Too Poor to Grow

Humberto López
World Bank

Luis Servén
World Bank

Development theorists have long been intrigued by a variety of mechanisms capable of generating vicious cycles of poverty and stagnation—broadly referred to as poverty traps. These mechanisms highlight different ways in which poverty may deter growth and become self-perpetuating. Such situation may arise through a number 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. When these are 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. One example along these lines is provided by Galor and Zeira (1993) who present a model in which credit constraints and indivisibilities in human capital investment hamper aggregate growth. The reason is that only sufficiently wealthy individuals can afford education, which is the force driving growth in the model.[1]

Another poverty-perpetuating mechanism is related to risk. As noted by Banerjee (2000), the poor are typically more risk averse than the rich because losses hurt them more severely. In the absence of

We thank Andrea Repetto and conference participants for useful comments. We are also grateful to Aart Kraay, Martin Ravallion, Guillermo Perry and seminar participants at the IMF and the World Bank for useful comments and suggestions on earlier drafts. However, they bear no responsibility for any remaining errors. Patricia Macchi provided excellent research assistance. The views expressed in this paper are ours only and should not be attributed to the World Bank, its Executive Directors or the countries they represent.

1. See also Dasgupta and Ray (1986), who develop a model focused on investments in health; and Banerjee and Newman (1993).

Economic Policies in Emerging-Market Economies, Festschrift in Honor of Vittorio Corbo, edited by Ricardo J. Caballero and Klaus Schmidt-Hebbel, Santiago, Chile.

well-functioning insurance and credit markets, the poor will skip profitable investment opportunities that they deem too risky. Such behavior makes poverty self-reinforcing as the poor minimize risk at the expense of their mean earnings.[2] In this vein, Dercon (2005) notes that existing empirical estimates (typically based on country case studies) suggest that if the poor could shelter themselves from shocks as well as the rich do, their incomes could be on average 25 to 50 percent higher.

Institutional arrangements that place economic opportunities beyond the reach of the poor can also result in reduced income growth. Along these lines, Mookherjee and Ray (2002) show that when employers or lenders have all the bargaining power in contracts with workers or borrowers, contractual distortions resulting from moral hazard can give rise to poverty traps. In turn, Engerman and Sokoloff (2006) argue that persistent poverty in former European colonies can be traced to the exclusionary institutional arrangements originally created by the colonial powers.

In spite of the diversity and popularity of these analytical models, evidence on their empirical relevance remains largely inconclusive (Durlauf, 2006). To assess it, some empirical studies have taken an indirect route. For example, Quah (1993) and Azariadis and Stachurski (2004) have explored the existence of convergence clubs by assessing the bimodality (or multi-modality) of the cross-country distribution of per capita income. On the whole, their findings lend support to the existence of rich and poor clubs at the two ends of the income distribution, although the robustness of this result remains disputed (Kremer, Onatski, and Stock, 2001).[3]

Strictly speaking, however, this could at most be viewed as consistent with, rather than proof of, the existence of poverty traps. An alternative, more direct empirical strategy is to investigate specific poverty trap mechanisms. One such approach is the calibration of macroeconomic models featuring threshold effects consistent with the poverty trap hypothesis. For example, Graham and Temple (2006) calibrate a two sector variable-returns-to-scale model. The model can account for some 40 to 50 percent of the observed variation in per capita income, which appears to lend some support to the poverty

2. The argument that risk aversion leads to underinvestment goes back to Stiglitz (1969). See also Agénor and Aizenman (2010), who argue that aid volatility could influence poverty traps in poor countries through a similar mechanism.

3. Bloom, Canning and Sevilla (2003) also find evidence of bimodality of the world distribution of per capita income after controlling for a number of exogenous geographic variables (such as distance from the equator, rainfall, temperature, etc.).

trap notion. In contrast, Kraay and Raddatz (2007) calibrate simple aggregate models capable of generating poverty traps through low saving and/or low technology at low levels of development. Their results cast doubt on the empirical relevance of these mechanisms for the existence of poverty traps. Calibration exercises reported by Caucutt and Kumar (2005) yield a similar conclusion.

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.

At the micro level, Jalan and Ravallion (2002), using household panel data from China, find (at the local level) a significant role of aggregate physical and human capital endowments for household consumption growth, which could be consistent with the existence of geographic poverty traps. Taking a more direct approach, McKenzie and Woodruff (2004) search for non-convexities in the production function generated by fixed investment costs. Using Mexican microenterprise data, they find little evidence in favor of this particular poverty trap mechanism. Similarly, Antman and McKenzie (2007) find no support for poverty traps in their analysis of the income dynamics of Mexican households. More recently, Dercon and Christiansen (2011) report evidence that lack of insurance mechanisms deters the adoption of modern production techniques by poorer Ethiopian farmers, leaving them trapped in low-risk low-return agriculture.

This paper takes a different approach to testing for the self-perpetuating effects of poverty. Its starting point is the observation that, if poverty hampers growth, then, *ceteris paribus,* countries with higher initial poverty should grow less rapidly than comparable countries with lower poverty. This hypothesis can be viewed as a weaker version of the poverty trap hypothesis, in that to support it we do not need to find evidence of multiple equilibria or income stagnation, but just empirical proof that poverty tends to hold back growth.[4]

The paper is also related to two other strands of empirical literature. One has explored the growth-poverty link focusing on

4. A related approach is that of Ravallion (2009), who is concerned with the lack of global poverty convergence.

the poverty-reducing effect of growth and the factors that shape it (Bourguignon, 2004; Ravallion, 2004; Kraay, 2006). This is exactly the reverse of the question pursued in this paper. The other strand of literature has been concerned with the growth impact of inequality, with less than unanimous conclusions.[5]

The paper's empirical strategy relies on the estimation of a reduced-form growth equation with poverty added to an otherwise standard set of growth determinants. We estimate the resulting specification on a large country panel data set, using a generalized method of moments approach to attempt to control for the potential endogeneity of the regressors.

On the whole, we find that poverty has a significant negative association with subsequent growth. This result holds irrespective of whether inequality is also added in the regressions, and hence we interpret it as representing a pure poverty effect rather than an indirect inequality effect on growth. Moreover, the result is robust to a variety of departures from the basic specification, namely: (i) the use of alternative poverty lines, (ii) the use of alternative poverty measures, (iii) the use of alternative sets of control variables in the regression, (iv) the use of alternative sets of instruments in the estimation, (v) the use of alternative estimation techniques, and (vi) allowing for non-linear effects of inequality on growth. When we go one step further and try to identify the specific mechanisms behind this poverty effect on growth, we find that it appears to operate through investment: poverty deters investment and thereby growth, and the effect is bigger at low levels of financial development.

The rest of the paper is structured as follows. In section 1 we illustrate how poverty can be a growth deterrent, using a simple model based on that of Aghion, Caroli and García-Peñalosa (1999), extended to include a minimum consumption subsistence level. In section 2 we describe our empirical strategy to test for the effect of poverty on growth in a panel context. Section 3 reports estimation results for the basic model and performs a variety of robustness checks. Section 4 explores the mechanism responsible for the effects of poverty on growth identified in section 3. Finally, section 5 concludes.

5. For example, Alesina and Rodrik (1994) and Perotti (1996) found a negative relationship between inequality and growth on the basis of cross section data, but subsequently Li and Zou (1998) and Forbes (2000) obtained the opposite result using aggregate panel data. In turn, 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.

1. An Illustrative Model

To illustrate the effects of poverty on growth, we sketch a model in the spirit of Aghion and others (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. In such setting, poor consumers (defined as those whose initial endowment is below the minimum consumption level) do not save and, in the absence of capital markets, cannot invest either.[6] Thus they do not contribute to the economy's aggregate growth.

1.1 Individuals

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

$$\lambda = p(w_t^i \leq \bar{c}) = F(\bar{c}) = \int_0^{\bar{c}} f(w_t^i) dw_t^i, \tag{1}$$

where p is probability, $f(.)$ and $F(.)$ respectively are the probability density function and the cumulative distribution functions of w_t^i. It follows that the poverty rate λ must be increasing (strictly speaking, non-decreasing) in the minimum consumption requirement $\bar{c}$. The utility of the *i-th* individual of generation t is given by:

$$\begin{aligned} U_t^i &= c_t^i \quad \text{if} \quad c_t^i < \bar{c} \\ &= \bar{c} + \ln(c_t^i - \bar{c}) + \rho \ln c_{t+1}^i \quad \text{if} \quad c_t^i > \bar{c}\ , \end{aligned} \tag{2}$$

6. More precisely, for this result to obtain, 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_t and c_{t+1} denote consumption when young and old, respectively.[7]

1.2 Production

Individual i uses his/her saving to purchase physical capital k_t^i, which fully depreciates within the period. Production takes place according to the technology:

$$y_t^i = A_t(k_t^i)^\alpha, \tag{3}$$

where A_t is the level of technical knowledge available to all individuals at time t, and $0<\alpha<1$. Like in Aghion and others (1999), we assume that there are learning-by-doing spillovers, so that $A_t = y_{t-1}$. 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 g depends on the distribution of individual investments, and is given by:

$$g_t = \ln(y_t / y_{t-1}) = \ln \int (k_t^i)^\alpha di = \ln E[(k_t^i)^\alpha]. \tag{4}$$

Notice that if all individuals invest the same amount, say k, then growth is just:

$$g_t = \ln \int k_t^\alpha di = \ln k^\alpha . \tag{5}$$

1.3 Consumption, Saving, and Growth

To sharpen the argument, we assume that capital markets do not exist. In their absence, the equilibrium levels of consumption and saving will vary across individuals depending on their initial endowments. In particular, for non-poor individuals (i.e., those with $w_t^i > \overline{c}$) we have:

$$c_t^i = \overline{c} + (1+\alpha\rho)^{-1}(w_t^i - \overline{c}), \tag{6}$$

$$k_t^i = \alpha\rho(1+\alpha\rho)^{-1}(w_t^i - \overline{c}) = s(w_t^i - \overline{c}), \tag{7}$$

7. 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, Parente and Rogerson (2002) for a similar approach.

where s is the saving rate; hence, saving and investment of the non-poor is just proportional to their initial wealth. In turn, poor individuals (i.e., those with $w_t^i < \bar{c}$) do not save and simply consume all their endowment:

$$c_t^i = w_t^i, \tag{8}$$

$$k_t^i = 0. \tag{9}$$

Aggregate investment is given by:

$$k_t = E[k_t^i] = (1-\lambda)E[k_t^i \mid w_t^i > \bar{c}] = (1-\lambda)E[s(w_t^i - \bar{c}) \mid w_t^i > \bar{c}], \tag{10}$$

which reflects the fact that only a fraction (1-λ) of the population invests. From (4), growth is given by:

$$g_t = \ln(1-\lambda) + \ln(s^\alpha E[(w_t^i - \bar{c})^\alpha \mid w_t^i > \bar{c})]). \tag{11}$$

It is clear from (11) that the growth rate depends on two factors. First, the poverty rate: given expected per capita investment of the non-poor—the second term on the right-hand side of (11)—higher poverty (as determined by, e.g., a higher minimum consumption requirement) will unambiguously lead to lower growth. Second, the expected output generated by the investment of the non-poor, which in turn depends on three other ingredients: (i) the initial endowments relative to the minimum consumption requirement —higher endowments yield higher investment and growth, for a given poverty rate; (ii) the distribution of the endowments among the non-poor—decreasing returns imply that, for given aggregate capital, a higher concentration of its ownership among fewer people will lower growth; and (iii) the preferences of individuals and the production technology—for a given poverty rate and endowment distribution, a higher ρ and/or higher α raise the propensity to save by the non-poor, and hence overall investment and growth.

