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Too Poor to Grow

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Abstract

Recent theoretical literature has suggested a variety of mechanisms through which poverty may deter growth and become self-perpetuating. A few papers have searched for empirical regularities consistent with those mechanisms—such as aggregate non-convexities and convergence clubs. However, a seemingly basic implication of the theoretical models, namely that countries suffering from higher levels of poverty should grow less rapidly, has remained untested. This paper attempts to fill that gap and provide a direct empirical assessment of the impact of poverty on growth. The paper's strategy involves including poverty indicators among the explanatory variables in an otherwise standard empirical growth equation. Using a large panel dataset, the authors find that poverty has a negative impact on growth that is significant both statistically and economically. This result is robust to a variety of specification changes, including (i) different poverty lines; (ii) different poverty measures; (iii) different sets of control variables; (iv) different estimation methods; (v) adding inequality as a control variable; and (vi) allowing for nonlinear effects of inequality on growth. The paper also finds evidence that the adverse effect of poverty on growth works through investment: high poverty deters investment, which in turn lowers growth. Further, the data suggest that this mechanism only operates at low levels of financial development, consistent with the predictions of theoretical models that underscore financial market imperfections as a key ingredient of poverty traps.

This paper—a product of the Growth and the Macroeconomics Team, Development Research Group—is part of a larger effort in the group to understand the relationship between poverty and growth. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at lserven@worldbank.org, and hlopez@worldbank.org.

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I. Introduction

A booming theoretical literature has proposed a variety of mechanisms capable of generating vicious cycles of poverty and stagnation – referred to as poverty traps.[2] Broadly, the idea underlying such models is that poverty prevents a significant share (or even all) of the population from helping ignite the growth engine. Under appropriate conditions, this may lead to multiple equilibria, making it possible for poverty to become self-reinforcing.

Such situation may arise through a number of channels. A prominent one involves the existence of 'threshold effects', resulting for example from indivisibilities or increasing returns to scale, so that below a certain level of income or wealth society is too poor to afford the investments (in human or physical capital) or the technologies necessary to set the growth process in motion. Along these lines, Galor and Zeira (1993) 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.[3]

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 well-functioning insurance and credit markets, the poor will skip profitable investment opportunities that they deem too risky.[4] Such behavior makes poverty self-reinforcing as the poor minimize risk at the expense of their mean earnings. In this vein, Dercon (2003) 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.

Institutions are another potential source of poverty traps. Institutional arrangements that place the economic opportunities created in the development process beyond the reach of large segments of society are likely to result in reduced growth rates, as modern economies require broad participation in entrepreneurship and innovation. Along these lines, Engerman and Sokoloff (2004) argue that persistent poverty in former European colonies can be traced to the organization of production and the institutional arrangements originally created by the colonial powers.

However, as noted by Durlauf (2004), in spite of the diversity and growing popularity of these analytical models, little is known about their empirical relevance. A few empirical studies have attempted to assess it taking an indirect route. In this vein, Quah (1993) and Azariadis and Stachurski (2004), among others, have explored the existence of convergence clubs by assessing the bimodality 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

[2] See Azariadis and Stachurski (2005) for a survey.
[3] See also Dasgupta and Ray (1986), who develop a model focused on investments in health, and Banerjee and Newman (1994), who consider threshold effects in a model with physical capital.
[4] The argument that risk aversion leads to underinvestment goes back to Stiglitz (1969).

the two ends of the income distribution.[5] At the micro level, Jalan and Ravallion (2002), using household panel data from China, find a significant role of aggregate (at the local level) physical and human capital endowments for household consumption growth, which they argue is consistent with the existence of geographic poverty traps.

Strictly speaking, the evidence uncovered by these studies could at most be viewed as consistent with, rather than proof of, the existence of poverty traps. An alternative empirical strategy is to investigate specific sources of non convexities and multiple equilibria. One such approach is the calibration of models consistent with the poverty trap hypothesis. Once a model has been calibrated, its empirical relevance can be assessed. For example, Graham and Temple (2004) 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 lends some support to the poverty trap notion. In turn, Kraay and Raddatz (2005) calibrate simple aggregate models capable of generating poverty traps through low savings and/or low technology at low levels of development. Their results cast doubt on the relevance of these mechanisms for the existence of poverty traps. At the micro level, McKenzie and Woodruff (2004) search for non-convexities in the production function generated by large fixed investment costs. Using Mexican microenterprise data, they find little evidence in favor of this particular poverty trap mechanism.

