Ref: *American Economic Review*, forthcoming

Why Don't We See Poverty Convergence?

Martin Ravallion[1]

Development Research Group, World Bank
1818 H Street NW, Washington DC, 20433, USA
mravallion@worldbank.org

Abstract: Average living standards are converging amongst developing countries and faster growing economies see more progress against poverty. Yet we do not find poverty convergence; countries starting with higher poverty rates do not see higher proportionate rates of poverty reduction. The paper tries to explain why. A new data set reveals an adverse effect on consumption growth of high initial poverty at a given initial mean. A high poverty rate also makes economic growth less effective in reducing poverty. For many poor countries, the growth advantage of starting out with a low mean is lost due to a high incidence of poverty.

Keywords: Poverty trap, middle class, inequality, economic growth

JEL: D31, I32, O15

[1] The author is grateful to Shaohua Chen and Prem Sangraula for help in setting up the data set used here. Helpful comments were received from Sebastian Galiani, Karla Hoff, Aart Kraay, Kalle Moene, Luis Servén, Dominique van de Walle, participants at presentations at the World Bank, the Courant Research Center, Göttingen, the 2009 meeting in Buenos Aires of the Network on Inequality and Poverty, Cornell University, the Center for Global Development, the University of California Berkeley, the University of Oslo, and the *Review*'s editor and anonymous referees. These are the views of the author and should not be attributed to the World Bank or any affiliated organization.

1. Introduction

Two prominent stylized facts about economic development are that there is an advantage of backwardness, such that on comparing two otherwise similar countries the one with the lower initial mean income will tend to see the higher rate of economic growth, and that there is an advantage of growth, whereby a higher mean income tends to come with a lower incidence of absolute poverty. Past empirical support for both stylized facts has almost invariably assumed that the dynamic processes for growth and poverty reduction do not depend directly on the initial level of poverty. Under that assumption, the two stylized facts imply that we should see poverty convergence: countries starting out with a high incidence of absolute poverty should enjoy a higher subsequent growth rate in mean consumption and (hence) a higher proportionate rate of poverty reduction.

That poses a puzzle. The data on poverty measures over time for about 90 developing countries assembled for this paper reveal little or no sign of poverty convergence. For example, Figure 1 plots the proportionate rate of change in poverty—specifically the annualized log difference between household surveys in the percentage of each country's population living below $2 a day at 2005 purchasing power parity—against its initial level. (The data are described later.) There is no sign of convergence; the regression line has a slope of 0.005 (with a robust standard that is about twice that figure). The overall poverty rate of the developing world has been falling since at least 1980 (Chen and Ravallion, 2010), but the proportionate rate of decline has been no higher in its poorest countries.

Clearly something important is missing from the story. Intuitively, one hypothesis is that either the growth rate in the mean, or the impact of growth on poverty, depends directly on the initial poverty rate, in a way that nullifies the "advantage of backwardness." To test this hypothesis, the paper estimates a model in which the proportionate rate of progress against poverty depends on the rate of growth in mean consumption and the poverty rate, while the rate of growth in the mean depends in turn on the initial poverty rate as well as the initial mean.

The results suggest that mean-convergence is counteracted by two distinct "poverty effects." First, there is an adverse direct effect of high initial poverty on growth—working against convergence in mean consumption. Second, high initial poverty dulls the impact of growth on poverty. On balance there is little or no systematic effect of starting out poor on the proportionate rate of poverty reduction.

In the process of documenting these findings the paper also explores the role played by other aspects of the initial distribution discussed in the literature, including inequality. These are found to play no more than a subsidiary role. For example, high initial inequality only matters to growth and poverty reduction in so far as it entails a high initial incidence of poverty relative to the mean. And the paper confirms that countries starting out with a small middle class—judged by developing country rather than Western standards—face a handicap in promoting growth and poverty reduction, but this too is largely accountable to differences in the incidence of poverty.

After reviewing the literature in the next section, the data are described in section 3 while section 4 tests for convergence in both the mean and the poverty rate. The main results, including various tests of their robustness, are then presented in sections 5 (on how poverty affects growth) and 6 (on how it affects the elasticity of poverty to growth). Section 7 brings these elements together to calibrate a decomposition of the speed of convergence in poverty, which answers the question in the paper's title.