1.4 Endowments, Inequality, and Growth

The effects of poverty and inequality on growth in this economy can be illustrated considering three different cases: (i) $\lambda = 1$; (ii) $\lambda = 0$; and (iii) $0 < \lambda < 1$.

i) $\lambda = 1$

When λ =1 all households are poor, and therefore investment and growth equal zero—an extreme version of a poverty trap. In such circumstances, an increase in initial endowments sufficient to bring some households out of poverty results in positive capital accumulation and growth.

Note also that for a given aggregate endowment, a higher level of inequality may also result in higher growth.[8] For example, consider the simple endowment rule:

$$w_t^i = a + \sigma\varepsilon_t^i \; , \tag{12}$$

where a>0, σ>0 and ε_t^i is distributed independently across agents with mean 0 and standard deviation 1; thus a is the expected value of each individual's endowment and σ the dispersion of endowments across individuals (i.e., initial inequality). Then (5) can be rewritten as:

$$\lambda = p(\sigma\varepsilon_t^i \le \overline{c} - a) = F\left((\overline{c} - a)/\sigma\right) = \int_{-\infty}^{(\overline{c}-a)/\sigma} f(\varepsilon_t^i)\, d\varepsilon_t^i . \tag{13}$$

For $\overline{c} > a$ (as would be the case in an economy where everybody is poor), this is decreasing in σ. Intuitively, in a very poor economy where the average per capita endowment is below survival needs, a perfectly egalitarian distribution would bring everybody below the poverty line and result in zero saving and zero growth. As inequality increases and an unchanged initial aggregate endowment is concentrated among fewer and fewer individuals, some of them will move above the poverty threshold and become able to invest; hence, growth is a positive function of σ.

ii) $\lambda = 0$

In this second scenario, all households are above the poverty line —because, e.g., the mean endowment a is sufficiently larger than $\overline{c}$. In this particular case, growth is given by an expression similar to that in Aghion and others (1999), who assume $\overline{c}$ =0:

$$g_t = \alpha \ln(s) + \ln E[(w_t^i - \overline{c})^{\alpha}]. \tag{14}$$

8. Of course, the welfare consequences of an increase in growth arising from higher inequality would vary across individuals.

Here higher inequality reduces growth due to the concavity of the production function. Note, however, that as α approaches 1 in (3), so that the production technology shows constant returns to capital, growth tends to:

$$g_t \to \ln(s) + \ln(a - \bar{c}), \tag{15}$$

so that in the limit, growth is unaffected by inequality. The reason is that as α approaches 1 the key determinant of growth is the aggregate stock of capital, irrespective of its distribution across individual investors; furthermore, when nobody is below the subsistence level, aggregate capital depends only on the aggregate endowment and not on its distribution among individuals.

iii) $0<\lambda<1$

In the general case, some, but not all, individuals are poor. A higher aggregate endowment, holding inequality constant (i.e., in terms of (12), an increase in a without change in σ) unambiguously leads to higher growth: it both reduces poverty and raises the investment of the non-poor.

In contrast, the impact on growth of changes in the inequality of the distribution of the endowment σ is less clear-cut: it depends on how inequality affects the two terms in (11). That is, whether higher inequality raises or lowers growth, depends on the sign of:

$$\frac{\partial g}{\partial \sigma} = -\frac{\partial \lambda / \partial \sigma}{(1-\lambda)} + \frac{\partial E[(w_t^i - \bar{c})^\alpha \mid w_t^i > \bar{c}] / \partial \sigma}{E[(w_t^i - \bar{c})^\alpha \mid w_t^i > \bar{c}]}. \tag{16}$$

Regarding the first term, from (13) we already know that $\partial\lambda / \partial \sigma$ is negative when $\bar{c} > a$ (i.e., the poverty line exceeds the mean endowment) and positive when $\bar{c} > a$ (when the poverty line is below the mean endowment). As for the second term, the sign $\partial E[(w_t^i - \bar{c})^\alpha \mid w_t^i > \bar{c}] / \partial \sigma$ of depends on two factors. On one hand, because the production function exhibits decreasing returns to capital, the higher the σ, the lower the expected value of the output associated with a given stock of aggregate capital. But, on the other hand, if $\bar{c} > a$**,** the overall capital stock of the non-poor rises along with σ, and this tends to affect growth in the opposite (i.e., positive) direction.[9] Thus for $\overline{c} > a$ the impact of inequality changes on the conditional expectation in (16) is ambiguous, while for $\overline{c} > a$ it is assured to be negative and hence runs counter to the effect on the poverty rate, the first term in (16), resulting also in an ambiguous overall effect. On the whole, therefore, the effect of inequality on aggregate investment and growth is not determined *a priori,* and depends on the economy's initial conditions.

In summary, poverty is a growth deterrent in this model as the poor cannot contribute to the growth process through the creation of physical capital. The ingredient responsible for this result is the model's minimum consumption threshold, which is the cause of the differential saving and investing behavior of poor and non-poor individuals.[10] However, 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. In contrast, the relationship between inequality and growth can take on either sign, depending on parameter values.

2. Empirical Implementation

To explore the links between poverty and growth in the data, our empirical strategy is based on the addition of a suitable measure of poverty to an otherwise standard empirical growth regression:

$$(y_{it} - y_{it-1}) = \delta y_{it-1} + \omega' x_{it} + \beta p_{it-1} + \nu_i + \upsilon_{it}, \qquad (17)$$

where y is the log of per capita income, p is a measure of poverty, x represents a set of control variables other than lagged income, which we shall discuss shortly, ν_i is a country-specific effect, and υ_{it} is an i.i.d.

9. Formally, $\partial E(k_t^i \mid w_t^i > \overline{c}) / \partial\sigma = \partial E\left(s(w_t^i - \overline{c}) \mid w_t^i > \overline{c}\right) / \partial\sigma = \partial E(s(w_t^i - \overline{c}) \mid e_t^i > (\overline{c} - a)/\sigma)/\partial\sigma$, so that the sign of the impact of inequality on the capital stock of the non-poor depends on the sign of $\partial\left[(\overline{c} - a)/\sigma\right]/\partial\sigma$, which is negative when $\overline{c} > a$ and positive when $\overline{c} < a$.

10. Atkeson and Ogaki (1996) and López, Schmidt-Hebbel and Servén (2000) offer empirical evidence supportive of this differing saving behavior of rich and poor individuals. The consequences for aggregate growth are stressed by Easterly (1994). See also Rebelo (1992).

error term. According to (17), growth depends on initial income, initial poverty, and current and/or lagged values of the control variables.

Our primary focus is the estimate of β in equation (17). If poverty is a growth deterrent, we should find $\beta < 0$.

However, even if poverty has no direct impact on growth, we might find $\beta \neq 0$ if inequality has an independent growth effect, as argued by a sizable theoretical and empirical literature. The reason is that poverty itself can be generally expressed as a (non-linear) function of inequality and average income, and hence the poverty coefficient in (17) could be capturing the inequality effect.[11] Thus, to ensure that our estimates do capture the poverty effect, we also consider empirical specifications of the type:

$$(y_{it} - y_{it-1}) = \delta y_{it-1} + \omega' x_{it} + \beta p_{it-1} + \rho g_{it-1} + \nu_i + \upsilon_{it} , \tag{18}$$

where g is a measure of income inequality (specifically, below we shall use the Gini coefficient). Equation (18) is a generalization of the standard empirical specification used in the literature concerned with the impact of inequality on growth. Note that in this setting the relationship between inequality and growth depends on how inequality affects poverty:

$$\frac{\partial (y_{it} - y_{it-1})}{\partial g_{it-1}} = \rho + \beta \frac{\partial p_{it-1}}{\partial g_{it-1}} . \tag{19}$$

Still, one might object that a non-zero estimate of β in (18) could just be capturing a non-linear effect of inequality on growth (as suggested by Banerjee and Duflo, 2003) rather than a true poverty effect. To address this concern, we also consider a specification of the form:

$$(y_{it} - y_{it-1}) = \delta y_{it-1} + \omega' x_{it} + \beta p_{it-1} + h(g_{it-1}) + \nu_i + \upsilon_{it} , \tag{20}$$

where $h(g_{it-1})$ is a quadratic function of the Gini coefficient (i.e., it includes the lagged Gini coefficient and its square).

11. See López and Servén (2011) for a detailed analysis of the relationship between the Gini coefficient and poverty measures of the Foster, Greer, and Thorbecke (FGT) (1984) class under the assumption of log normality.