This paper takes a different approach to testing for the deterrent effects of poverty on growth. 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 is a weaker version of the predictions derived from the analytical models mentioned above, in that to support it we do not need to find evidence of multiple equilibria, but just empirical proof that poverty tends to hold back growth.

The paper is also related to two other strands of empirical literature. One has explored the growth-poverty link focusing on the poverty-reducing effect of growth and the factors that shape it (Bourguignon 2004, Ravallion 2004, and Kraay 2005). 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.[6] It is important to stress that the core hypothesis of that literature is different from ours in that our concern is not so much the relative distribution of income, but rather the interaction between relative distribution and average income (i.e., the size distribution of *absolute* income) – which underlies measured poverty.

[5] Bloom, Canning and Sevilla (2003) also test for the existence of convergence clubs controlling for a number of exogenous geographic variables (such as distance from the equator, rainfall, temperature, etc). Their findings also support the hypothesis that the distribution of income is bimodal.

[6] 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 may 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.

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 control for the potential endogeneity of the regressors.

On the whole we find that poverty has a significant negative impact on 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 nonlinear 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 the lower the degree of financial development.

The rest of the paper is structured as follows. In section II we illustrate how poverty can be a growth deterrent, using a simple model that is just a modified version of Aghion *et al*. (1999), extended to include a minimum consumption subsistence level. In Section III we describe our empirical strategy to test for the effect of poverty on growth in a panel context. Section IV reports estimation results for the basic model and performs a variety of robustness checks. Section V explores the mechanism responsible for the effects of poverty on growth identified in section IV. Finally, Section V concludes.

II. An illustrative model

To illustrate the effects of poverty 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. With a subsistence consumption requirement, poor consumers (defined as those whose initial endowment is below the minimum consumption level) cannot save and, in the absence of capital markets, cannot invest either.[7] Thus they do not contribute to the economy's aggregate growth.

II.1 Individuals

There is a continuum of non-altruistic overlapping generations individuals, indexed $i \in [0,1]$ that 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

[7] 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.

denote by λ the share of the population with initial endowment below survival needs, to which we will 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 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:

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

where c_t and c_{t+1} denote consumption when young and old respectively.[8]

II.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 *et al*. (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

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

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

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

II.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

[8] 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.

depending on their initial endowments. In particular, for non-poor individuals (i.e., those with $w_t^i > \bar{c}$) we have:

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

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

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 in 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.

II.4 Endowments, inequality, and growth

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

i) λ =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.[9] 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

$$\lambda = p(\sigma\varepsilon_t^i \le \bar{c} - a) = F\big((\bar{c} - a)/\sigma\big) = \int_{-\infty}^{(\bar{c}-a)/\sigma} f(\varepsilon_t^i)d\varepsilon_t^i \tag{13}$$

For $\bar{c} > a$ (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) λ =0

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

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

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

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

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<λ <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 of $\partial E[(w_t^i - \bar{c})^\alpha \mid w_t^i > \bar{c}] / \partial \sigma$ depends on two factors. On the one hand, because the production function exhibits decreasing returns to capital, the higher 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.[10] Thus for $\bar{c} < a$ the impact of inequality changes on the conditional expectation in (16) is ambiguous, while for $\bar{c} > a$ it is assured to be negative and hence runs counter the effect on the poverty rate (the first term in (16)) resulting also on an overall ambiguous 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.[11] However, similar results would obtain in the presence of threshold effects arising instead from some other source – e.g., investment indivisibilities (as in Azariadis and Drazen 1990,

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

[11] Atkeson and Ogaki (1996) and Lopez, 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).

for example) or increasing returns to scale, so that below a certain level of income or wealth society is "too poor" to acquire the assets (human or physical capital) or the technologies necessary to set the growth process in motion; see Azariadis and Stachursky (2005) for a variety of examples.

III. 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:

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

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 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 – as argued by the literature on poverty traps, for example – 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.[12] The reason is that poverty itself is a (nonlinear) function of inequality and average income, and hence the poverty coefficient in (17) could be capturing the inequality effect.[13] 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, we use the Gini coefficient). Equation (18) is a generalization of the standard empirical specification used in the literature to estimate the impact of inequality on growth. Note that in this model the relationship between inequality and growth depends on how inequality affects poverty:

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

[12] Such effect might arise through a variety of mechanisms, including political economy channels (which may result in a negative growth impact of inequality, as argued by Alesina and Rodrik 1994 and Perotti 1996) or wage incentive effects (which would result in a positive impact; e.g., Mirrless 1971).

