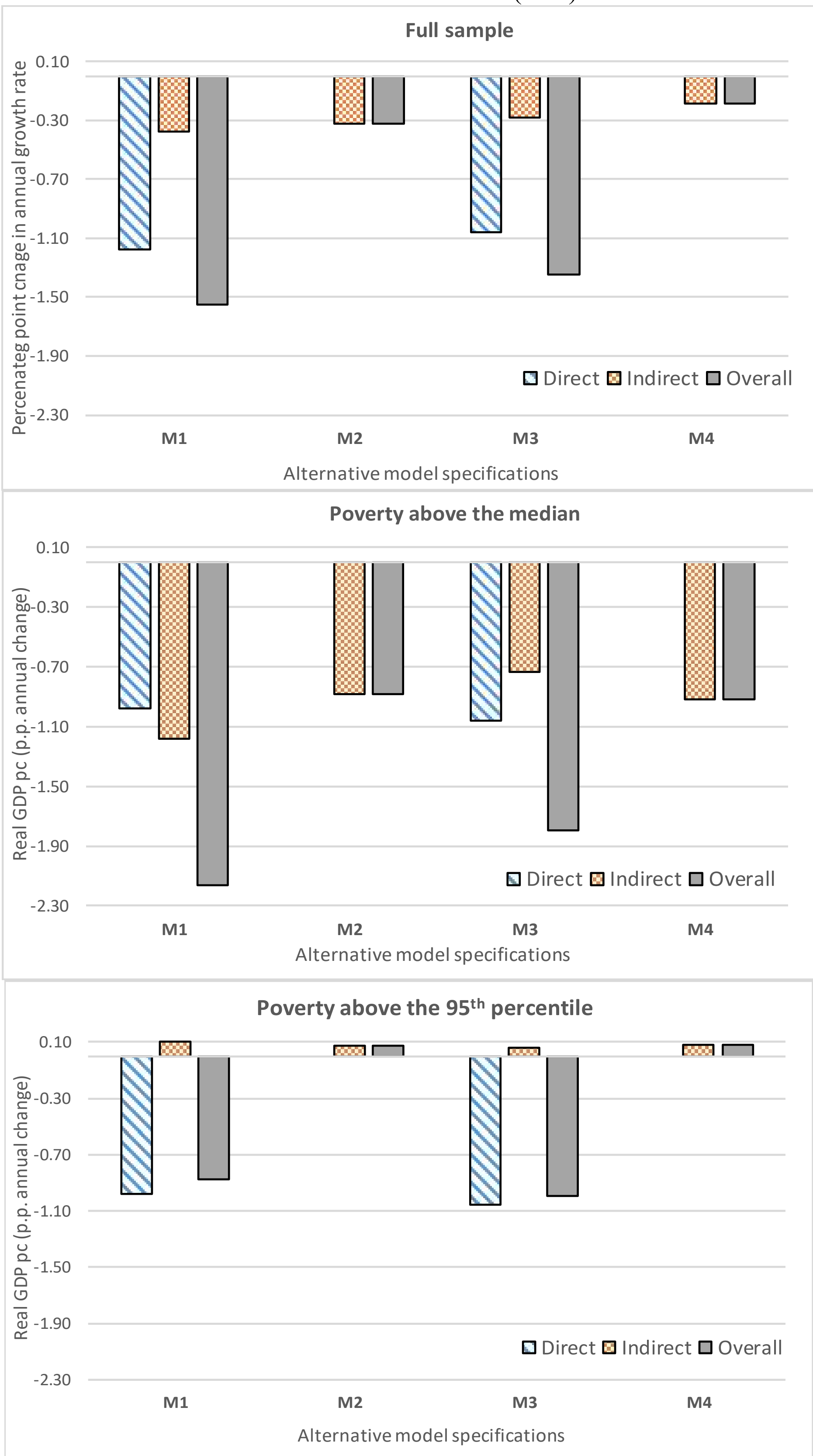


Figure 3. Inequality and growth under different poverty regimes

Direct, indirect and total effect on growth of a 1-standard deviation (0.10) increase in the Gini coefficient from its median (0.40)