2.1 Econometric Issues

One potential issue with our empirical strategy is the simultaneous determination of poverty and growth, which could result in biased estimates of β in the above equations. Our empirical setting, like the standard growth regression model, lacks obvious outside instruments to deal with this potential endogeneity. However, the fact that poverty is pre-determined in (17) should help alleviate these concerns. Moreover, it should be noted that even if poverty were endogenous rather than predetermined in the equation of interest, the parameters of the growth-poverty system would continue to be identified as long as the poverty measure is a non-linear function of income (and possibly other variables) as is the case under standard parameterizations of the distribution of income (e.g., lognormal, Pareto, Weibull) such as the one adopted below.[12]

Aside from these issues, estimation of (17) and related equations on a short panel—as will be the case here—still has to overcome two standard problems, namely the presence of country-specific effects potentially correlated with the explanatory variables, and the possible simultaneity of some of the contemporaneous control variables with growth. To address these problems in the absence of suitable external instruments, we employ the GMM estimator system of Blundell and Bond (1998), based on the use of internal instruments. It essentially amounts to estimation of (17), using lagged differences of the explanatory variables as instruments, jointly with a first-differenced version of (17)—to remove time-invariant country effects—using lagged levels of the explanatory variables as instruments. Thus, in the resulting two-equation system, predetermined and endogenous variables in first differences are instrumented with suitable lags of their own levels, while variables in levels are instrumented with suitable lags of their own first differences.

A well-known shortcoming of panel GMM estimators in small samples is their tendency to result in over-fitting and downward-biased standard errors—a consequence of the relatively large number of instruments available for estimation (see, e.g., Ziliak, 1997). To reduce this bias, in the estimations below we limit the number of over identifying restrictions by building only one instrument from each variable and lag distance rather than building one separate instrument from each variable and lag distance in each time period.

12. Drawing from Fisher (1961), it can be shown that the identifying information follows from the very non-linearity of the poverty equation.

Consistency of the GMM estimator obviously depends on the validity of the instrument set constructed in this way, and this in turn is determined by the autocorrelation structure of the error term. For example, if v_{it} is serially uncorrelated then y_{it-2}, x_{it-2}, p_{it-2} and g_{it-2} and their earlier lags would be valid instruments for the variables in differences, but if v_{it} displays first order serial correlation, the instrument set would have to be restricted to y_{it-3}, x_{it-3}, p_{it-3}, g_{it-3} and earlier lags. To assess the validity of the proposed instrument sets, we report two standard specification tests. The first is Hansen's J-test of over identifying restrictions, which examines the correlation between the instruments and the regression residuals. The second test examines the autocorrelation structure of the regression residuals themselves.

2.2 Control Variables

Lastly, we need to specify the control variables included in x. The empirical growth literature has experimented with a vast number of alternative sets of explanatory variables.[13] Rather than adding to the already huge variety of growth models contributing yet another idiosyncratic set of regressors, we opt for considering three alternative growth specifications in order to explore the sensitivity of our results to the specific choice of variables.

The first set of control variables, taken from the empirical literature on inequality and growth, is that used by Perotti (1996), Forbes (2000), Banerjee and Duflo (2003), and Knowles (2005). It includes the average years of secondary education of the male population, the average years of secondary education of the female population, and a measure of market distortions given by the price of investment goods relative to that of the U.S.

The second specification we consider is focused on standard policy indicators. It includes the inflation rate as an indicator of macroeconomic stability, the adjusted volume of trade as an indicator of the degree of openness of the economy,[14] and the ratio of public consumption to GDP as an indicator of the burden imposed by the government on the economy.

13. As noted by Durlauf and Quah (1999), by 1998 the number of individual regressors that had been considered as potential explanatory variables in growth regressions exceeded the number of countries in the standard growth dataset.

14. We use the residuals of a regression of openness on country size and two dummies indicating whether the country is landlocked and whether it is an oil exporter.

Finally, the third model we consider includes two variables from the preceding specifications—female education and inflation—and adds infrastructure, whose empirical significance for growth has been recently stressed by Calderón and Servén (2010). In the empirical specification we use the number of main telephone lines per capita as an infrastructure measure.

2.3 Data

Despite the progress made in recent years, mainly through the expanding international coverage of 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. In our case their scarcity becomes severely binding because GMM estimation requires a minimum of three poverty observations per country in order to allow generating instruments from the lagged values of the poverty measure.

To overcome this limitation, rather than using LSMS-based poverty data we construct a set of poverty figures using a lognormal approximation.[15] We base this choice on recent work by López and Servén (2011), who compare the quintile income shares generated by a lognormal distribution with their observed counterparts using data from over 1,000 household surveys. They find that the lognormal approximation fits the data extremely well, and are unable to reject the null hypothesis that per-capita income follows a lognormal distribution.

15. The use of the lognormal approximation to the distribution of income dates back to Gibrat (1931). Under lognormality, given the Gini coefficient (g) it is possible to compute the standard deviation (σ) of the log of income as $\sigma=\sqrt{2}\Phi^{-1}\left(\frac{1+g}{2}\right)$, 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:

$$P_0 = \Phi\left(\frac{\log(z)-y}{\sigma}+\frac{\sigma}{2}\right),$$

$$P_1 = \Phi\left(\frac{\log(z)-y}{\sigma}+\frac{\sigma}{2}\right)-\frac{e^y}{z}\Phi\left(\frac{\log(z)-y}{\sigma}-\frac{\sigma}{2}\right),$$

$$P_2 = \Phi\left(\frac{\log(z)-y}{\sigma}+\frac{\sigma}{2}\right)-2\frac{e^y}{z}\Phi\left(\frac{\log(z)-y}{\sigma}-\frac{\sigma}{2}\right)+\left(\frac{e^y}{z}\right)^2 e^{\sigma^2}\Phi\left(\frac{\log(z)-\nu}{\sigma}-\frac{3\sigma}{2}\right).$$

In view of these results, we construct our poverty figures on the basis of the observed per capita income levels and Gini coefficients —which are available much more widely than survey-based poverty data. The per capita income data is from the PWT 6.1, whereas the inequality data is taken from Dollar and Kraay (2002).[16] In our regressions, we use three alternative poverty measures constructed in this manner—the headcount (henceforth denoted P_0), the poverty gap (P_1) and the squared poverty gap (P_2). In each case we experiment with three alternative poverty lines (US$ 2, US$ 3 and US$ 4 per person per day). The rest of the variables used in the regressions are taken from Loayza and others (2005), except for the education variables, which are from Barro and Lee (2001).

The regressions are conducted using an unbalanced panel of non-overlapping five-year periods spanning the years 1960-2000. The full sample comprises 85 countries and over 300 observations.

Table 1. Summary Statistics

	Median	*Mean*	*Standard Deviation*	*Maximum*	*Minimum*
Income	5,523	7,937	6,735	34,372	467
Inequality	0.384	0.391	0.100	0.765	0.178
P_0($2)	0.024	0.111	0.185	0.834	0.000
P_0($3)	0.068	0.179	0.248	0.937	0.000
P_0($4)	0.129	0.237	0.289	0.977	0.000
P_1($2)	0.004	0.046	0.091	0.507	0.000
P_1($3)	0.045	0.115	0.150	0.595	0.000
P_1($4)	0.099	0.173	0.195	0.637	0.000
P_2($2)	0.002	0.026	0.058	0.385	0.000
P_2($3)	0.006	0.047	0.088	0.484	0.000
P_2($4)	0.013	0.069	0.114	0.564	0.000

Notes: This table reports the summary statistics o income per capita, a measure o income inequality (the Gini coefficient) and all the poverty measures used in this paper: headcount ratio (P_0), poverty gap (P_1) and squared poverty gap (P_2). Each poverty measure is defined using three alternative poverty lines ($2, $3, and $4 per person per day).

16. The income and inequality data used for this purpose pertain to the latest available year within each given period. The original data sources for the inequality indices show a high degree of diversity across countries. The data are sometimes based on income figures 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 the approach of Dollar and Kraay (2002).

Table 1 presents summary statistics for income, inequality and the constructed poverty measures.[17] The table shows the wide range of per capita income levels in the sample—from less than $500 (Tanzania in the mid-1990s) to almost $35,000 (Luxembourg in the mid-1990s). The median observation corresponds to Mexico in the mid-1970s, with per capita income about $5,500.[18] Regarding inequality, the Gini indices range from a low 0.17 (the Slovak Republic in the early 1990s) to a high 0.76 (Namibia in the mid-1990s), with a median of 0.38. Regarding the poverty figures, by construction they must rise with the poverty line and decline as the poverty measure changes from P_0 to P_2 (i.e., as one considers more bottom-sensitive measures). Table 1 shows that, depending on the poverty line used, median headcount poverty ranges from 2.4 percent (using US$2 per day as the poverty line) to about 13 percent (with US$4 per day), whereas the median poverty gap ranges from less than 1 percent (US$2) to about 10 percent (US$4), and the square poverty gap from 0.1 percent (US$2) to slightly above 1 percent (US$4). In turn, the ranges of the various poverty measures run from a minimum of zero (reflecting the presence of some high-income countries in the sample) to a maximum whose value depends on the particular poverty measure under consideration—from 80 to 100 percent for P_0, 50 to 60 percent for P_1, and 40 to 60 percent for P_2.[19]

3. Results

Table 2 reports estimates of the growth equation using Perotti (1996)'s set of control variables, and with poverty measured by the headcount ratio (P_0). The instrument sets for GMM estimation are constructed under the assumption that the time-varying disturbance is serially uncorrelated. The first three columns of the table report the estimates obtained using each of the poverty lines under consideration (US$2, US$3 and US$4 per day, respectively) to

17. Preliminary analysis prompted us to remove two outliers: Sierra Leone (1990-1995) and Moldova (1990-1995). Their inclusion or exclusion from the sample, however, is of no material consequence for the paper's main empirical results.

18. The figure in the text is the median income from the pooled (unbalanced) sample. However, the cross-country median (i.e., the median of the country averages) is very similar ($5,400).

19. The maximum corresponds in all cases to Tanzania.

construct the poverty figures, and employing specifications excluding inequality from the equation—i.e., based on equation (17).

The results in the first three columns of table 2 consistently show that higher initial poverty is associated with lower subsequent growth: in all three cases, the headcount ratio carries a negative and highly significant coefficient. The magnitude of the coefficient declines somewhat as the poverty line rises from US$2 per day in the first column to US$4 per day in the third. Furthermore, the effect of poverty also appears economically significant in all three cases: according to the estimates in the table, a 10 percentage point increase in poverty is associated with a decline of annual per capita growth by 0.8 to 1.1 percentage points.