[13] See Lopez and Servén (2005) for a detailed analysis of the relationship between the Gini coefficient and poverty measures of the Foster-Greer-Thorbecke (FGT) (1984) class under the assumption of log normality.

Still, one might object that a nonzero estimate of β in (18) could just be capturing a nonlinear 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 an empirical model like:

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

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

III.1 Econometric issues

In equations (17) and (18) above, poverty is pre-determined, which in principle should help alleviate concerns with simultaneity (more on this later). This in turn should offer some reassurance that empirical estimates of β capture the effect of poverty on growth rather than the impact of growth on poverty explored, for example, by Kraay (2005).

However, it is important to note that even if poverty were endogenous rather than predetermined in the equations of interest, the parameters of the growth-poverty system would continue to be identified as long as the poverty measure is a nonlinear function of income (and possibly other variables such as inequality) – as will be the case here (we shall return to this below).[14]

Estimation of equations (17), (18) and (20) still has to overcome two main challenges, namely the presence of country-specific effects potentially correlated with the explanatory variables, and the possible simultaneity of some of the control variables with growth. To address these problems, Arellano and Bond (1991) propose differencing the equations to eliminate the country specific effect so that, after rearranging, (18), say, can be rewritten as:

$$\begin{aligned}(y_{it} - y_{it-1}) &= (1+\delta)(y_{it-1} - y_{it-2}) + \omega'(x_{it} - x_{it-1}) + \beta(p_{it-1} - p_{it-2}) \\ &+ \rho(g_{it-1} - g_{it-2}) + (\nu_{it} - \nu_{it-1})\end{aligned} \qquad (21)$$

which relates changes in the growth rate to changes in poverty and inequality and the control variables. If $\delta = 0$ and the x variables are exogenous, OLS on (21) will yield consistent estimates. But if δ is not equal to zero, and/or some or all of the x are determined simultaneously with y, the OLS estimates will be inconsistent, and an instrumental variable procedure is needed to obtain consistent estimates of the parameters.

Absent exogenous variables that can provide outside instruments, a GMM estimator based only on internal instruments can be constructed along the lines of Arellano and Bover

[14] Drawing from Fisher (1961), it can be shown that the identifying information follows from the very nonlinearity of the poverty equation. Likewise, if we were to expand the analysis to allow also for the endogeneity of inequality, the growth equation (18) would still be identified if, in addition to the nonlinearity of poverty, we are willing to assume that the (unspecified) inequality equation includes some exogenous variable that is excluded from the growth equation.

(1995) and Blundell and Bond (1997), who propose a system estimator combining the regressions in differences and levels. To compute the system estimator, 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.[15]

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 υ_{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 υ_{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.

III.2 Control variables

We turn to the specification of the set of control variables included in *x*. The empirical growth literature has experimented with a vast number of alternative sets of explanatory variables.[16] 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 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. All these variables are measured in levels at the beginning of the period.

The second specification we consider is more 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;[17] and the ratio of public consumption to GDP as an indicator of the burden imposed by the government on the

[15] 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 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.

[16] 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.

[17] 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.

economy. As in Loayza, Fajnzylber and Calderón (2002), these variables are measured as contemporaneous period averages.

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 (2004). In the empirical specification we use as infrastructure measure the number of main telephone lines per capita, expressed as the average over the preceding period.

III.3 Data

Despite the huge progress made in recent years, poverty data are still very 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 estimation of (21) above requires a minimum of two poverty observations per country – and a minimum of at least three in order to allow generating instruments from the lagged values of the poverty measure.

To overcome this limitation, we adopt a different strategy: rather than using LSMS-based poverty data, we construct a set of poverty figures using a lognormal approximation.[18] We base this choice on recent work by Lopez and Servén (2005), who compare the quintile income shares generated by a lognormal distribution with their observed counterparts using data from approximately 800 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. In the case of per capita expenditure, the lognormal specification can be formally rejected, but it still provides an excellent empirical approximation to the data.

In view of these results, we construct our poverty figures on the basis of the observed per capita income levels and Gini coefficients. In our regressions, we use three alternative poverty measures – the headcount, the poverty gap and the squared poverty gap – constructed in this manner, and in each case we experiment with three alternative poverty

[18] 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 Φ(.) 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:

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

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

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

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 *et al*. (2002), except for the education variables, which are from Barro and Lee (2001).