2. Past theories and evidence

A number of papers have demonstrated that an economy's growth path can depend on parameters of the initial distribution of income. The parameter that has received most attention is inequality. One way that high inequality can reduce an economy's aggregate output is when borrowing constraints stemming from credit market failures leave unexploited opportunities for investment in physical and human capital (Galor and Zeira, 1993, Bénabou, 1996; Aghion and Bolton, 1997).[2] With diminishing marginal products of capital, mean future wealth will be a quasi-concave function of the distribution of current wealth. Thus higher current inequality implies lower future mean wealth at a given current mean wealth. A similar result can be obtained when high inequality prompts distortionary policy responses (as in Alesina amd Rodrik, 1994) or restricts efficiency-enhancing cooperation, such that key public goods are underprovided or efficiency-enhancing reforms are blocked (as in the models reviewed in Bardhan et al., 2000).

Motivated by these theoretical arguments, a subset of the (large) empirical literature on the determinants of economic growth has included explicit measures of inequality as regressors for growth, although inferences are clouded by the fact that the regressions often also include

[2] Also see the discussions in Perotti (1996), Hoff (1996), Aghion et al. (1999), Bardhan et al. (2000), Banerjee and Duflo (2003), Azariadis (2006) and World Bank (2006, Chapter 5).

variables that are implicitly functions of inequality, such as human development attainments, aggregate investment shares and measures of financial-sector development.[3] A number of empirical papers have reported adverse effects of inequality on growth.[4] The precise measure that has received most attention in the empirical literature is income or consumption inequality, as typically measured by the Gini index.[5]

Another strand of the literature has argued that the size of a country's middle class matters to economic growth, by fostering entrepreneurship, or shifting the composition of consumer demand, or making it more politically feasible to attain policy reforms and institutional changes conducing to growth.[6]

While this literature has focused on inequality or the middle class, arguments can also be made suggesting that poverty may well be the more relevant parameter of the initial distribution.

- In a model of growth with borrowing constraints (based on Banerjee and Duflo, 2003), Ravallion (2009) shows that higher current poverty incidence—defined by any poverty line up to the minimum level of initial wealth needed to not be liquidity constrained in investment choices—yields lower growth at a given level of mean current wealth.
- Another way this can happen is illustrated by Lopez and Servén (2009) who introduce a subsistence consumption requirement into the utility function in the model of Aghion et al. (1999) and show that higher poverty incidence (failure to meet the subsistence requirement) implies lower growth.

---

3 Basic schooling and health attainments (often significant in growth regressions) are one of the potential channels linking initial distribution to growth, as in Galor and Zeria (1993). Similarly, while the share of investment in GDP has often been used as a predictor of growth rates (Levine and Renelt, 1992), this is one of the channels identified in the theoretical literature linking inequality to growth. The same argument can be made about private credit (as a share of GDP) as a measure of "financial sector development" (Beck et al., 2007); growth theories based on borrowing constraints suggest that the aggregate flow of credit depends on the initial distribution.

4 Support for the view that higher initial inequality impedes growth has been reported by Alesina and Rodrik (1994), Persson and Tabellini (1994), Birdsall et al., (1995), Clarke (1995), Perotti (1996), Deininger and Squire (1998), Ravallion (1998), Knowles (2005) and Voitchovsky (2005) (amongst others). Not all the evidence has been supportive; also see Li and Zou (1999), Barro (2000) and Forbes (2000). The main reason why the latter studies have been less supportive appears to be that they have allowed for additive country-level fixed effects in growth rates; I will return to this point.

5 Wealth inequality is arguably more relevant though this has rarely been used due to data limitations. An exception is Ravallion (1998), who studies the effect of geographic differences in the distribution of wealth on growth in China and finds evidence that high wealth-inequality impedes growth.

6 Analyses of the role of the middle class in promoting entrepreneurship and growth include Acemoglu and Zilibotti (1997) and Doepke and Zilibotti (2005). Middle-class demand for higher quality goods plays a role in the model of Murphy et al. (1989). Birdsall et al. (2000) conjecture that support from the middle class is crucial to reform. Sridharan (2004) describes the role of the Indian middle class in promoting reform. Easterly (2001) finds evidence that a larger income share controlled by the middle three quintiles promotes economic growth.

- This is also suggested by models of poverty traps based on impatience for consumption—high time preference rates associated with low life expectancy—leading to low savings and investment rates by the poor.[7] Here too, while the theoretical literature has focused on initial inequality, it can also be argued that a higher initial incidence of poverty implies a higher proportion of impatient consumers and hence lower growth.
- Yet another example is found in how work productivity is affected by past nutritional and health status. Only when past nutritional intakes have been high enough (above basal metabolic rate) will it be possible to do any work, but diminishing returns will set in later; see the model in Dasgupta and Ray (1986). Following Cunha and Heckman (2007), this type of argument can be broadened to include other aspects of child development that have lasting impacts on learning ability and earnings as an adult. By implication, having a larger share of the population who grew up in poverty will have a lasting negative impact on an economy's aggregate output.