Table 2. Estimation Results: Baseline Model

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	7
Income (in logs) (t-1)	-0.009	-0.018	-0.020	0.021	-0.014	-0.021	-0.022
t-stat	-2.17	-3.84	-2.86	2.75	-3.20	-4.12	-4.04
Female education (t-1)	-0.009	-0.013	-0.017	-0.010	-0.017	-0.021	-0.024
t-stat	-1.25	-2.18	-2.83	-1.41	-2.50	-3.51	-4.48
Male education (t-1)	0.008	0.015	0.018	0.003	0.020	0.024	0.027
t-stat	1.28	2.87	4.00	0.38	3.26	4.73	6.14
PPP (t-1)	-0.022	-0.018	-0.018	-0.033	-0.024	-0.021	-0.023
t-stat	-5.76	-4.79	-3.71	-4.67	-5.54	-4.50	-4.79
Inequality (t-1)				0.071	0.061	0.045	0.052
t-stat				2.02	2.66	2.18	2.88
P_0($2) ($t$-1)	-0.106				-0.123		
t-stat	-4.84				-4.80		
P_0($3) ($t$-1)		-0.093				-0.104	
t-stat		-5.27				-5.75	
P_0($4) ($t$-1)			-0.083				-0.093
t-stat			-4.31				-5.71
Observations	325	325	325	325	325	325	325
Countries	85	85	85	85	85	85	85
Hansen Test p-value	0.23	0.18	0.14	0.46	0.31	0.31	0.31
AR(2) p-value	0.09	0.12	0.12	0.14	0.10	0.14	0.15

Source: Authors' estimations.

Notes: The table reports regression results with income growth as dependent variable; and income per capita (in logs), average years of secondary education of the female and male population, a measure of market distortion (given by the price of investment goods) and headcount poverty P_0 (corresponding to poverty lines of $2, $3, and $4) as explanatory variables. Regressions (4), (5), (6) and (7) also include a measure of income inequality (the Gini coefficient). All the explanatory variables are lagged one period. All regressions include a constant. The regressions are calculated using system GMM estimators and allowing the instrument set to start with lagged levels at t-1. Robust t-statistics are reported below the coefficients.

Regarding the coefficients of the other control variables, both lagged income and the market distortions proxy carry significant negative coefficients, as expected. In turn, the education variables carry coefficients of opposite signs, in line with the findings of other studies such as Perotti (1996), Forbes (2000) and Knowles (2005), in spite of the fact that their data samples are very different from the one employed here.[20]

We next assess whether our finding of a significant poverty coefficient is just a result of excluding inequality from the regression, so that we are forcing inequality's impact on growth to occur through poverty. Hence in columns (4) to (7) in table 2 we include inequality as an explanatory variable in the regression. In column (4) we omit poverty, i.e., we set $\beta = 0$ in (18); and hence, the specification is similar to that employed by Forbes (2000). The result is also similar to hers: inequality carries a positive and significant coefficient. In columns (5) to (7) we include both inequality and poverty in the regression. Inequality consistently exhibits a positive and significant coefficient, while the pattern of the other coefficients is very similar to that in the first three columns of the table. In particular, poverty continues to carry a negative and significant coefficient.

3.1 Robustness to Alternative Instruments

The last two rows of table 2 report the Hansen and second-order serial correlation tests, both of which provide an assessment of the validity of the instrument set employed in the GMM estimation. While the Hansen test shows no evidence against the null hypothesis that the instruments are valid, the test for second-order serial correlation comes close to rejecting the null at the 10 percent level in several cases, and it actually rejects the null in the specification reported in the first column. This suggests that the instruments underlying the estimations in table 2 might be invalid due to the presence of second-order serial correlation of the (differenced) residuals.

20. See e.g., table 4 in Perotti (1996) and tables 1 and 3 in Knowles (2005). Forbes (2000, table 3) also obtains coefficients of opposite sign, but their sign pattern —a negative coefficient for male education and a positive one for female education—is reversed relative to ours, Perotti's and Knowles's.

Table 3. Estimation Results: Baseline Model - Alternative Instrument Set

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Income (in logs) (t-1)	-0.011	-0.024	-0.034	0.008	-0.003	-0.014	-0.025
t-stat	-2.36	-3.78	-4.15	1.91	-0.73	-2.46	-3.27
Female education (t-1)	-0.004	-0.004	-0.005	-0.001	-0.002	-0.001	-0.001
t-stat	-0.57	-0.65	-0.81	-0.21	-0.32	-0.17	-0.14
Male education (t-1)	0.003	0.006	0.009	-0.006	-0.002	-0.001	0.001
t-stat	0.50	1.03	1.49	-0.73	-0.25	-0.17	0.18
PPP (t-1)	-0.011	-0.008	-0.008	-0.015	-0.022	-0.021	-0.023
t-stat	-3.26	-2.39	-2.16	-2.54	-4.63	-4.50	-4.58
Inequality (t-1)				-0.065	-0.046	-0.058	-0.068
t-stat				-2.22	-1.68	-2.31	-2.94
P_0($2) ($t$-1)	-0.109				-0.058		
t-stat	-3.90				-2.49		
P_0($3) ($t$-1)		-0.110				-0.081	
t-stat		-4.95				-3.90	
P_0($4) ($t$-1)			-0.121				-0.097
t-stat			-5.54				-4.41
Observations	325	325	325	325	325	325	325
Countries	85	85	85	85	85	85	85
Hansen Test p-value	0.23	0.19	0.15	0.62	0.43	0.45	0.46
AR(3) p-value	0.40	0.52	0.66	0.56	0.45	0.50	0.57

Source: Authors' estimations.
Notes: The table reports regression results with income growth as dependent variable; and income per capita (in logs), average years of secondary education of the female and male population, a measure of market distortion (given by the price of investment goods) and headcount poverty P_0 (corresponding to poverty lines of $2, $3, and $4) as explanatory variables. Regressions (4), (5), (6) and (7) also include a measure of income inequality (the Gini coefficient). All the explanatory variables are lagged one period. All regressions include a constant. The regressions are calculated using system GMM estimators and allowing the instrument set to start with lagged levels at t-2. Robust t-statistics are reported below the coefficients.

To explore this further, in table 3 we repeat the estimations lagging the instruments one more period than in the previous exercises so that the instrument set remains valid even in the presence of second (but no higher) order serial correlation of the residuals. The results reported in the table confirm the basic result found above regarding the estimated poverty coefficient, which remains negative and highly significant, and in most cases (i.e., except for column (6) of the table) of the same magnitude as in table 2. As before, this result holds irrespective of the poverty line chosen and regardless of the inclusion or exclusion of inequality in the regression. In contrast, the parameter estimate of the inequality variable is now negative and significant in all the specifications in table 3, regardless of whether poverty is included in the regression, and of the specific poverty measure selected. As for the other control variables, the distortions proxy continues to carry a negative and significant coefficient, while the coefficients of the two education variables become small and insignificant. Finally, the two test statistics show little evidence against the model's specification. Thus, we conclude that the poverty coefficient estimate is robust to the use of alternative instruments. This, however, is not the case for the estimated impact of inequality on growth, which changes drastically with the instrument set.

3.2 Robustness to Different Control Variables

Given the huge variety of explanatory variables considered in the empirical growth literature, one may wonder if the above results are driven by our particular choice of control variables. To explore this issue, in table 4 we experiment with two alternative sets of control variables. The top panel reports estimates obtained using a model that includes as regressors the inflation rate, trade openness and government size (in logs). The bottom panel reports results for an alternative model including inflation, female education, and lagged infrastructure. Since the coefficient estimates on the controls themselves are of no direct interest here, they are omitted from the table to save space.[21]

Preliminary experiments with both specifications again suggested the presence of second-order autocorrelation of the (differenced) residuals, and hence the instrument sets for the estimations in table 4 allow for this fact. Focusing first on the top panel, the parameter estimates of the poverty headcount continue to be negative and highly significant in all cases—regardless of whether inequality is included in the regression. Furthermore, their magnitude is very similar to that obtained in the preceding models. In contrast, the parameter of the inequality variable in the last four columns changes sign across specifications and is not estimated precisely.

21. Note that sample sizes decline somewhat relative to tables 2 and 3, due to the limited availability of some of the explanatory variables.

Table 4. Estimation Results: Alternative Control Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model with inflation, trade (in logs), and government size (in logs)							
Inequality (t-1)				-0.039	0.051	0.017	-0.010
t-stat				-0.67	1.15	0.47	-0.26
P_0(\$2) (t-1)	-0.086				-0.098		
t-stat	-2.57				-3.34		
P_0(\$3) (t-1)		-0.080				-0.091	
t-stat		-3.17				-4.04	
P_0(\$4) (t-1)			-0.070				-0.089
t-stat			-3.23				-4.25
Observations	289	289	289	289	289	289	289
Hansen Test p-value	0.27	0.35	0.46	0.66	0.43	0.52	0.58
AR(3) p-value	0.80	0.81	0.79	0.71	0.76	0.76	0.77
Model with inflation, lagged female education, and lagged infrastructure							
Inequality (t-1)				0.004	0.040	0.000	-0.021
t-stat				0.09	1.01	-0.01	-0.56
P_0(\$2) (t-1)	-0.123				-0.149		
t-stat	-3.37				-4.24		
P_0(\$3) (t-1)		-0.127				-0.129	
t-stat		-4.45				-5.31	
P_0(\$4) (t-1)			-0.132				-0.124
t-stat			-4.81				-5.34
Observations	306	306	306	306	306	306	306
Hansen Test p-value	0.41	0.43	0.41	0.44	0.47	0.47	0.47
AR(3) p-value	0.82	0.67	0.55	0.92	0.80	0.61	0.51

Source: Authors' estimations.

Notes: The table reports regression results with income growth as dependent variable; and the lagged income per capita (in logs), headcount poverty P_0 (corresponding to poverty lines of \$2, \$3, and \$4) and two sets of control variables. The top panel includes as control variables the inflation rate, the adjusted volume of trade (in logs), and the ratio of public consumption to GDP (in logs). The second panel includes as control variables the inflation rate, the average years of secondary education of the female population (lagged) and an infrastructure measure (lagged average number of telephone lines). The coefficients of the control variables are not reported. Regressions (4), (5), (6) and (7) also include a lagged measure of income inequality (the Gini coefficient). All regressions include a constant. The regressions are calculated using system GMM estimators and allowing the instrument set to start with lagged levels at t-2. Robust t-statistics are reported below the coefficients.