Our regressions are conducted using an unbalanced panel of non-overlapping five-year periods spanning the years 1960-2000. Income and inequality data pertain to the latest available year within each given period. The original income data is from the PWT 6.1 whereas the original inequality data comes from Dollar and Kraay's (2002) database on inequality.[19]

Table 1 presents summary statistics for income, inequality and the constructed poverty measures.[20] 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.[21] 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.[22]

IV. Results

Table 2 reports estimates of the growth equation using Perotti's (1996) 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)

[19] The data sources used to compute the inequality indices show a high degree of diversity across countries. The original data is 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 as described by Dollar and Kraay (2002).

[20] 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.

[21] 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).

[22] The maximum corresponds in all cases to Tanzania.

to 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 poverty leads to lower 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 appears also economically significant in all three cases: according to the estimates in the table, a 10 percentage point increase in poverty reduces annual per capita growth by 0.8 to 1.1 percentage points.

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.[23]

We next assess whether our finding of a significant effect of poverty on growth is just a result of excluding inequality from the regression, so that we are forcing its 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 exerts a positive and significant effect on growth. In columns (5) to (7) we include both inequality and poverty in the regression. Inequality consistently carries 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.

IV.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.

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 impact of

[23] 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'.

poverty on growth, 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 estimated effect of poverty on growth 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.

IV.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.[24]

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.

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

IV.3 Robustness to non-linearities

The results presented so far are in line with the predictions from the analytical model outlined earlier: poverty has an unambiguous negative effect on growth, while the impact of inequality is ambiguous. However, one might wonder if, rather than capturing a true poverty

[24] Note that sample sizes decline somewhat relative to Tables 2 and 3, due to the limited availability of some of the explanatory variables.

effect, the negative coefficient on the poverty measure may just be capturing a nonlinear effect of inequality on growth.[25] To explore this issue, we estimate equation (20) using the following specification for $h(g_{it-1})$:

$$h(g_{it-1}) = h_1 g_{it-1} + h_2 g_{it-1}^2 . \qquad (22)$$

where h_1 and h_2 are parameters to be estimated. If the poverty coefficient in the previous regression is really capturing nonlinear effects of inequality, we should expect its size and significance 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 effect of inequality is not robust across specifications, even when we allow for nonlinearities. 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 somewhat. In particular, for the models in columns (5) and (6) we cannot reject the joint null hypothesis that h_1 and h_2 in (22) are both equal to zero (i.e., that inequality does not belong in the regression). The third set of controls again yields a negative coefficient for the level of inequality and a positive one for its square, although neither is statistically significant, and the joint null that h_1 and h_2 are both equal to zero is rejected at the 10 percent level only in the model in column (7).

IV.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 impact on growth 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

[25] Recall that, as discussed earlier, the poverty measures we are using can be expressed as nonlinear functions of both per capita income and inequality.

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.

IV.5 Robustness to alternative estimation methods

One criticism that could be made to the previous results is that the internal instruments used in the GMM procedure may not fully eliminate the potential reverse causality bias if the variables (with poverty among them) are highly persistent. This, of course, should have been flagged by the specification tests reported above, but the skeptical reader might doubt their power, and wonder if the estimated negative effect of poverty on growth might be, at least in part, a spurious reflection of the poverty-reducing effect of growth.

To fully resolve this concern we would need a set of valid external instruments, which is not available. As an alternative, Table 8 reports the results of estimating models (17) and (18) exploiting only the cross section dimension of the data. More 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.[26] This should alleviate any concerns with reverse causality, since in this specification the poverty variable pre-dates growth by at least two decades. 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. The exercise is similar to the one reported by Perotti (1996), but in this case the emphasis is on the impact of poverty on growth.

The results in Table 8 echo the GMM dynamic panel estimates. 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.

V. Uncovering the transmission channel

The previous section has presented fairly robust evidence that, other things equal, poverty deters growth, a result consistent with the analytical literature on poverty traps.[27] What is the mechanism responsible for such effect? One way to approach this question is in

[26] 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.