These arguments point to the importance of poverty as a constraint on growth, which is our first clue as to why we do not find poverty convergence. However, while all these arguments suggest that the growth rate may depend on parameters of the initial distribution, it is unclear whether inequality, poverty or the size of the middle class is the most relevant parameter. The fact that very few encompassing tests are found in the literature,[8] and that these different measures of distribution are clearly not independent, leaves one in doubt about what aspect of distribution really matters. For example, when the initial value of mean income is included in a growth regression alongside initial inequality, but initial poverty is an excluded but relevant variable, the inequality measure may pick up the effect of poverty rather than inequality *per se*.

A second clue to the puzzle of why we do not see poverty convergence can be found in the literature on the effects of growth on poverty in developing countries. The consensus in that literature is that higher growth rates tend to yield more rapid rates of absolute poverty reduction.[9] There is also evidence that inequality matters to how much impact a given growth rate in the

[7] See, for example, Azariadis (2006), though Kraay and Raddatz (2007) argue that poverty traps arising from low savings (high time preference rates) in poor countries are hard to reconcile with the data.

[8] By an encompassing test I mean that a nested test of the competing hypotheses is employed. In this instance, the encompassing test entails putting all the parameters of the initial distribution in the growth regression.

[9] See World Bank (1990, 2000), Ravallion (1995, 2001, 2007), Fields (2001) and Kraay (2006). Also see the review of the arguments and evidence on this point in Ferreira and Ravallion (2009). (Relative poverty measures are less responsive to growth since the poverty lines rises with the mean.)

mean has on poverty.[10] Intuitively, in high inequality countries the poor will tend to have a lower share of the gains from growth in the mean. Ravallion (1997, 2007) examines this issue empirically using household surveys for multiple countries over time and finds evidence of a strong interaction effect between initial inequality and the growth rate in the mean when explaining the proportionate rate of poverty reduction. In the most parsimonious specification, which also fits the data for developing countries well, the expected value of the log difference in the poverty rate over time is directly proportional to the "distribution-corrected" growth rate, given by the ordinary growth rate in the mean times one minus an index of inequality. Easterly (2009) conjectures that the initial poverty rate is likely to be a better predictor of the elasticity than the initial level of inequality, though no evidence is provided.

The rest of the paper presents new evidence consistent with both clues from the literature.

3. Data and descriptive statistics

In keeping with the bulk of the literature, the country is the unit of observation.[11] However, unlike past data sets in the literature on growth empirics, this one is firmly anchored to the household surveys, in keeping with the focus on the role played by poverty and inequality, which is measured from surveys. By calculating the poverty and inequality statistics directly from the primary data, at least some of the comparability problems found in existing data compilations from secondary sources can be eliminated. However, there is no choice but to use household consumption or income, rather than the theoretically preferable concept of wealth.

I found 99 developing and transition countries with at least two suitable household surveys since about 1980. (For about 70 of these countries there are three or more surveys.) Virtually all of the surveys are nationally representative.[12] For the bulk of the analysis I restrict the sample to the 92 countries in which the earliest available survey finds that at least some households lived below the average poverty line for developing countries (described below).[13] This happens mechanically given that log transformations are used. However, it also has the defensible effect of dropping a number of the countries of Eastern Europe and Central Asia

[10] See Ravallion (1997, 2007); World Bank (2000, 2006); Bourguignon (2003) and Lopez and Servén (2006).

[11] It is known that aggregation can hide the true relationships between the initial distribution and growth, given the nonlinearities involved at the micro level (Ravallion, 1998); identifying the deeper structural relationships would require micro data, and even then the identification problems can be formidable.

[12] The only exception was that urban surveys were also used (for both the first and last survey) for Uruguay where over 90% of the population lives in urban areas. Results were robust to dropping these urban surveys.

[13] The data set was constructed from *PovcalNet* in December 2008.