The bottom panel of table 4 tells a very similar story, in spite of the different choice of control variables: poverty consistently retains a negative and significant coefficient, while that of inequality is sometimes positive, sometimes negative, and always insignificant. Finally, the specification tests at the bottom of table 4 fail to show any sign of misspecification.

3.3 Robustness to Non-Linearities

The results presented so far are in line with the analytical model outlined in section 2, which predicts a negative effect of poverty on growth, along with an ambiguous impact of inequality. However, one might wonder if, rather than capturing a true poverty effect, the negative coefficient on the poverty measure may just be capturing a non-linear effect of inequality on growth.[22] To explore this issue, we estimate equation (20) using a quadratic specification for $h(g_{it\text{-}1})$:

$$h(g_{it-1}) = h_1 g_{it-1} + h_2 g_{it-1}^2, \tag{21}$$

where h_1 and h_2 are parameters to be estimated. If the poverty coefficient in the previous regression is really capturing non-linear effects of inequality, we should expect its significance (and perhaps also its size) to decline in these specifications. Table 5 reports the results obtained with each of the three sets of control variables considered.

Two results from these experiments are worth stressing. First, in all specifications the parameter estimate of the poverty variable is negative, significant and of comparable magnitude to those reported previously. Second, the opposite happens with the inequality parameter estimates: they are not robust across specifications. With the first set of controls, the growth effect of the level of inequality is significantly positive and that of its square is significantly negative. With the second set of controls, the sign pattern is reversed, although the precision of the estimates declines. In particular, for the models in columns (5) and (6) we cannot reject the joint null hypothesis that h_1 and h_2 in (21) are both equal to zero (i.e., that inequality does not belong in the regression). The third set of controls, shown in columns (7)-(9), again yields a negative coefficient for the level of inequality and a positive one for its square, although neither is individually significant, and they are jointly significant only in column (9).

22. Recall that, as discussed earlier, the poverty measures we are using can be expressed as non-linear functions of both per capita income and inequality.

Table 5. Estimation Results: Non Linear Effects of Inequality

	Baseline model			*Model with inflation, trade (in logs), and government size (in logs)*			*Model with inflation, lagged female education, and lagged infrastructure*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
Inequality (t-1)	0.408	0.328	0.233	-0.179	-0.232	-0.275	-0.147	-0.160	-0.201
t-stat	2.52	2.03	1.47	-0.97	-1.50	-1.91	-0.80	-0.84	-0.99
Squared inequality (t-1)	-0.605	-0.526	-0.415	0.287	0.283	0.292	0.162	0.106	0.134
t-stat	-2.99	-2.58	-2.12	1.40	1.61	1.78	0.68	0.45	0.54
P_0($2) ($t$-1)	-0.059			-0.132			-0.162		
t-stat	-3.41			-5.68			-4.79		
P_0($3) ($t$-1)		-0.085			-0.117			-0.137	
t-stat		-5.47			-6.12			-6.47	
P_0($4) ($t$-1)			-0.104			-0.109			-0.141
t-stat			-6.25			-6.15			-6.82
Observations	325	325	325	289	289	289	306	306	306
Countries	85	85	85	80	80	80	85	85	85
Hansen Test p-value	0.20	0.19	0.17	0.30	0.40	0.51	0.33	0.33	0.36
AR(3) p-value	0.59	0.58	0.61	0.82	0.82	0.85	0.97	0.80	0.65
Ho: h_1=h_2=0	0.00	0.00	0.00	0.03	0.25	0.15	0.64	0.06	0.01

Source: Authors' estimations.

Notes: The table reports regression results with income growth as dependent variable; and the lagged income per capita (in logs), the Gini coefficient and its square value, headcount poverty P_0 (corresponding to poverty lines of $2, $3, and $4) and three sets of control variables. The first panel includes as control variables lagged average years of secondary education of the female and male population and a lagged measure of market distortion (given by the price of investments goods). The second panel includes as control variables the inflation rate, the adjusted volume of trade (in logs), and the ratio of public consumption to GDP (in logs). The third panel includes as control variables the inflation rate, the lagged average years of secondary education of the female and the lagged infrastructure measure. The coefficients of the control variables are not reported. All regressions include a constant. The regressions are calculated using system GMM estimators and allowing the instrument set to start with lagged levels at t-2. Robust t-statistics are reported below the coefficients. Ho: h_1= h_2=0 tests whether the coefficients of inequality and squared inequality are jointly equal to zero.

3.4 Robustness to Alternative Poverty Measures

The empirical exercises reported so far take the poverty headcount as the preferred measure of poverty. However, the headcount is just one among many possible poverty measures. To assess whether our results are robust to the use of alternative poverty measures, we next re-estimate the empirical growth equation using, instead, the poverty gap and the squared poverty gap, and employing the three alternative sets of control variables considered above.

Tables 6 and 7 report the results obtained using the poverty gap and the squared poverty gap, respectively. They are easily summarized. With very few exceptions, poverty generally carries a negative and significant coefficient regardless of the poverty measure chosen, the poverty line considered, the control variable set employed, and whether inequality is included or not in the regression. There are a few cases in which the poverty coefficient loses significance (two in table 6 and three in table 7, using 10 percent significance as the benchmark), but its sign is always negative. As for inequality, its parameter estimate is affected by the choice of control variables and poverty measure. When poverty is measured by the poverty gap (table 6), the inequality coefficient is positive in five instances (and significant at the 10 percent level or better in two of them) and negative in four (significant in two). When poverty is measured instead by the squared poverty gap, the estimate is positive in six instances (five significant) and negative in three (of which one significant). Moreover, the estimates are always negative when using Perotti's (1996) control variable set and positive in most cases when using the alternative sets of control variables.

3.5 Robustness to Alternative Estimation Methods

The empirical experiments reported so far strongly suggest that poverty belongs in the growth equation with a negative sign. However, one might still doubt the ability of the GMM estimation approach to deal with potential simultaneity biases, especially if poverty is highly persistent at the 5 to 10-year horizon. This, of course, should have been flagged by the specification tests reported above, but the skeptical reader might doubt their small sample power.

Table 6. Estimation Results: Poverty Measured by the Poverty Gap

	(1)	(2)	(3)	(4)	(5)	(6)
Baseline model						
Inequality (t-1)				-0.039	-0.055	-0.063
t-stat				-1.59	-2.49	-2.34
P_0($2) ($t$-1)	-0.186			-0.067		
t-stat	-2.75			-1.29		
P_0($3) ($t$-1)		-0.218			-0.169	
t-stat		-5.14			-4.05	
P_0($4) ($t$-1)			-0.183			-0.181
t-stat			-5.02			-4.42
Observations	325	325	325	325	325	325
Model with inflation, trade (in logs), and government size (in logs)						
Inequality (t-1)				0.086	0.013	0.022
t-stat				1.72	0.35	0.58
P_0($2) ($t$-1)	-0.103			-0.187		
t-stat	-1.40			-2.57		
P_0($3) ($t$-1)		-0.138			-0.160	
t-stat		-3.00			-3.78	
P_0($4) ($t$-1)			-0.086			-0.123
t-stat			-2.63			-3.48
Observations	289	289	289	289	289	289
Model with inflation, lagged female education, and lagged infrastructure						
Inequality (t-1)				0.112	0.007	-0.029
t-stat				2.52	0.19	-0.76
P_0($2) ($t$-1)	-0.199			-0.341		
t-stat	-2.45			-3.70		
P_0($3) ($t$-1)		-0.235			-0.241	
t-stat		-4.49			-5.82	
P_0($4) ($t$-1)			-0.210			-0.194
t-stat			-4.82			-5.09
Observations	306	306	306	306	306	306

Source: Authors' estimations.

Notes: The table reports regression results with income growth as dependent variable; and the lagged income per capita (in logs), the poverty gap P_1 (corresponding to poverty lines of $2, $3, and $4) and three sets of control variables. The first panel includes as control variables lagged average years of secondary education of the female and male population and a lagged measure of market distortion (given by the price of investments goods). The second panel includes as control variables the inflation rate, the adjusted volume of trade (in logs), and the ratio of public consumption to GDP (in logs). The third panel includes as control variables the inflation rate, the lagged average years of secondary education of the female and the lagged infrastructure measure. The coefficients of the control variables are not reported. Regressions (4), (5), and (6) include also also the Gini coefficient. All regressions include a constant. The regressions are calculated using system GMM estimators and allowing the instrument set to start with lagged levels at t-2. Robust t-statistics are reported below the coefficients.

Table 7. Estimation results: Poverty Measured by the Squared Poverty Gap

	(1)	(2)	(3)	(4)	(5)	(6)
Baseline model						
Inequality (t-1)				-0.039	-0.036	-0.037
t-stat				-1.83	-1.50	-1.54
P_0(\$2) (t-1)	-0.191			-0.058		
t-stat	-1.71			-0.64		
P_0(\$3) (t-1)		-0.211			-0.096	
t-stat		-2.99			-1.70	
P_0(\$4) (t-1)			-0.192			-0.110
t-stat			-3.63			-2.45
Observations	325	325	325	325	325	325
Model with inflation, trade (in logs), and government size (in logs)						
Inequality (t-1)			0.096	0.083		0.070
t-stat			1.94	1.70		1.55
P_0(\$2) (t-1)	-0.071		-0.239			
t-stat	-0.57		-1.91			
P_0(\$3) (t-1)		-0.124		-0.205		
t-stat		-1.58		-2.70		
P_0(\$4) (t-1)						-0.181
t-stat						-3.19
Observations	289	289	289	289	289	289
Model with inflation, female education, and lagged infrastructure						
Inequality (t-1)	-0.246			0.139	0.104	0.073
t-stat	-1.89			2.81	2.41	1.80
P_0(\$2) (t-1)				-0.528		
t-stat				-3.11		
P_0(\$3) (t-1)		-0.193			-0.366	
t-stat		-2.39			-3.91	
P_0(\$4) (t-1)			-0.216			-0.291
t-stat			-3.23			-4.46
Observations	306	306	306	306	306	306

Source: Authors' estimations.