[27] Strictly speaking, our empirical findings are consistent with a 'weak' version of the predictions of the poverty trap literature, in that the finding that poverty lowers growth does not necessarily rule out the convergence of income predicted by the neoclassical model. However, the empirical estimates presented above do imply the existence of a threshold poverty level beyond which divergence would occur. For example, with the estimates in the first column of table 3 there would be divergence for levels of the poverty headcount (with a US$2 per day poverty line) above 10 percent.

terms of the stylized model introduced in Section II. 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 has a negative impact on investment. Second, this is the relevant mechanism at work – i.e., once we control for investment, poverty has no significant impact on growth. Third, the adverse effect of poverty on investment is driven by financial market imperfections – with perfect capital markets, poverty should have no impact on growth. Below we test 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.

V.I 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 (1995). We rank 99 countries for which we have income, poverty and investment data according to their per capita income in the mid 1990s[28]. 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 (panel A), poverty (US$2 poverty line) in panel B, and gross fixed capital formation relative to GDP (GFCF) in panel C.[29] 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 (panel 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.

V.II Poverty, investment and growth

The first issue we explore is whether investment may be the channel of transmission through which poverty affects growth. The empirical growth models estimated in the previous section follow the conventional reduced-form approach in which investment has been "substituted out". A considerable literature, starting with the classic study by Levine

[28] We pick the 1990s because it is the period over which more poverty observations are available.
[29] The results remain virtually unchanged if one uses gross capital formation (GFC) as investment measure.

and Renelt (1992), and reaching up to the recent paper by Hendry and Krolzig (2004), finds that investment is one of the few robust determinants of long-term 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 panel A we report the results for fixed investment (GFCF) and in panel 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 panel B as the only exception, with a p-value of 0.10.[30]

V.III Poverty and investment

Given that poverty drops out of the investment – augmented growth equation, we next explore if poverty has a negative impact on investment. We follow a strategy similar to that in the previous section and estimate a model of the type:

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

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 (23), we consider a basic investment model with the following control variables: (i) the GDP growth rate, consistent with the simple accelerator model; (ii) the level of per capita GDP, which serves the purpose of controlling for the initial resources of the country; (iii) the price of investment goods; and (iv) terms of trade changes, which capture the economy's external conditions.[31]

The first six columns of Table 10 report the results of estimating equation (23). Columns 1-3 use the GFCF definition of investment, while columns 4-6 use GCF. In every case, the estimates show that higher poverty leads to lower investment, regardless of the poverty line used: the headcount ratio carries a negative and significant coefficient, with a 10 percentage point increase in poverty lowering investment by between 6.5 and 8 percentage points of GDP.

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

[30] 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.

[31] Given the illustrative character of these empirical equations, we do not pursue formally the issue of identification of the growth-investment system that results. Note, however, that the proposed investment equations and the controls considered in the growth regressions always yield enough exclusion restrictions to identify both equations.

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.

V.IV Poverty, investment and financial sector development

Finally, we check if the impact of poverty on investment depends on the degree of financial sector development, as assumed by the analytical model in section II. For this purpose we consider the following variation of (23):

$$I_{it} = \eta_i + \alpha I_{it-1} + \psi' z_{it} + \pi_{LFD} P_{it-1}^{LFD} + \pi_{HFD} P_{it-1}^{HFD} + u_{itj}, \qquad (24)$$

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 (24) we would expect $\pi_{LFD} < \pi_{HFD}$.

In order to empirically implement (24) we need to assign the different observations to the two states of financial sector development – low and high. To do so we take as yardstick the stock of credit to the private sector relative to GDP. 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.

Columns 7 to 9 and 10 to 12 in Table 10 report the results of estimating (24) 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 impact of poverty on investment is more adverse in countries with less developed financial sectors, which appears broadly consistent with the model in section II. 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 our results show no significant impact of poverty on investment 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.

VI. Conclusions

A rapidly growing theoretical literature has suggested a variety of mechanisms through which poverty may deter growth and generate self-perpetuating poverty traps. However, the effects of poverty on growth 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 offered a first empirical assessment of the impact of poverty on growth. The paper's strategy involves the estimation of a growth equation with poverty added to an otherwise standard set of growth determinants. To this basic framework we further add inequality as another explanatory variable, in order to assess if any effects of poverty on growth present in the data reflect just the effects of inequality acting through poverty. Thus, the framework is very similar to that employed in recent 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 using a GMM approach to deal with the potential endogeneity of the regressors. On the whole, the results reveal a consistently negative and strongly significant impact of poverty on growth, which is also economically significant: our estimates suggest that a 10 percentage-point increase in the headcount poverty rate reduces annual per capita growth by about 1 percentage point. 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.