Note: The direct effect is given by φ (the inequality coefficient in the growth equation in (12)), while the overall effect is calculated from (13). The indirect effect is the difference between the two. For the calculations, the top graph uses estimates of δ and φ from Table 3 (top-right panel), along with the poverty-inequality coefficient estimated from (14). The middle and bottom graphs use estimates of δ and φ from Table 6, along with the poverty-inequality coefficient estimated from (16) and (17), respectively. When the estimated coefficients in Tables 3 or 6 are not significant, we set their value equal to zero. M1, M2, M3 and M4 denote the alternative sets of control variables included in the empirical growth equation as described in Section III.

Table 1. Summary statistics

	Median	Mean	Std	P10	P90	Min.	Max.
Annual Growth	0.025	0.025	0.030	-0.012	0.061	-0.086	0.201
Real pc Income	5531.0	9489.2	10245.4	837.1	25408.0	207.5	73243.0
Gini coefficient	0.398	0.403	0.100	0.280	0.541	0.157	0.742
P0(US$ 1.25)	0.005	0.096	0.174	0.000	0.357	0.000	0.906
P0 (US$ 2)	0.027	0.163	0.246	0.000	0.602	0.000	0.969
P0 (US$ 4)	0.139	0.291	0.335	0.000	0.875	0.000	0.999
P1 (US$ 1.25)	0.001	0.040	0.086	0.000	0.143	0.000	0.602
P1 (US$ 2)	0.006	0.073	0.132	0.000	0.265	0.000	0.722
P1 (US$ 4)	0.038	0.151	0.212	0.000	0.518	0.000	0.855
P2 (US$ 1.25)	0.000	0.023	0.056	0.000	0.077	0.000	0.497
P2 (US$ 2)	0.002	0.044	0.089	0.000	0.156	0.000	0.594
P2 (US$ 4)	0.016	0.100	0.156	0.000	0.354	0.000	0.750

Note: This table reports the summary statistics of annual growth, income per capita, the Gini coefficient, and the headcount poverty rate (*P0*), poverty gap (*P1*) and the squared of the poverty gap (*P2*) for alternative poverty lines (US$ 1.25, US$ 2 and US$4, per person per day).