Notes: The table reports regression results with income growth as dependent variable; and the lagged income per capita (in logs), the square poverty gap P_2 (corresponding to poverty lines of \$2, \$3, and \$4) and three sets of control variables. The first panel includes as control variables lagged average years of secondary education of the female and male population and a lagged measure of market distortion (given by the price of investments goods). The second panel includes as control variables the inflation rate, the adjusted volume of trade (in logs), and the ratio of public consumption to GDP (in logs). The third panel includes as control variables the inflation rate, the lagged average years of secondary education of the female and the lagged infrastructure measure. The coefficients of the control variables are not reported. Regressions (4), (5), and (6) include also also the Gini coefficient. All regressions include a constant. The regressions are calculated using system GMM estimators and allowing the instrument set to start with lagged levels at t-2. Robust t-statistics are reported below the coefficients.

Table 8. Estimation Results: Cross Section with Robust Standard Errors

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Income (in logs) (t-1)	-0.016	-0.023	-0.030	-0.002	-0.013	-0.019	-0.023
t-stat	-2.64	-3.24	-3.35	-0.62	-2.39	-3.02	-2.69
Female education (t-1)	-0.004	-0.003	-0.005	-0.010	-0.006	-0.005	-0.006
t-stat	-0.56	-0.55	-0.74	-1.48	-0.87	-0.88	-1.07
Male education (t-1)	0.011	0.012	0.013	0.011	0.010	0.010	0.012
t-stat	1.77	2.03	2.26	1.69	1.63	1.84	2.02
PPP (t-1)	-0.017	-0.017	-0.017	-0.019	-0.017	-0.017	-0.018
t-stat	-2.45	-2.45	-2.53	-2.95	-2.65	-2.67	-2.73
Inequality (t-1)				-0.063	-0.051	-0.051	-0.046
t-stat				-2.61	-2.23	-2.13	-1.83
P_0($2) ($t$-1)	-0.063				-0.049		
t-stat	-2.73				-2.49		
P_0($3) ($t$-1)		-0.068				-0.055	
t-stat		-3.13				-2.80	
P_0($4) ($t$-1)			-0.076				-0.058
t-stat			-3.17				-2.36
Observations	75	75	75	75	75	75	75
R^2	0.24	0.25	0.25	0.25	0.30	0.31	0.30

Source: Authors' estimations.
Notes: The table reports regression results with income growth as dependent variable; and income per capita (in logs), average years of secondary education of the female and male population, a measure of market distortion (given by the price of investment goods) and headcount poverty P_0 (corresponding to poverty lines of $2, $3, and $4) as explanatory variables. Regressions (4), (5), (6) and (7) also include also the Gini coefficient. All regressions include a constant. Robust t-statistics are reported below the coefficients. Niger has been removed from the sample.

To fully address this concern we would need a set of valid external instruments, which unfortunately is not available. As an alternative, table 8 reports the results of re-estimating equations (17) and (18) exploiting only the cross section dimension of the data. Specifically, we regress the average growth rate over the period 1960-2000 (or longest available span) on the set of controls in 1960, plus initial poverty.[23] This specification should help mitigate concerns with reverse causality stemming from the persistence of poverty since it amounts to lagging the poverty variable further relative to the

23. To save space, we only report estimates using the baseline model. However, the use of other sets of control variables does not change the qualitative conclusions. The results in table 8 are based on 75 observations out of a potential 76. This is due to the elimination of a big outlier (Niger) from the sample.

dependent variable. In exchange, the cross-country regression may suffer from heterogeneity bias due to the presence of unobserved country-specific factors for which we cannot control without making use of the time-series dimension of the data (as done in the GMM procedure). This exercise is similar to the one reported by Perotti (1996), but in this case the emphasis is on the growth impact of poverty, rather than inequality.

The results in table 8 echo the GMM estimates. Initial poverty deters growth, regardless of the specific poverty line chosen and irrespective of whether inequality is included in the regression. The main difference relative to the panel results in table 3 is the smaller magnitude of the estimated poverty coefficients shown in table 8.

4. Uncovering the Transmission Channel

The previous section has presented fairly robust evidence suggesting that, other things being equal, poverty deters growth. What is the mechanism responsible for such effect? One way to approach this question is in terms of the stylized model introduced in section 2. In the model, poverty affects growth only through its negative impact on investment, and such impact arises because of the absence of well-developed capital markets. This amounts to three testable predictions. First, poverty is negatively associated with investment. Second, if this is the relevant mechanism at work, then poverty should not belong in the growth regression once we control for investment. Third, the negative relation between poverty and investment is driven by financial market imperfections—with perfect capital markets, poverty should have no impact on growth. Below we offer a preliminary assessment of these three hypotheses. Throughout we focus on headcount poverty P_0; results with the other poverty measures are qualitatively similar and thus not reported to save space.

4.1 Income, Poverty, and Investment

Before proceeding with the formal econometric tests, we document some stylized facts on investment, poverty, and income levels. Little is known about the impact of poverty on investment, and as a first approximation to the issue we follow an approach similar to that of Ben-David (1998). We rank 99 countries for which we have income, poverty and investment data according to their per capita income in the mid-1990s.[24] Then we partition those countries into 10 groups of 10 countries each (with the exception of the last group that has 9 countries only). The poorest countries in the sample are in the first group, the next 10 countries are in group 2, and so on; thus the 10 richest countries form group 10.

Figure 1 plots median (log) income for each group (figure1.A), poverty (US$2 poverty line) in figure1.B, and gross fixed capital formation relative to GDP (GFCF) in figure1.C.[25] Inspection of this figure reveals a clear non-linear pattern in the relationship between income, poverty and investment. For example, headcount poverty falls dramatically between the first and fourth group—from about 66 percent to less than 8 percent, but after that it declines much more modestly as we move further up along the income group classification. Similarly, investment increases from 14 to about 22 percent of GDP between the first and fourth group, and then remains virtually constant between the fourth and tenth group. Note that these non-linearities are not driven by the underlying income data (figure1.A), whose association with investment seems to be well described by a linear pattern.

As a result, there seems to be a closer association between poverty and investment than between income levels and investment. In fact, the correlation coefficient between the income series in figure 1.A and the investment series in figure 1.C is about 0.55 (i.e., investment tends to be higher in richer countries), whereas the correlation coefficient between the investment series and the poverty series in figure 1.B is - 0.77.

4.2 Poverty, Investment, and Growth

The first issue we explore is whether investment may be behind the negative association between poverty and growth. The empirical growth models estimated in the previous section follow the conventional approach in which investment has been "substituted out." A considerable literature (e.g., Levine and Renelt, 1992; Hendry and Krolzig, 2004) finds that investment is one of the few robust determinants of long-term

24. We pick the 1990s because it is the period over which more poverty observations are available.

25. The results remain virtually unchanged if one uses gross capital formation (GCF) as investment measure.

growth. Thus, we proceed to re-estimate (17) adding investment back to the set of regressors.

Table 9 reports the results for the three sets of controls used in the growth regressions and the two definitions of investment. In figure 1.A we report the results for fixed investment (GFCF) and in figure 1.B for total investment (GCF). Inspection of the table suggests the investment rate belongs to the growth equation regardless of the definition used. Its estimated coefficient ranges between 0.20 and 0.25, which is fully consistent with earlier literature. Poverty, however, does not enter significantly in any equation, with column (6) of figure 1.B as the only exception, with a p-value of 0.10.[26]

4.3 Poverty and Investment

The fact that poverty drops out of the investment—augmented growth equation strongly suggests the need to examine the association between investment and poverty. Since this task would well merit a separate paper, we limit ourselves to a brief empirical illustration. We follow a strategy similar to that in the previous section and estimate a simple equation of the type

$$I_{it} = \eta_i + \alpha I_{it-1} + \psi' z_{it} + \pi P_{it} + u_{itj}, \tag{22}$$

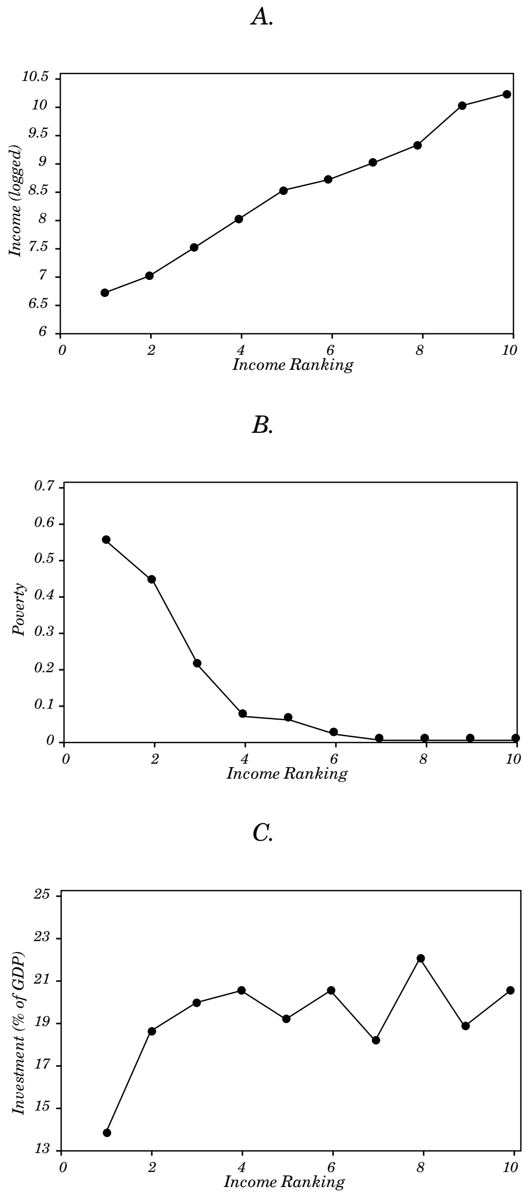
where I is the investment rate, z represents a set of control variables and P is a measure of poverty. Here η_i denotes a country-specific effect, and u_{it} is an i.i.d. error term. If poverty deters investment, we should find that $\pi < 0$.