The finding that poverty has a negative impact on growth 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 nonlinear effects of inequality on growth.

The paper has also attempted to shed light on the mechanism through which the adverse effect of poverty on growth operates. The evidence suggests that poverty deters investment, especially when the degree of financial development is limited. While still tentative, this result appears consistent with stylized theoretical models in which financial market imperfections prevent the poor from taking advantage of their investment opportunities.

The result that poverty tends to deter growth also has 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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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 of income per capita, a measure of income inequality (the Gini coefficient) and all the poverty measures used in the 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).

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

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.

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

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.

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

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 that instrument set to start with lagged levels at t-2. Robust t-statistics are reported below the coefficients.

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: $h_1 = h_2 = 0$	p-value	0.00	0.00	0.00	0.03	0.25	0.15	0.64	0.06	0.01

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 squared 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 the lagged average years of secondary education of the female and male population and a lagged measure of market distortion (given by the price of investment 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: h1=h2=0 tests whether the coefficients of inequality and squared inequality are jointly equal to zero.

Table 6. Estimation results: Alternative poverty measures - 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_1 ($2) (t-1)	-0.186			-0.067		
t-stat	*-2.75*			*-1.29*		
P_1 ($3) (t-1)		-0.218			-0.169	
t-stat		*-5.14*			*-4.05*	
P_1 ($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_1 ($2) (t-1)	-0.103			-0.187		
t-stat	*-1.40*			*-2.57*		
P_1 ($3) (t-1)		-0.138			-0.160	
t-stat		*-3.00*			*-3.78*	
P_1 ($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_1 ($2) (t-1)	-0.199			-0.341		
t-stat	*-2.45*			*-3.70*		
P_1 ($3) (t-1)		-0.235			-0.241	
t-stat		*-4.49*			*-5.82*	
P_1 ($4) (t-1)			-0.210			-0.194
t-stat			*-4.82*			*-5.09*
# Observations	306	306	306	306	306	306

Notes: The table reports regression results with the 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 the lagged average years of secondary education of the female and male population and a lagged measure of market distortion (given by the price of investment 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 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: Alternative poverty measures - 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_2 ($2) (t-1)	-0.191			-0.058		
t-stat	*-1.71*			*-0.64*		
P_2 ($3) (t-1)		-0.211			-0.096	
t-stat		*-2.99*			*-1.70*	
P_2 ($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_2 ($2) (t-1)	-0.071			-0.239		
t-stat	*-0.57*			*-1.91*		
P_2 ($3) (t-1)		-0.124			-0.205	
t-stat		*-1.58*			*-2.70*	
P_2 ($4) (t-1)			-0.130			-0.181
t-stat			*-2.14*			*-3.19*
# Observations	289	289	289	289	289	289
Model with inflation, female education, and lagged infrastructure						
Inequality (t-1)				0.139	0.104	0.073
t-stat				*2.81*	*2.41*	*1.80*
P_2 ($2) (t-1)	-0.246			-0.528		
t-stat	*-1.89*			*-3.11*		
P_2 ($3) (t-1)		-0.193			-0.366	
t-stat		*-2.39*			*-3.91*	
P_2 ($4) (t-1)			-0.216			-0.291
t-stat			*-3.23*			*-4.46*
# Observations	306	306	306	306	306	306

Notes: The table reports regression results with the income growth as dependent variable; and the lagged income per capita (in logs), the squared 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 the lagged average years of secondary education of the female and male population and a lagged measure of market distortion (given by the price of investment 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 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-squared	0.24	0.25	0.25	0.25	0.30	0.31	0.30

Notes: The table reports regression results with income growth as dependent variable; and income per capita (in logs), the average years of secondary education of the female and male population, and 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) 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.