Table 2. Growth, poverty and inequality: panel OLS estimates

	M1. Skeleton Model		M2. Extended with Education & Inv. Prices		M3. Extended with policy variables		M4. Extended with policy and Infrastructures	
Pooled-OLS Robust estimates								
P0, lag		-0.0440***		-0.0288***		-0.0391***		-0.0430***
		(-5.71)		(-3.39)		(-4.78)		(-4.03)
Gini, lag	-0.0398***	-0.0393***	-0.0302**	-0.0311***	-0.0388***	-0.0382***	-0.0357**	-0.0366***
	(-3.49)	(-3.50)	(-2.55)	(-2.67)	(-3.26)	(-3.24)	(-2.48)	(-2.60)
log y, lag	-0.00137	-0.00873***	-0.00353***	-0.00840***	-0.00303***	-0.00938***	-0.0144***	-0.0215***
	(-1.55)	(-5.88)	(-2.83)	(-4.34)	(-3.20)	(-6.02)	(-4.24)	(-6.31)
Inv. deflactor, lag			-0.0150***	-0.0117***				
			(-4.98)	(-3.97)				
Female educ., lag			-0.00198	-0.00134			0.00363**	0.00509***
			(-0.73)	(-0.51)			(2.40)	(3.48)
Male educ., lag			0.00592**	0.00528**				
			(2.16)	(1.99)				
Inflation					-0.00905	-0.0132**	-0.0165**	-0.0217***
					(-1.53)	(-2.10)	(-2.57)	(-3.31)
Trade openness (log)					0.0136***	0.0114***		
					(5.06)	(4.26)		
Gov. size (log)					-0.00189	-0.00116		
					(-0.67)	(-0.42)		
Infrastructure, lag							0.00852***	0.00754***
							(2.90)	(2.70)
R2-adjusted	0.072	0.112	0.126	0.139	0.112	0.141	0.127	0.161
Within Group (WG) robust estimates								
P0, lag		-0.0764***		-0.0793***		-0.0869***		-0.0633***
		(-4.45)		(-4.66)		(-4.49)		(-2.82)
Gini, lag	0.0372	0.0643**	0.0451	0.0749**	0.0593**	0.0884***	0.0453	0.0641**
	(1.26)	(2.27)	(1.46)	(2.47)	(2.06)	(3.05)	(1.47)	(2.05)
log y, lag	-0.0304***	-0.0429***	-0.0259***	-0.0426***	-0.0556***	-0.0709***	-0.0580***	-0.0674***
	(-4.91)	(-6.18)	(-4.05)	(-5.87)	(-6.56)	(-8.32)	(-8.01)	(-8.18)
Inv. deflactor, lag			-0.0121**	-0.00848**				
			(-2.32)	(-2.20)				
Female educ., lag			-0.0114	-0.00205			0.00250	0.00603**
			(-1.50)	(-0.27)			(0.99)	(2.39)
Male educ., lag			0.0141*	0.00943				
			(1.76)	(1.16)				
Inflation					-0.0279***	-0.0281***	-0.0370***	-0.0366***
					(-4.39)	(-4.28)	(-5.42)	(-5.10)
Trade openness (log)					0.0302***	0.0226***		
					(3.43)	(3.36)		
Gov. size (log)					-0.0184**	-0.0238***		
					(-2.46)	(-3.17)		
Infrastructure, lag							0.0235***	0.0170***
							(5.86)	(3.44)
R2-adjusted	0.175	0.216	0.196	0.235	0.308	0.354	0.330	0.350
Num. Obs	750	745	678	674	656	654	479	477
Num. groups	157	156	131	130	148	147	89	88

Note: Unbalanced panel with data at 5-year intervals over 1960- 2010. The dependent variable is the annual growth rate of per capita income. The explanatory variables are: real per capita income (in logs), the headcount poverty rate (P0) using US$ 2 as poverty line, the Gini coefficient, and alternative sets of additional controls that vary across models M1 (skeleton model), M2 (education and investment prices), M3 (policy variables) and M4 (policy variables and infrastructures). Explanatory variables are all lagged one period (5 years), with the exception of the policy variables in models M3 and M4, which are taken as contemporaneous 5-year averages. A constant term and time dummies (and regional dummies for pooled OLS) are also included in all models. Robust *t* statistics in parentheses. *** denotes significance at 1%, ** at 5%, * at 10%.