(EECA) (including the former Soviet Union); indeed, all of the countries with an initial poverty rate (by developing country standards) of zero are in EECA. As is well known, these countries started their transitions from socialist command economies to market economies with very low poverty rates, but poverty measures then rose sharply in the transition.[14] The earliest available surveys pick up these low poverty rates, with a number of countries having no sampled household living below the poverty lines typical of developing countries. With the subsequent rise in poverty incidence, this looks like "convergence," but it has little or nothing to do with neoclassical growth processes—rather it is a "policy convergence" effect associated with the transition. The experience of these countries is clearly not typical of the developing world.

The longest available spell between two surveys is used for each country. Both surveys use the same welfare indicator, either consumption or income per person, following standard measurement practices. When both are available, consumption is preferred, in the expectation that it is both a better measure of current economic welfare and that it is likely to be measured with less error than incomes.[15] Three-quarters of the spells use consumption.

Naturally the time periods between surveys are not uniform. The median year of the first survey is 1991 while the median for the second is 2004. The median interval between surveys is 13 years and it varies from three to 27 years. All changes between the surveys are annualized. Given the most recent survey for date t_i in country *i* and the earliest available survey for date $t_i - \tau_i$, the growth rate for the variable *x* is $g_i(x_{it}) \equiv \ln(x_{it} / x_{it-\tau}) / \tau$ (dropping the *i* subscript on *t* and τ for brevity). National accounts and social indicators are also used, matched as closely as possible to survey dates. All monetary measures are in constant 2005 prices (using country-specific Consumer Price Indices) and are at Purchasing Power Parity (PPP) using the individual consumption PPPs from the 2005 International Comparison Program (World Bank, 2008).

Poverty is mainly measured by the headcount index (H_{it}), given by the proportion of the population living in households with consumption per capita (or income when consumption is not available) below the poverty line. For the bulk of the analysis the poverty line is set at $2.00 per person per day at 2005 PPP, which is the median poverty line amongst developing countries based on the compilation of national poverty lines in Ravallion et al. (2009). $2 a day is also very

---

[14] Prior to the global financial crisis there were signs that poverty measures were finally falling in the region, since the later 1990s; see Chen and Ravallion (2010).

[15] The only exception was Peru, for which incomes allowed a much longer time period.

close to the median consumption per person in the developing world for 2005; see Chen and Ravallion (2010) which also describes the methods used here in measuring poverty and inequality. The (unweighted) mean poverty rate for the $2 line fell from 46.4% in the earliest round of surveys to 39.8% in the latest rounds. This line is clearly somewhat arbitrary; for example, there is no good reason to suppose that $2 a day corresponds to the point where credit constraints cease to bite, but nor is there any obviously better basis for setting a threshold. I will also consider a lower line of $1.25 a day and a much higher line of $13 a day in 2005, corresponding to the US poverty line. The $1.25 line is the mean of the poorest 15 countries in terms of consumption per person (Ravallion et al., 2009) while $13 per person per day is the official poverty line in the US for a family of four in 2005.[16]

Inequality is measured by the usual Gini index (G_{it}).The initial index ranged from 19.4% (Czech Republic) to 62.9% (Sierra Leone), both around 1990, and about one quarter of the sample had a Gini index below 30% while one quarter had an index above 50%. Between the earliest and latest surveys, the mean Gini index stayed roughly unchanged at about 42%.[17]

Four measures of the middle class are used. The first is the population share living between $2 and $13 a day, denoted $MC_{it} \equiv F_{it}(13) - F_{it}(2)$ where $F_{it}(z)$ is the distribution function for country *i* at date *t* (so $H_{it} = F_{it}(2)$). This is interpreted as the middle class by developing-country standards; while the bounds are somewhat arbitrary, this definition appears to accord roughly with the idea of what it means to be "middle class" in China and India (Ravallion, 2010). By contrast, those living above $13 a day can be thought of as the "middle class and rich" by Western standards. These are absolute measures. The third measure uses a relative definition of the middle class, namely the consumption or income share controlled by the middle three quintiles, denoted MQ_{it}, as used by Easterly (2001). Finally, I will also consider the "miser index" proposed by Lind and Moene (2010); this is a measure of polarization between the rich and poor, and so it can be thought of as an inverse measure of the size of the middle class. More precisely, the miser index is $H_{it}(\mu_{it} - \mu_{it}^H)$ where μ_{it} is the overall mean and μ_{it}^H is the mean below the poverty line. Thus the miser index is higher when there is a high poverty rate and mean income of the poor is low relative to the overall mean.

[16] See Department of Health and Human Services.
[17] Summary statistics for all variables are reported in the working paper version (Ravallion, 2009).