To implement (22), we consider a basic investment model with the following control variables: (i) the GDP growth rate, consistent with the simple accelerator model; (ii) the initial level of per capita GDP; (iii) the price of investment goods; and (iv) the terms of trade changes, which capture the economy's external conditions.[27]

26. Other empirical experiments, not reported to save space, investigated possible effects of poverty on the efficiency of investment, adding to these specifications an interaction between investment and poverty. Its coefficient estimate, however, was never significant.

27. Formally speaking, (17) and (22) form a two-equation (sub) system, whose identifiability would need to be considered. Given the illustrative character of (22), we do no pursue this issue here. Note, however, that the specifications employed in the text would yield enough exclusion restrictions to identify both equations.

Figure 1. Income Poverty and Investment



Source: Authors' calculations.

Table 9. Estimation Results: Investment as an Extra Control Variable

	Model with lagged female and male education, and lagged market distortions proxy			*Model with inflation, trade (in logs), and government size (in logs)*			*Model with inflation, lagged female education, and lagged infrastructure*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
GFCF (t)	0.237	0.238	0.237	0.211	0.210	0.221	0.238	0.234	0.231
t-stat	9.27	9.53	9.92	12.84	11.50	10.96	8.93	8.71	8.48
P_0(\$2) (t-1)	-0.002			0.000			0.009		
t-stat	-0.10			-0.02			0.56		
P_0(\$3) (t-1)		0.003			0.005			0.006	
t-stat		0.17			0.35			0.42	
P_0(\$4) (t-1)			0.007			0.020			0.008
t-stat			0.42			1.14			0.51
Observations	316	316	316	284	284	284	301	301	301
Countries	84	84	84	80	80	80	84	84	84
Hansen Test p-value	0.25	0.23	0.26	0.22	0.21	0.23	0.45	0.43	0.45
AR(2) p-value	0.54	0.52	0.52	0.12	0.11	0.11	0.23	0.22	0.22

Table 9. (continued)

	Model with lagged female and male education, and lagged market distortions proxy			*Model with inflation, trade (in logs), and government size (in logs)*			*Model with inflation, lagged female education, and lagged infrastructure*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
GFCF (t)	0.231	0.236	0.236	0.214	0.218	0.235	0.265	0.259	0.254
t-stat	10.25	10.34	10.55	11.84	10.73	10.24	9.78	9.94	9.86
P_0($2) ($t$-1)	0.003			0.002			0.022		
t-stat	0.20			0.16			1.20		
P_0($3) ($t$-1)		0.008			0.009			0.019	
t-stat		0.51			0.68			1.19	
P_0($4) ($t$-1)			0.014			0.028			0.020
t-stat			0.81			1.63			1.03
Observations	321	321	321	287	287	287	303	303	303
Countries	84	84	84	80	80	80	84	84	84
Hansen Test p-value	0.21	0.20	0.23	0.28	0.29	0.36	0.43	0.43	0.44
AR(2) p-value	0.31	0.30	0.30	0.09	0.09	0.09	0.22	0.20	0.19

Source: Authors' estimations.

Notes: The table reports regression results with income growth as dependent variable; and the lagged income per capita (in logs),investment (i.e., gross fixed capital formation), headcount poverty P_0 (corresponding to poverty lines of $2, $3, and $4) and three sets of control variables. The first panel includes as control variables lagged average years of secondary education of the female and male population and a lagged measure of market distortion (given by the price of investments goods). The second panel includes as control variables the inflation rate, the adjusted volume of trade (in logs), and the ratio of public consumption to GDP (in logs). The third panel includes as control variables the inflation rate, the lagged average years of secondary education of the female and the lagged infrastructure measure. The coefficients of the control variables are not reported. All regressions include a constant. The regressions are calculated using system GMM estimators and allowing the instrument set to start with lagged levels at t-1. Robust t-statistics are reported below the coefficients.

The first six columns of table 10 report the results of estimating equation (22). Columns 1-3 use the GFCF definition of investment, while columns 4-6 use GCF. In every case, the estimates show that higher poverty is associated with lower investment, subsequently, regardless of the poverty line used, the headcount ratio carries a negative and significant coefficient in all specifications.

The estimates of the other control variables are in line with those reported by existing studies, except for the initial income level, for which we find a negative parameter in contrast with the positive coefficient commonly encountered in the literature. Note, however, that there is another indirect effect of income on investment operating in the opposite direction through the impact of income on poverty.

4.4 Poverty, Investment, and Financial Sector Development

Finally, we check if the poverty-investment relation depends on the degree of financial sector development, as assumed by the analytical model in section 2. For this purpose we consider the following variation of (22):

$$I_{it} = \eta_i + \alpha I_{it-1} + \psi' z_{it} + \pi_{LFD} P_{it-1}^{LFD} + \pi_{HFD} P_{it-1}^{HFD} + u_{itj}, \qquad (23)$$

where P_{it-1}^{LFD} and P_{it-1}^{HFD} now distinguish poverty levels according to the degree of financial sector development of the country under consideration. The superscripts *LFD* and *HFD* denote low and high degrees of financial sector development, respectively. The underlying idea is that the higher the degree of financial sector development, the easier it will be for the poor to borrow and take advantage of their investment opportunities. Hence, in (23) we would expect $\pi_{LFD} < \pi_{HFD}$.

In order to empirically implement (23) we need to assign the different observations to the two states of financial sector development—low and high. To do so we take the stock of credit to the private sector relative to GDP as a yardstick. When the value of this variable is below its sample median we assign the observation to the low financial sector development state. Conversely, values above the median are classified as belonging to the high financial sector development state.

Table 10. Estimation Results: Investment as the Dependent Variable

	Model 1						*Model 2*					
	GFCF			*GCF*			*GFCF*			*GCF*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
Investment (t-1)	0.658	0.691	0.717	0.652	0.664	0.690	0.721	0.716	0.735	0.653	0.656	0.674
t-stat	11.15	11.17	11.63	19.05	17.03	16.64	16.36	15.99	16.23	24.34	22.86	22.03
Income (in logs) (t-1)	-0.009	-0.014	-0.019	-0.012	-0.018	-0.020	-0.005	-0.011	-0.010	-0.005	-0.006	-0.002
t-stat	-1.58	-2.07	-2.30	-2.29	-2.66	-2.27	-1.55	-2.60	-1.68	-1.61	-1.23	-0.31
Growth (t)	0.539	0.512	0.498	0.550	0.549	0.547	0.524	0.507	0.498	0.620	0.616	0.612
t-stat	8.87	8.36	8.16	9.28	9.10	8.95	14.59	14.29	12.87	14.39	13.67	13.28
PPP (t-1)	-0.010	-0.010	-0.011	-0.014	-0.014	-0.017	-0.004	0.001	-0.001	0.000	0.000	-0.001
t-stat	-1.66	-1.62	-1.80	-1.84	-1.87	-2.29	-0.81	0.21	-0.27	-0.06	0.03	-0.15
Terms of trade (t)	0.064	0.074	0.078	0.132	0.133	0.133	0.079	0.089	0.100	0.071	0.078	0.079
t-stat	1.60	1.87	2.00	3.02	3.07	3.09	3.97	4.28	4.52	3.02	3.15	3.05
P_0(\$2) (t-1)	-0.079			-0.105								
t-stat	-1.88			-2.74								
P_0(\$3) (t-1)		-0.065			-0.088							
t-stat		-1.81			-2.48							
P_0(\$4) (t-1)			-0.064			-0.073						
t-stat			-1.80			-1.92						
P_0^{HFD}(\$2) (t-1)							0.031			0.016		
t-stat							0.90			0.47		
P_0^{LFD}(\$2) (t-1)							-0.055			-0.057		
t-stat							-2.03			-2.52		

Table 10. (continued)

	Model 1						Model 2					
	GFCF			GCF			GFCF			GCF		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$P_0^{\mathrm{HFD}}(\$3)$ (t-1)								-0.002			0.011	
t-stat								-0.08			0.41	
$P_0^{\mathrm{LFD}}(\$3)$ (t-1)								-0.059			-0.038	
t-stat								-2.47			-1.70	
$P_0^{\mathrm{HFD}}(\$4)$ (t-1)									0.003			0.025
t-stat									0.13			0.97
$P_0^{\mathrm{LFD}}(\$4)$ (t-1)									-0.039			-0.010
t-stat									-1.43			-0.40
Observations	338	338	338	345	345	345	308	308	308	311	311	311
Countries	108	108	108	108	108	108	103	103	103	103	103	103
Hansen Test p-value	0.29	0.32	0.37	0.34	0.34	0.39	0.47	0.57	0.59	0.28	0.31	0.37
AR(2) p-value	0.33	0.33	0.32	0.30	0.28	0.27	0.36	0.36	0.35	0.43	0.42	0.40

Source: Authors' estimations.

Notes: The table reports regression results with investment (i.e., gross fixed capital formation or gross fixed capital), as dependent variable; and lagged investment, the lagged per capita income (in logs), the income growth rate, a lagged measure of market distortion (given by the price of investments goods), the terms of trade, the lagged measure of credit to private sector (in logs), and neither the lagged headcount poverty P_0 (corresponding to poverty lines of \$2, \$3, and \$4) or the lagged upper and lower headcount poverty P_0 (corresponding to poverty lines of \$2, \$3, and \$4) taking into account the median of the credit to private sector to divide the samples. The coefficients of the control variables are not reported. All regressions include a constant. The regressions are calculated using system GMM estimators and allowing the instrument set to start with lagged levels at t-1. Robust t-statistics are reported below the coefficients.

Columns 7 to 9 and 10 to 12 in table 10 report the results of estimating (23) using as dependent variable the gross fixed capital formation and gross capital formation measures of investment, respectively. On the whole, the estimates imply that the negative relation between initial poverty and investment arises only in conditions of low financial development, which appears broadly consistent with the model in section 2. In fact, poverty does not seem to have any effect on investment at high levels of financial sector development. However, when the poverty line is set at US$4 a day the estimates cease to be significant even at low levels of financial development—perhaps reflecting the need for a more flexible parameterization of the relation between financial development and poverty effects on investment.

5. Conclusions

An abundant theoretical literature has suggested a variety of mechanisms through which poverty may deter growth and become self-perpetuating. However, the growth consequences of poverty have attracted only limited interest in the empirical literature. This stands in contrast with the ample attention devoted by recent empirical work to closely related issues such as the poverty-reducing effects of growth or the consequences of inequality for growth.