Table 3. Growth, poverty and inequality: alternative GMM estimates

	First difference GMM				Baseline system GMM			
	M1	M2	M3	M4	M1	M2	M3	M4
P0, lag	-0.0981***	-0.150***	-0.127***	-0.0945***	-0.102***	-0.0878***	-0.0773***	-0.0503**
	(-2.63)	(-5.17)	(-4.29)	(-3.10)	(-4.11)	(-4.39)	(-4.70)	(-2.32)
Gini, lag	0.113	0.131**	0.168**	0.158**	-0.118**	-0.0454	-0.106***	-0.0346
	(1.10)	(2.01)	(2.47)	(2.37)	(-2.36)	(-1.27)	(-3.14)	(-1.25)
log y, lag	-0.119***	-0.0948***	-0.141***	-0.107***	-0.0196***	-0.0160***	-0.0206***	-0.0299***
	(-5.45)	(-4.47)	(-6.68)	(-5.71)	(-5.35)	(-5.14)	(-6.62)	(-3.29)
Num. Obs	502	467	448	345	745	676	656	477
Hansen (p-val)	0.0238	0.416	0.289	0.916	0.296	0.163	0.348	0.477
m2-test (p-val)	0.568	0.336	0.729	0.236	0.267	0.107	0.523	0.313
AR(3) (p-val)	0.0571	0.330	0.124	0.468	0.637	0.778	0.527	0.746
Num. groups	130	113	123	79	156	131	147	88
Num. instruments	54	99	96	96	55	100	97	97
Diff-Hansen for levels (p-val)	--	--	--	--	0.840	0.664	0.548	0.850
	System GMM (collapse)				**System GMM (collapse and reduce)**			
	M1	**M2**	**M3**	**M4**	**M1**	**M2**	**M3**	**M4**
P0, lag	-0.169***	-0.144***	-0.131***	-0.0934***	-0.179***	-0.149***	-0.145***	-0.0884***
	(-3.99)	(-5.76)	(-3.35)	(-3.34)	(-5.04)	(-5.74)	(-2.90)	(-2.64)
Gini, lag	-0.0613	0.0575	-0.0897	-0.0506	-0.313	-0.161	-0.123	-0.0353
	(-0.54)	(1.35)	(-1.24)	(-1.03)	(-1.38)	(-1.11)	(-1.25)	(-0.65)
log y, lag	-0.0280***	-0.0259***	-0.0265***	-0.0458***	-0.0362***	-0.0286***	-0.0289***	-0.0445***
	(-4.46)	(-4.93)	(-4.59)	(-5.59)	(-4.56)	(-4.36)	(-3.41)	(-5.85)
Hansen (p-val)	0.740	0.833	0.504	0.709	0.335	0.752	0.364	0.848
m2-test (p-val)	0.00479	0.0834	0.147	0.297	0.452	0.566	0.738	0.112
AR(3) (p-val)	0.192	0.0464	0.496	0.399	0.717	0.299	0.670	0.416
Num. Obs	745	676	656	477	745	676	656	477
Num. groups	156	131	147	88	156	131	147	88
Num. instruments	40	70	68	68	22	34	33	33
Diff-Hansen for levels (p-val)	0.118	0.650	0.687	0.403	0.452	0.566	0.958	0.207

Note: Unbalanced panel with data at 5-year intervals over 1960- 2010. The dependent variable is the annual growth rate of per capita income. The explanatory variables are: real per capita income (in logs), the headcount poverty rate (P0) using US$ 2 as poverty line, the Gini coefficient, and alternative sets of additional controls that vary across models M1 (skeleton model), M2 (education and investment prices), M3 (policy variables) and M4 (policy variables and infrastructures). Explanatory variables are all lagged one period (5 years), with the exception of the policy variables in models M3 and M4, which are taken as contemporaneous 5-year averages. A constant term and time dummies are included in all models. Estimation is done using 2-step first difference GMM (top-left panel) and 2-step system GMM in the rest of cases: reducing the number of instrument lags to one (top-right panel), collapsing the matrix of instruments and using all lags (bottom-left panel) and collapsing and reducing the number of instruments to two lags (bottom-right panel). In all cases, the instrument set starts at t-3, and the variance covariance matrix is computed using the small sample correction of Windmeijer (2005). The difference Hansen test assesses the validity of the instruments for the level equation in system GMM. Robust *t* statistics in parentheses. *** denotes significance at 1%, ** at 5%, * at 10%