The average size of the middle class (by developing-country standards) increased, from a mean $MC_{it-\tau}$ of 48% to a mean MC_{it} of 53%. The middle-class expanded in 64 countries and contracted in 35. There is also a bimodality in the distribution of countries by the size of their middle class, as is seen in Figure 2, which plots the kernel densities of MC_{it} and $MC_{it-\tau}$. Taking 40% as the cut-off point, 30 countries are in the lower mode and 69 are in the upper one for the most recent survey; the corresponding counts for the earliest surveys are 42 and 57.[18] The relative measure of the middle class behaves differently, with little change in the mean *MQ* over time and the density function is unimodal in both the earliest and latest surveys.

There are some strong correlations amongst these parameters of the initial distribution. The Gini index is highly correlated with *MQ* (r=-0.971 for the earliest surveys and -0.968 for the latest).[19] The poverty measures are also strongly correlated with the survey means; $\ln H_{it-\tau}$ and $\ln \mu_{it-\tau}$ have a correlation of -0.851 (while it is -0.836 for $\ln F_{it-\tau}(1.25)$ and $\ln \mu_{it-\tau}$). The least-squares elasticity of $H_{it-\tau}$ with respect to the initial survey mean (i.e., the regression coefficient of $\ln H_{it-\tau}$ on $\ln \mu_{it-\tau}$) is -1.305 (t=13.340). (All t-ratios in this paper are based on White standard errors.) There is a very high correlation between the poverty measures using \$1.25 a day and \$2.00 a day (r=0.974). There are weaker correlations between the two poverty measures and the initial Gini index (r= 0.241 and 0.099 for z=1.25 and z=2.00). However, there is also a strong multiple correlation between the poverty measures (on the one hand) and the log mean and log inequality (on the other); for example, regressing $\ln H_{it-\tau}$ on $\ln \mu_{it-\tau}$ and $\ln G_{it-\tau}$ one obtains R^2=0.802. The log Gini index also has a strong partial correlation with the log of the poverty rates holding the log mean constant (t=4.329 for $\ln H_{it-\tau}$).

The size of the middle class is also highly correlated with the poverty rate; the correlation coefficient between $MC_{it-\tau}$ and $H_{it-\tau}$ is -0.975; 95% of the variance in the initial size of the middle class is accountable to differences in the initial poverty rate. (The bimodality in terms of the size of the middle class in Figure 2 reflects a similar bimodality in terms of the \$2 a day poverty rate.) Across countries, 80% of the variance in the changes over time in MC_{it} can also be

[18] For further discussion of the developing world's rapidly expanding middle class, and the countries left behind in this process, see Ravallion (2009).

[19] The working paper version gives a complete correlation matrix (Ravallion, 2009).

attributed to the changes in H_{it}.[20] The absolute and relative measures of the size of the middle class are positively correlated but not strongly so. The miser index is more strongly correlated with the relative measure of the middle class (r=-0.637 for the miser index for the first survey with $MQ_{it-\tau}$) than the absolute measure (r=0.218 with $MC_{it-\tau}$).

There is a strong correlation between the proportionate rate of change in poverty $(g_i(H_{it}))$ and the ordinary growth rate in the survey mean $(g_i(\mu_{it}))$. The regression coefficient is -1.372 (t=-5.948) with R^2=0.363.

Since the time period between surveys (τ) figures in the calculation of the growth rates it might be conjectured that poorer countries have longer periods between surveys, biasing this paper's results. However, the correlation coefficients between τ and the various measures of initial distribution are all small (most well under 0.2 in absolute value); see Ravallion (2009).

While this paper focuses mainly on the developing world as a whole, one region stands out: Sub-Saharan Africa (SSA). By the \$2.00 a day line, the mean of $H_{it-\tau}$ for SSA is 76.04% as compared to 29.51% for non-SSA countries; the difference is significant (t=8.84). Similarly, in terms of the size of its middle class, SSA is concentrated in the lower mode in Figure 2. Two-thirds (20 out of 29) of SSA countries are in the lower mode for the earlier survey round; the corresponding means of $MC_{it-\tau}$ are 22.9% (s.e.=3.6%) and 59.1% (3.0%) for SSA and non-SSA countries and the difference is significant at the 1% level. Inequality too is higher in SSA; the mean Gini index in the earliest surveys is 47.4% (1.8%) for SSA versus 39.0% (1.7%) in non-SSA countries, and the difference is significant (t=7.68). There is clearly a "SSA effect" in both growth and poverty reduction.