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
GFC (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

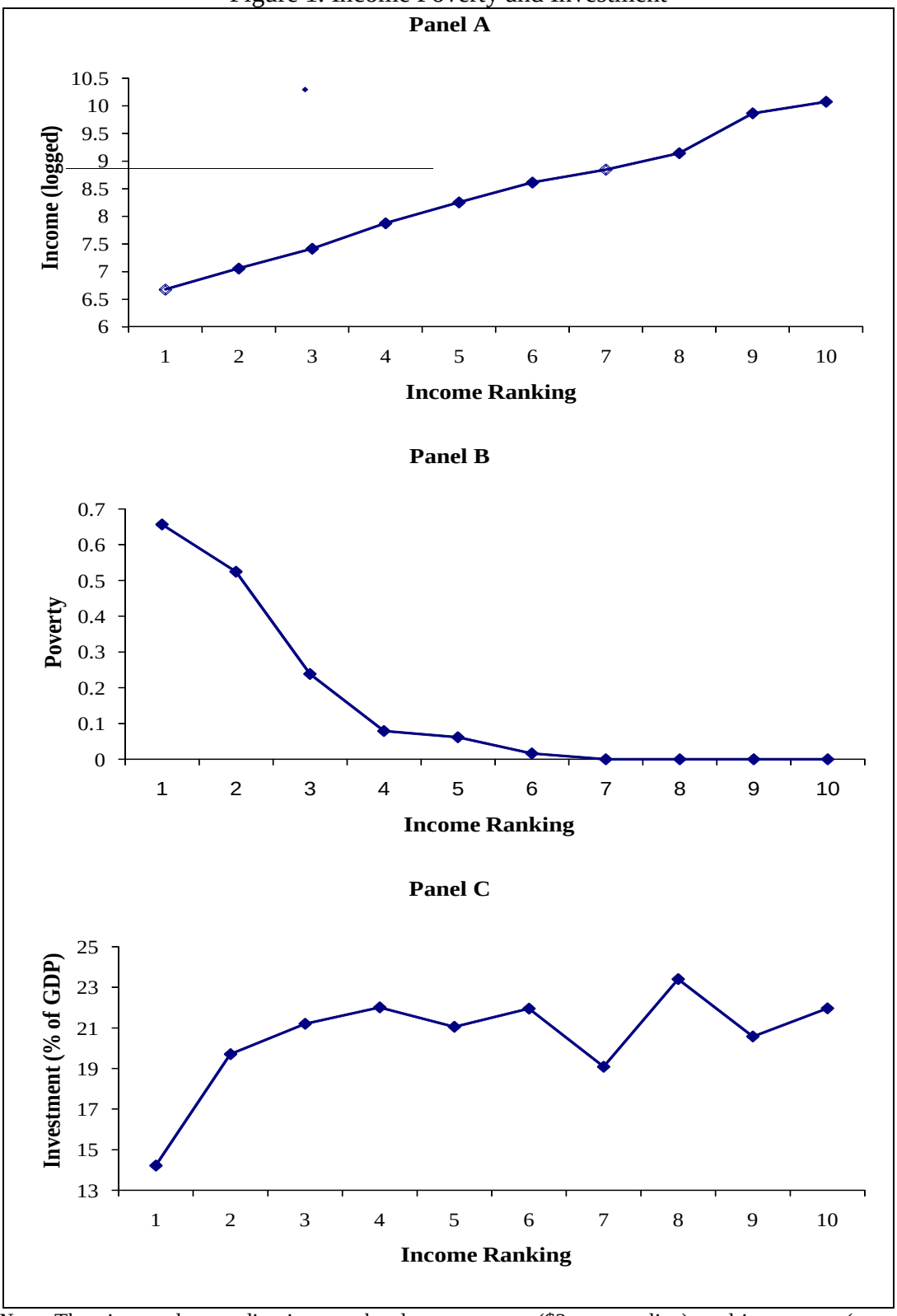
Notes: The table reports regression results with income growth as dependent variable; and the lagged income per capita (in logs), investment (i.e., gross fixed capital formation or gross capital formation), headcount poverty P0 (corresponding to poverty lines of $2, $3, and $4) and three sets of control variables. The first panel includes as control variables the lagged average years of secondary education of the female and male population and a lagged measure of market distortion (given by the price of investment 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.

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*		
P_0^{HFD} ($3) (t-1)								-0.002			0.011	
t-stat								*-0.08*			*0.41*	
P_0^{LFD} ($3) (t-1)								-0.059			-0.038	
t-stat								*-2.47*			*-1.70*	
P_0^{HFD} ($4) (t-1)									0.003			0.025
t-stat									*0.13*			*0.97*
P_0^{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

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 investment 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 P0 (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.

Figure 1. Income Poverty and Investment



Note: The picture plots median income, headcount poverty ($2 poverty line), and investment (gross fixed capital formation as a percentage of GDP) by group of countries. Countries have been ranked by their income in the 1990s and then grouped in 10 groups of 10