Table 4. Weak instruments analysis for system GMM estimations

	Baseline system GMM				System GMM (collapse and reduce)			
	M1	**M2**	**M3**	**M4**	**M1**	**M2**	**M3**	**M4**
A. First difference equation								
A.1. Underidentification Test								
SW Chi-2 (p-val) (P0, lag)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SW Chi-2 (p-val) (Gini, lag)	0.328	0.00	0.00	0.00	0.39	0.700	0.008	0.284
A.2. Weak identification Test								
SW F-stat (P0, lag)	7.25	3.46	13.74	7.39	8.26	3.43	7.92	5.34
SW F-stat (Gini, lag)	1.03	1.97	2.71	3.47	1.00	0.64	2.63	1.16
Stock-Yogo, 30% maximal IV relative bias	4.39	4.11	4.11	4.11	5.15	4.75	4.75	4.75
B. Level equation								
B.1. Underidentification Test								
SW Chi-2 (p-val) (P0, lag)	0.00	0.00	0.00	0.00	0.00	0.00	0.074	0.00
SW Chi-2 (p-val) (Gini, lag)	0.00	0.00	0.00	0.00	0.344	0.3179	0.200	0.236
B.2. Weak identification Test								
SW F-stat (P0, lag)	4.46	3.84	10.02	9.49	6.50	6.83	1.79	4.98
SW F-stat (Gini, lag)	5.34	4.31	14.24	7.93	1.10	1.13	1.35	1.26
Stock-Yogo, 30% maximal IV relative bias	4.46	4.15	4.16	4.16	5.15	4.75	4.75	4.75

Note: This table reports weak instruments tests (Sanderson and Windmeijer, 2016) for the system GMM specifications shown in the right-hand panel of Table 3. The tests considered are, first, a *F*-based test allowing for separate weak-instruments diagnosis for lagged poverty and the lagged Gini coefficient (Angrist and Pischke, 2009); and second, a Chi-2 under-identification test, which is also reported separately for lagged poverty and the lagged Gini coefficient. To calculate the tests, we construct the exact instrument matrix for the difference and the level equations for each system GMM estimator, and then apply the standard 2SLS regression and tests (see Bun and Windmeijer, 2010). For the *F*-based test, we use the reference values provided by Stock and Yogo (2005). An *F* statistic below the reference value in Stock and Yogo represents evidence that the coefficient estimate of the variable under consideration suffers from a weak instruments problem.

Table 5. Estimation results: alternative poverty lines and poverty measures
Baseline system GMM