4. Testing for convergence in both mean consumption and poverty

Intuitively, the twin stylized facts that there is convergence in mean consumption and that growth in the latter reduces the incidence of absolute poverty imply that we should see poverty convergence, as discussed in the introduction. Indeed, an even stronger result is implied by the standard log-linear models for growth and poverty reduction found in the literature, with parameters independent of the initial level of poverty. Then the speed of convergence will be the

---

[20] R^2 =0.826 for the regression of $MC_{it} - MC_{it-\tau}$ on $F_{it}(2) - F_{it-\tau}(2)$; the regression coefficient is -0.896 (t=-25.496; n=92), which is significantly different from -1 (t=2.946).

same for the mean as the poverty measure. To see this, consider the most common empirical specification for the growth process in the mean:

$$\Delta \ln \mu_{it} = \alpha_i + \beta_i \ln \mu_{it-1} + \varepsilon_{it} \tag{1}$$

where α_i is a country-specific effect, β_i is a country-specific convergence parameter and ε_{it} is a zero-mean error term. (To simplify notation I assume evenly spaced data for now.) Next let the headcount index of poverty be a log-linear function of the mean:

$$\ln H_{it} = \delta_i + \eta_i \ln \mu_{it} + \nu_{it} \tag{2}$$

Where δ_i is a country-specific effect, η_i is interpretable as the (country-specific) elasticity of poverty to the mean (with the expectation that $\eta_i < 0$) and ν_{it} is a zero-mean error term. The implied model of the growth rate in poverty is then:

$$\Delta \ln H_{it} = \alpha_i^* + \beta_i^* \ln H_{it-1} + \varepsilon_{it}^* \tag{3}$$

for which it is readily verified that $\alpha_i^* = \alpha_i \eta_i - \beta_i \delta_i$, $\beta_i^* = \beta_i$ and $\varepsilon_{it}^* = \varepsilon_{it}\eta_i + \nu_{it} - (1+\beta_i)\nu_{it-1}$. The parameters of (1) and (2) ($\alpha_i, \beta_i, \delta_i, \eta_i$) can vary across counties but (for the sake of this argument) suppose they do so independently of $H_{it-\tau}$. Comparing (1) and (3) it can be seen that the "speed of convergence" for the poverty measures, $\partial \Delta \ln H_{it} / \partial \ln H_{it-1} = \beta_i$, is the same as that for the mean, $\partial \Delta \ln \mu_{it} / \partial \ln \mu_{it-1} = \beta_i$.

However, this prediction is not borne out by the data, as we saw in Figure 1. Table 1 gives standard convergence tests for mean consumption based on the regression coefficient of $g_i(\mu_{it})$ on $\ln \mu_{it-\tau}$, with and without controls.[21] The controls included initial consumption per capita from the national accounts, primary school enrollment rate, life expectancy at birth, and the price index of investment goods from Penn World Tables (6.2), which is a widely-used measure of market distortions; all three variables are matched as closely as possible to the date of the earliest survey. It can be seen from Table 1 that the survey means exhibit convergence; the β coefficient is -0.013 (t=-3.412) without the controls and -0.042 (t=-7.435) with them.

[21] Alternatively one can estimate the convergence parameter using a nonlinear regression $g(\mu) = \alpha - [(1-e^{\beta\tau})/\tau]\ln \mu_{-\tau} + \varepsilon$ (as in Barro and Sala-i-Martin, 1992). This gave a very similar result to (1) in Table 1, namely $\hat{\beta} = -0.012$. (t=-2.865). Clearly, the approximation that $e^{\beta\tau} = 1 + \beta\tau$ (linearizing the nonlinear regression specification) works well.

Unconditional convergence is weaker using means from consumption surveys only (Column 2) or national accounts (Column 3), though conditional convergence is still evident.

However, as can be seen from Table 2, there is no sign of convergence for the poverty measures, with or without the controls.[22] The proportionate rates of poverty reduction are roughly orthogonal to initial levels, as we saw in Figure 1.[23]

One can also form a subsample of about 70 countries with at least three surveys.[24] This extra round of surveys can be used to test for convergence more robustly to measurement errors.[25] One way of doing this is to calculate the trend over the three surveys and test if this is correlated with the starting value. On estimating the trend for each country by regressing the logs of the three (date-specific) means for that country on time and similarly for the headcount indices, convergence in the mean is still evident; the regression coefficient of the estimated trend on the log mean from the earliest survey is -0.009 (t=-2.052), which is significant at the 4% level. And again there is no significant correlation between these trends in poverty reduction and the initial poverty measures; the regression coefficient of the estimated trend on the log headcount index from the earliest survey is 0.007 (t=0.805).