This paper has attempted to shed light on a simple hypothesis consistent with the growth-deterrent effect of poverty advanced by the theoretical literature—namely that, other things being equal, higher poverty should be reflected in slower growth. The paper's strategy is based on the estimation of a growth equation with poverty added to an otherwise standard set of growth determinants. Thus, the framework is similar to that employed in empirical studies of the effects of inequality on growth, but shifting the emphasis from inequality to poverty.

The resulting empirical specifications are estimated on a large panel dataset. On the whole, the results reveal a consistently negative and strongly significant association between the level of poverty and subsequent growth, which is also economically significant: the estimates suggest that a ten percentage-point increase in the headcount poverty rate is associated with a decline in annual per capita growth by about one percentage point.

The negative poverty-growth link survives a battery of robustness checks, including (i) the use of alternative poverty lines, (ii) the use of alternative poverty measures, (iii) the use of alternative sets of control variables in the regression, (iv) the use of alternative sets of instruments in the estimation, (v) the use of alternative estimation methods, and (vi) allowing for linear and non-linear effects of inequality on growth. When we add inequality to the regressions, the sign, significance and magnitude of the poverty effect remain essentially unchanged, suggesting that it does capture a true poverty effect rather than an inequality effect. In contrast, the link between inequality and growth is empirically fragile, consistent with the mixed findings of earlier literature.

The paper has also attempted to shed light on the mechanism underlying the negative poverty-growth link. While tentative, the evidence in the paper is consistent with the view that poverty deters investment, especially when the degree of financial development is limited. This result is in line with stylized theoretical models in which financial market imperfections prevent the poor from taking advantage of their investment opportunities in human and/or physical capital.

References

Agénor, R. and J. Aizenman. 2010. "Aid Volatility and Poverty Traps." *Journal of Development Economics* (91): 1–7.

Aghion, P., E. Caroli, and C. García-Peñalosa. 1999. "Inequality and Economic Growth: The Perspective of the New Growth Theories." *Journal of Economic Literature* (37): 1615–60.

Alesina, A. and D. Rodrik. 1994. "Distributive Policies and Economic Growth." *Quarterly Journal of Economics* (109): 465–90.

Antman, F. and D. McKenzie. 2007. "Poverty Traps and Non-linear Income Dynamics with Measurement Error and Individual Heterogeneity." *Journal of Development Studies* (43): 1057–83.

Atkeson, A. and M. Ogaki. 1996. "Wealth-Varying Intertemporal Elasticities of Substitution: Evidence from Panel and Aggregate Data." *Journal of Monetary Economics* (38): 507–34.

Azariadis, C. and A. Drazen. 1990. "Threshold Externalities in Economic Development." *Quarterly Journal of Economics* (105): 501–26.

Azariadis, C. and J. Stachurski. 2004. "A Forward Projection of the Cross Country Income Distribution." Unpublished manuscript, Université Catholique de Louvain.

————. 2005. "Poverty Traps." In *Handbook of Economic Growth*, edited by P. Aghion and S. Durlauf. Amsterdam: Elsevier.

Banerjee, A. 2000. "The Two Poverties." Working Paper 01–16, Department of Economics, M.I.T.

Banerjee, A. and E. Duflo. 2003. "Inequality and Growth: What Can the Data Say?" *Journal of Economic Growth* (8): 267–99.

Banerjee, A. and A. Newman. 1993. "Occupational Choice and the Process of Development." *Journal of Political Economy* (101): 274–98.

Barro, R. 2000: "Inequality and Growth in a Panel of Countries." *Journal of Economic Growth* (5): 5–32.

Barro, R. and J.W. Lee. 2001. "International Data on Educational Attainment Updates and Implications." *Oxford Economic Papers* 53(3): 541–63.

Ben-David, D. 1998. "Convergence Clubs and Subsistence Economies." *Journal of Development Economics* (55): 155–71.

Bloom, E., D. Canning and J. Sevilla. 2003. "Geography and Poverty Traps." *Journal of Economic Growth* (8): 355–78.

Bourguignon, F. 2004. "The Poverty-Growth-Inequality Triangle." Unpublished manuscript, World Bank.

Blundell, R. and S. Bond. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics* (87): 115–43.

Calderón, C. and L. Servén. 2010. "Infrastructure in Latin America." Policy Research Working Paper 5317, World Bank.

Caucutt, E. and K. Kumar. 2005. "Evaluating Explanations for Stagnation." 2005 Meeting Papers 387, Society for Economic Dynamics.

Dasgupta, P. and D. Ray. 1986. "Inequality as a Determinant of Malnutrition and Unemployment: Theory." *Economic Journal* 96(384): 1011–34.

Dercon, S. 2005. "Risk, Poverty and Vulnerability in Africa." *Journal of African Economies* (14): 483–88.

Dercon, S. and L. Christiansen. 2011. "Consumption Risk, Technology Adoption and Poverty Traps: Evidence from Ethiopia." *Journal of Development Economics* (96): 159–73.

Dollar, D. and A. Kraay. 2002. "Growth is Good for the Poor." *Journal of Economic Growth* (7): 195–225.

Durlauf, S. 2006. "Groups, Social Influences, and Inequality." In *Poverty traps*, edited by S. Bowless, S. Durlauf, and K. Hoff. Princeton, NJ: Princeton University Press.

Durlauf, S. and D. Quah. 1999. "The New Empirics of Economic Growth." In *Handbook of Macroeconomics*, edited by J. Taylor and M. Woodford, Amsterdam: North-Holland.

Easterly, W. 1994. "Economic Stagnation, Fixed Factors, and Policy Thresholds." *Journal of Monetary Economics* (33): 525–57.

————. 2006. "Reliving the 1950s: the Big Push, Poverty Traps, and Takeoffs in Economic Development". *Journal of Economic Growth* (11): 289–318.

Engerman, S. and K. Sokoloff. 2006. "The Persistence of Poverty in the Americas: The Role of Institutions." In *Poverty traps*, edited by S. Bowless, S. Durlauf, and K. Hoff. Princeton, NJ: Princeton University Press.

Fisher, F. 1961. "Identifiability Criteria in Non-linear Systems." *Econometrica* (29): 574–90.

Forbes, K. 2000. "A Reassessment of the Relationship between Inequality and Growth." *American Economic Review* 90(4): 869–87.

Foster, J., J. Greer, and E. Thorbecke. 1984. "A Class of Decomposable Poverty Measures." *Econometrica* (52): 761–66.

Galor, O. and J. Zeira. 1993. "Income Distribution and Macroeconomics." *Review of Economic Studies* 60(1): 35–52.

Gibrat, R. 1931. *Les Inégalités Économiques.* Paris: Sirey.
Gollin, D., S. Parente, and R. Rogerson. 2002. "The Role of Agriculture in Development." *American Economic Review* 92(2): 160–64.
Graham, B. and J. Temple. 2006. "Rich Nations, Poor Nations: How Much Can Multiple Equilibria Explain?" *Journal of Economic Growth* (11): 5–41.
Hendry, D.F. and H-M. Krolzig. 2004. "'We Ran One Regression." *Oxford Bulletin of Economics and Statistics* (66): 799–810.
Jalan, J. and M. Ravallion. 2002. "Geographic Poverty Traps? A Micro Model of Consumption Growth in Rural China." *Journal of Applied Econometrics* 17(4): 299–314.
Kraay, A. 2006. "When is Growth Pro-Poor? Evidence from a Panel of Countries." *Journal of Development Economics* (80): 198–227.
Kraay, A. and C. Raddatz. 2007. "Poverty Traps, Aid and Growth." *Journal of Development Economics* (82): 315–47.
Kremer, M., A. Onatski, and J. Stock. 2001. "Searching for Prosperity." *Carnegie-Rochester Conference Series on Public Policy* 55(1): 275–303.
Knowles, S. 2005. "Inequality and Economic Growth: The Empirical Relationship Reconsidered in the Light of Comparable Data." *Journal of Development Studies* (41): 135–59.
Levine, R. and D. Renelt. 1992. "A Sensitivity Analysis of Cross-Country Growth Regressions." *American Economic Review* 82(4): 942–63.
Li, H. and H. Zou. 1998. "Income Inequality is not Harmful for Growth: Theory and Evidence." *Review of Development Economics* 2(3): 318–34.
Loayza, N., P. Fajnzylber, and C. Calderón. 2005. *Economic Growth in Latin America and the Caribbean.* Washington D.C.: The World Bank.
López, H. and L. Servén. 2011. "A Normal Relationship? Poverty, Growth and Inequality." Unpublished manuscript, World Bank.
López, H., K. Schmidt-Hebbel, and L. Servén. 2000. "How Effective is Fiscal Policy in Raising National Saving?" *Review of Economics and Statistics* (82): 226–38.
McKenzie, D. and C. Woodruff. 2006. "Do Entry Costs Provide an Empirical Basis for Poverty Traps? Evidence from Mexican Microenterprises." *Economic Development and Cultural Change* (55): 3–42.
Mookherjee, D. and D. Ray. 2002. "Contractual Structure and Wealth Accumulation." *American Economic Review* (92): 818–49.

Perotti, R. 1996. "Growth, Income Distribution and Democracy." *Journal of Economic Growth* (1): 149–87.

Quah, D. 1993. "Empirical Cross-section Dynamics in Economic Growth." *European Economic Review* (37): 426–34.

Ravallion, M. 2004. "Pro-Poor Growth: A Primer." Policy Research Working Paper 3242, World Bank.

———. 2009. "Why Don't We See Poverty Convergence?" Policy Research Working Paper 4974, World Bank.

Rebelo S. 1992. "Growth in Open Economies." *Carnegie-Rochester Conference Series on Public Policy* (36): 5–46.

Stiglitz, J. 1969. "The Effects of Income, Wealth and Capital Gains Taxation on Risk-Taking." *Quarterly Journal of Economics* (83): 263–83.

Ziliak, J. 1997. "Efficient Estimation with Panel Data when Instruments Are Predetermined: An Empirical Comparison of Moment-Condition Estimators." *Journal of Business and Economic Statistics* (15): 419–31.