	M1			M2			M3			M4		
Poverty lines	**US$ 1.25**	**US$ 2**	**US$ 4**	**US$ 1.25**	**US$ 2**	**US$ 4**	**US$ 1.25**	**US$ 2**	**US$ 4**	**US$ 1.25**	**US$ 2**	**US$ 4**
Headcount Poverty Rate, P0												
P0, lag	-0.102***	-0.102***	-0.130***	-0.0840***	-0.0878***	-0.107***	-0.0913***	-0.0773***	-0.0839***	-0.0584***	-0.0503**	-0.0629***
	(-4.01)	(-4.11)	(-5.13)	(-3.66)	(-4.39)	(-5.02)	(-3.83)	(-4.70)	(-4.58)	(-2.71)	(-2.32)	(-2.62)
Gini, lag	-0.102*	-0.118**	-0.0900**	-0.0522	-0.0454	-0.0382	-0.0962***	-0.106***	-0.102***	-0.0346	-0.0346	-0.0206
	(-1.96)	(-2.36)	(-2.03)	(-1.42)	(-1.27)	(-0.97)	(-2.79)	(-3.14)	(-2.97)	(-1.46)	(-1.25)	(-0.58)
log y, lag	-0.0142***	-0.0196***	-0.0307***	-0.0120***	-0.0160***	-0.0247***	-0.0175***	-0.0206***	-0.0266***	-0.0319***	-0.0299***	-0.0368***
	(-4.98)	(-5.35)	(-5.08)	(-4.00)	(-5.14)	(-5.96)	(-5.54)	(-6.62)	(-5.86)	(-4.06)	(-3.29)	(-4.99)
Hansen (p-val)	0.278	0.296	0.187	0.107	0.163	0.173	0.367	0.348	0.330	0.499	0.477	0.543
Poverty Gap, P1												
P1, lag	-0.210***	-0.152***	-0.151***	-0.136***	-0.121***	-0.120***	-0.184***	-0.136***	-0.112***	-0.121**	-0.0854**	-0.0709**
	(-3.30)	(-3.98)	(-4.17)	(-2.77)	(-3.80)	(-5.46)	(-3.63)	(-4.30)	(-5.24)	(-2.45)	(-2.57)	(-2.33)
Gini, lag	-0.0807	-0.0953*	-0.111**	-0.0475	-0.0473	-0.0396	-0.0785**	-0.0952***	-0.106***	-0.0182	-0.0356	-0.0326
	(-1.41)	(-1.88)	(-2.34)	(-1.28)	(-1.28)	(-1.14)	(-2.41)	(-2.79)	(-3.08)	(-0.57)	(-1.10)	(-1.08)
log y, lag	-0.0124***	-0.0153***	-0.0244***	-0.00977***	-0.0130***	-0.0190***	-0.0158***	-0.0187***	-0.0243***	-0.0349***	-0.0333***	-0.0356***
	(-4.17)	(-5.10)	(-5.35)	(-3.09)	(-4.29)	(-5.98)	(-5.18)	(-5.98)	(-6.86)	(-3.93)	(-3.83)	(-4.97)
Hansen (p-val)	0.275	0.323	0.324	0.115	0.0993	0.175	0.455	0.349	0.385	0.630	0.470	0.540
Squared Poverty Gap, P2												
P2, lag	-0.333***	-0.212***	-0.162***	-0.173**	-0.147***	-0.129***	-0.283***	-0.189***	-0.137***	-0.197**	-0.116**	-0.0833**
	(-2.78)	(-3.64)	(-4.02)	(-2.18)	(-3.06)	(-4.49)	(-2.98)	(-3.96)	(-5.33)	(-2.56)	(-2.41)	(-2.26)
Gini, lag	-0.0723	-0.0810	-0.106**	-0.0469	-0.0464	-0.0438	-0.0719**	-0.0836**	-0.103***	-0.00956	-0.0241	-0.0327
	(-1.19)	(-1.45)	(-2.26)	(-1.31)	(-1.24)	(-1.21)	(-2.34)	(-2.51)	(-2.99)	(-0.30)	(-0.81)	(-1.55)
log y, lag	-0.0114***	-0.0135***	-0.0196***	-0.00861***	-0.0109***	-0.0161***	-0.0147***	-0.0169***	-0.0220***	-0.0358***	-0.0346***	-0.0349***
	(-3.74)	(-4.51)	(-5.42)	(-2.72)	(-3.47)	(-5.10)	(-4.84)	(-5.39)	(-7.15)	(-4.78)	(-3.90)	(-4.21)
Hansen (p-val)	0.269	0.308	0.347	0.121	0.105	0.107	0.450	0.427	0.325	0.662	0.622	0.603
Num. Obs.	745	745	745	676	676	676	657	657	657	477	477	477
Num. countries	156	156	156	131	131	131	147	147	147	88	88	88
Num. Instruments	55	55	55	100	100	100	97	97	97	97	97	97

Note: See the note to Table 3. This table reports estimates of the model shown in the top right-hand panel of Table 3, using alternative poverty measures (the headcount poverty rate (P0), the poverty gap (P1) and the squared poverty gap (P2)) for alternative poverty lines ($1.25, $2 and $4).