Another method of testing for convergence in these data is to form means from the first two surveys and look at their relationship with the changes observed between the last survey and the middle one. Define the mean from the first two surveys as $M_i(x_{it-\tau_2}) \equiv (x_{it-\tau_2} + x_{it-\tau_1-\tau_2})/2$ while the growth rate is $g_i(x_{it}) \equiv \ln(x_{it} / x_{it-\tau_2})/\tau_2$. Using this method, I found that the unconditional mean convergence is no longer evident (though conditional convergence is still found) but there is an indication of poverty <u>divergence</u>; regressing $g_i(H_{it})$ (the proportionate change in the poverty measure between the middle and final rounds) on $M_i(H_{it-\tau_2})$; the

---

22 This was also true for the $13 line, for which the convergence parameter was -0.009 (t=-0.480). Again, the nonlinear specification gave a very similar result in all cases.

23 Recall that poverty convergence is defined in proportionate rather than absolute terms. The absence of poverty convergence by this definition implies that poorer countries tend to see larger absolute reductions in their poverty rate.

24 When there were more than three surveys I picked the one closest to the midpoint of the interval between the latest survey and the earliest.

25 As is well known, measurement errors can create spurious signs of convergence; if the initial mean is over- (under-) estimated then the subsequent growth rate will be lower (higher).clearly stems in part at least from this problem. It is notable that the β coefficient drops using only the consumption surveys (Table 4) or national accounts consumption. However, significant conditional convergence in the means (including those only from consumption surveys) and national accounts consumption is still evident.

coefficient is 0.029, which is significant at the 6% level (t=1.901). There is still some contamination due to measurement error in these tests.

Yet another method is to regress $g_i(x_{it})$ on the corresponding measure from the earliest survey ($\ln x_{it-\tau_1-\tau_2}$); the result is similar, namely little sign of (unconditional) mean convergence but mild divergence for poverty (a β coefficient of 0.027 with t=1.819).

In summary, there are no signs of poverty convergence and even some signs of divergence. The rest of this paper will try to explain why. It will be argued that the initial poverty rate matters to the subsequent rate of poverty reduction through two distinct channels, namely the growth rate in mean consumption and the elasticity of poverty to the mean. First, it will be shown in the following section that the parameter α_i (in equation 1) is a decreasing function of the initial poverty rate. Second, section 6 will be shown that the elasticity of poverty to the mean, $-\eta_i$ (equation 2), is a decreasing function of the initial level of poverty. Section 7 will bring these two elements together to answer the question posed in the title to this paper.

5. The relevance of initial poverty to the growth rate in the mean

The section begins with "benchmark regressions" for growth. A causal interpretation of these regressions requires that the initial distribution (in the earliest survey used to construct each spell) is exogenous to the subsequent rate of growth. This can be questioned. I shall test encompassing models with controls for other factors. I also provide results for an instrumental variables estimator under widely-used (though still questionable) exclusion restrictions.

5.1 Growth regressions with poverty as an initial condition

Table 3 gives estimates of the following benchmark regression:[26]

$$g_i(\mu_{it}) = \alpha + \beta \ln \mu_{it-\tau} + \gamma \ln H_{it-\tau} + \varepsilon_{it} \tag{4}$$

The result using the full sample is given in column (1) of Table 3. This suggests that differences in the initial poverty rate have sizeable negative impacts on the growth rate in the mean at a given initial mean. A one standard deviation increase in $\ln H_{it-\tau}$ would come with 0.021 (2% points) decline in the growth rate for the survey mean. Columns (2) and (3) give the

[26] The regressions are consistent with a derivative of $\ln \mu_{it}$ with respect to $\ln \mu_{it-\tau}$ that is less than unity, but fades toward zero at sufficiently long gaps between survey rounds; for example, column (1) in Table 2 implies a derivative that is less than unity for $\tau < 29$ years; the largest value of τ in the data is 27 years.

corresponding estimates using consumption surveys only (dropping the 22 surveys for which only income was available) and using growth rates in national-accounts consumption respectively. (I will return to discuss the alternative estimates in columns (4)-(6).) Estimating the regression solely on consumption surveys strengthens the result; the conditional convergence effect is even stronger, as is the poverty effect. The results are robust to using consumption from the national accounts. The notable differences are that the convergence parameter in (4) is lower, $-\hat{\beta} = 0.02$ (column 3, Table 3) and that the headcount index based on the $1.25 line is a slightly stronger predictor of the national accounts consumption growth rate. (The results using national accounts consumption are less sensitive to the poverty line between $2.00 and $1.25 a day.)