Table 6. Estimation results: poverty and inequality regimes
Baseline system GMM

	M1	M2	M3	M4
		Poverty regimes		
P0, lag (P0$\leq$ $Median$)	-0.101	-0.944	-0.444	0.635
	(-0.16)	(-1.29)	(-0.52)	(0.75)
P0, lag (P0$>$ $Median$)	-0.124***	-0.0928***	-0.0770***	-0.0966**
	(-5.04)	(-5.25)	(-2.75)	(-2.22)
Gini, lag (P0$\leq$ $Median$)	-0.0589	-0.00504	-0.0736	-0.0635
	(-1.24)	(-0.10)	(-1.24)	(-0.90)
Gini, lag (P0$>$ $Median$)	-0.0980***	-0.0547	-0.106***	-0.0815
	(-2.63)	(-1.46)	(-2.76)	(-1.50)
log y, lag	-0.0275***	-0.0236***	-0.0241***	-0.0394***
	(-5.31)	(-6.43)	(-3.14)	(-2.68)
Hansen (p-val)	0.256	0.354	0.469	0.172
m2 (p-val)	0.205	0.168	0.419	0.447
Num. Instruments	85	130	127	84
		Inequality regimes		
P0, lag (Gini $\leq$ $Median$)	-0.0957***	-0.0928***	-0.0681***	-0.0569**
	(-4.04)	(-2.86)	(-3.09)	(-2.15)
P0, lag (Gini$>$ $Median$)	-0.115***	-0.0696***	-0.0822***	-0.118***
	(-3.93)	(-3.07)	(-3.64)	(-3.65)
Gini, lag (Gini$\leq$ $Median$)	-0.0374	0.0802	-0.0461	0.0103
	(-0.48)	(0.45)	(-0.73)	(0.15)
Gini, lag (Gini$>$ $Median$)	-0.0484	0.0156	-0.0648	0.0100
	(-0.91)	(0.10)	(-1.51)	(0.19)
log y, lag	-0.0203***	-0.0159***	-0.0190***	-0.0349***
	(-6.25)	(-2.62)	(-6.21)	(-4.13)
Hansen (p-val)	0.168	0.435	0.373	0.0738
m2 (p-val)	0.142	0.0827	0.440	0.286
Num. Instruments	85	130	127	84
Num.obs	745	676	659	479
Num.groups	156	131	147	88

Note: See the note to Table 3. This table reports estimates of the model shown in the top right-hand panel of Table 3, allowing the estimated coefficients on the poverty rate P0 and the Gini coefficient to differ depending on whether P0 is above or below its sample median (top panel), or whether the Gini coefficient is above or below its sample median (bottom panel).

Appendix A. The database

Despite the progress made in recent years, mainly through the expanding international coverage of Living Standards Measurement Surveys (LSMS) and similar surveys, poverty data are still scarce, at least in relation to the size of the standard cross-country time-series growth dataset. Thus, following López and Servén (2006), as noted in the main text, we construct a set of poverty figures (the headcount ratio, P0, the poverty gap, P1 and the squared poverty gap, P2) using a lognormal approximation on the basis of the observed per capita income levels and Gini coefficients, which are available much more widely than survey-based poverty data.[38]

As a measure of average income, we use the 2005 PPP-adjusted GDP per capita from PWT 7.1, available for a total of 189 countries from 1960 to 2010. To measure average income, Sala-i-Martin (2006) and Dollar and Kraay (2002), among others, emphasize the advantages of using per capita GDP instead of the mean level of household income obtained directly from the survey. First, the survey mean usually does not match per capita income from the national accounts, because of differences in concepts and methodology, methods of data collection, misreporting in the surveys, etc. Second, and probably most important, data availability: on one hand, for many of the country-year observations for which we have information on income distribution, we do not have the corresponding information on mean income from the same source; national accounts data, on the other hand, are reported by the PWT yearly for all countries and using an homogenous methodology, which, additionally, allows us to compare our results with the related literature on income inequality and growth.

The data on income distribution are drawn from two main sources. The primary source is the UN-WIID2 (2008) database, which includes 5,313 surveys for 154 countries from 1950 to

[38] The use of the lognormal approximation to the distribution of income dates back to Gibrat (1931). The literature employs also other functional forms, such as the Pareto, the gamma or the Weibull distribution, but the log-normal is the more widely used. Indeed, López and Servén (2006) compare the quintile income shares generated by a lognormal distribution with their observed counterparts using data from over 1,000 household surveys, and find the lognormal approximation fits the data extremely well, so that they are unable to reject the null hypothesis that per-capita income follows a lognormal distribution. Under log-normality, given the Gini coefficient (g) the standard deviation (σ) of the log of income is given by $\sigma = \sqrt{\Phi^{-1}\left(\frac{1+g}{2}\right)}$, where $\Phi(.)$ is the standard normal cumulative distribution function. Using this expression and the log of per capita income (y), we can compute the FGT family of poverty measures for a given poverty line z as:

$$P0 = \Phi(\frac{\log(z)-y}{\sigma}+\frac{\sigma}{2})$$

$$P1 = \Phi(\frac{\log(z)-y}{\sigma}+\frac{\sigma}{2}) - \frac{e^y}{z}\Phi(\frac{\log(z)-y}{\sigma}-\frac{\sigma}{2})$$

$$P2 = \Phi(\frac{\log(z)-y}{\sigma}+\frac{\sigma}{2}) - 2\frac{e^y}{z}\Phi(\frac{\log(z)-y}{\sigma}-\frac{\sigma}{2}) + \left(\frac{e^y}{z}\right)^2 e^{\sigma^2}\Phi(\frac{\log(z)-\nu}{\sigma}-\frac{3\sigma}{2}).$$

2006.[39] We complete this database with the POVCAL database, which includes 912 surveys for 123 developing countries between 1981 and 2008. Since the UN-WIID2 database already reports many of the surveys included in POVCAL, this latter database only adds 122 country-year (16 countries) observations to the previous source.

These databases (especially the UN-WIID2) contain a very large number of surveys, some of them referring to the same country-year but with different coverage or using different concepts of income. Thus, we restrict our sample to income distribution measures based on nationally-representative surveys (in terms of area, population and age), disregarding those surveys considering only 'urban' areas, or 'economically active' or 'working-age' population. In spite of this initial selection, data are sometimes based on income and other times on expenditure figures; income is net of transfers and taxes in some cases and not in others; the unit of analysis may be the individual or the household, etc. To correct at least in part for this heterogeneity, we adjust the original data following Dollar and Kraay (2002).[40]

Since our interest is in medium to long-run growth, and because we do not want our sample to be unduly affected by cyclical growth fluctuations, rather than annual data we use non-overlapping 5-year periods from 1960 to 2010. Income and most other variables (education, inflation, etc.) are available every 5 years starting in 1960. However, this is not quite the case for inequality data from the surveys. Thus, whenever the data on inequality is not available exactly at the required date, we adopt a proximity criteria to assign it to the appropriate period, using a distance limit of 2 years (i.e., a value for 2002 is assigned to 2000, while a value for 2003 is assigned to 2005), and taking averages when more than one observation is available within a particular interval. Because of the strong inertia of inequality and poverty, using alternative strategies in the same spirit (i.e., using a limit of 1 year of difference or not using means) yield very similar results (Dollar and Kraay, 2002; Pinkovsky and Sala-i-Martin, 2013, 2014).

[39] We disregard observations of the 1950's because most other variables are unavailable in those years. Moreover, since poverty and inequality are measured at the beginning of the period in the regression analysis, and we use non-overlapping 5-year periods, it is not necessary to collect these variables beyond 2005.

[40] Specifically, we pool the sample and regress the Gini coefficient on a constant, regional dummies and dummy variables indicating whether the survey is stated in terms of gross income or consumption (the omitted category is income net of taxes and transfers). We then subtract the estimated mean difference between these two alternatives and the omitted category to arrive at a set of Gini indices that notionally correspond to the distribution of income net of taxes and transfers. The results of these adjustment regressions are available upon request, but they show similar conclusions as in Dollar and Kraay (2002).