It might be conjectured that the poverty measure (at given initial mean) is picking up some other aspect of the initial distribution, such as inequality (the variable identified in much of the empirical literature referred to in section 2). Indeed, if we imagine $\ln H_{it-\tau}$ to be a linear function of $\ln \mu_{it-\tau}$ and $\ln G_{it-\tau}$ (which fits the data quite well as noted in section 3) then one can re-write (4) in a reduced form similar to the past papers in the literature which find that inequality impedes growth at a given mean (section 2). An encompassing test is needed. Adding the log of the initial Gini index to equation (4) does not change the result; the coefficient on the Gini index is not significantly different from zero and the coefficient on $\ln H_{it-\tau}$ remains (highly) significant in the augmented version of (4). It is poverty not inequality that is doing the work.

To investigate this further, I added inequality ($\ln G_{it-\tau}$), the income share of the middle three quintiles ($\ln MQ_{it-\tau}$), the share of the Western middle class and rich ($1 - F_{it-\tau}(13)$), the "miser index", primary school enrollment rate, life expectancy at birth, and the relative price index of investment goods.[27] Table 4 gives the augmented models using both survey means and consumption from national accounts. The table also gives restricted forms that pass comfortably. The initial poverty rate remains a strong and significant predictor of growth in these encompassing models. The size of the Western middle class, life expectancy and the price of investment are also significant predictors. The relative share of the middle quintiles is significant for the growth rates in the survey means (but not national accounts consumption), though with a

[27] This is a common measure of policy distortions, derived from Penn World Tables (following Lopez and Servén, 2009). As noted in section 2, schooling and health attainments can also be interpreted as channels linking initial distribution to growth rather than as independent effects, so the interpretation of the poverty coefficient in these augmented regressions is not strictly the same as for the benchmark regression.

negative sign. The miser index has no significant effect on growth (as also found by Lind and Moene, 2010).

The two regional effects that have been identified in the literature on growth empirics are for Sub-Saharan Africa (negatively) and East Asia (positively). In testing augmented versions of the regressions in Table 4, with dummy variables for these two regions, I find no sign of an SSA effect in any specification and a negative East Asia effect though only mildly significant (at the 8% level). Of course (as noted), there are unconditional effects on growth in both regions. But these are largely captured within the model.

I also tried adding two interaction effects. In the first, I added an interaction effect between inequality and the initial mean; this is highly insignificant (t-ratio of -0.063). Second, adding $\ln G_{it-\tau}.\ln H_{it-\tau}$ I find that it has a positive coefficient though not significantly different from zero at even the 15% level.

While inequality and the income share of the middle quintiles are insignificant when one controls for initial poverty (though, of course, inequality can be one factor leading to higher poverty), the population share of the Western middle class and rich emerges with a significant <u>negative</u> coefficient (Table 4). The jointly negative coefficients on the poverty rate and the share of the Western middle class imply that a higher population share in the developing-world middle class is growth enhancing. Thus the data can also be well described by a model relating growth to the population share of the developing world's middle class. (As one would expect, replacing $\ln H_{it-\tau}$ and $1-F_{it-\tau}(13)$ by $\ln[F_{it-\tau}(13)/H_{t-\tau}]$ gave a very similar overall fit, though not quite as good as Table 4.) The negative (conditional) effect of the poverty rate may well be transmitted through differences in the size of the middle class.

While the above results appear to be convincing in suggesting that it is high poverty not inequality that retards growth, it is important to recall that the poverty effect only emerges when one controls for the initial mean. The between-country differences in the incidence of poverty at a given mean reflect differences in relative distribution. While those differences are not simply a matter of "inequality" as normally defined, they are correlated with inequality. The predicted values of the growth rates from the regression in column (1) of Table 3 are significantly correlated with inequality; r=-0.442. Since higher inequality tends to imply higher poverty at a given mean (section 3), it also implies lower growth prospects.

5.2 Robustness tests

It might be conjectured that the effect of $\ln H_{it-\tau}$ in (4) reflects a misspecification of the functional form for the convergence effect, noting that the poverty measure is a nonlinear function of mean income. To test for this, I re-estimated (4) using cubic functions of $\ln \mu_{it-\tau}$ to control for the initial mean. While I found some sign of higher-order effects of $\ln \mu_{it-\tau}$, these made very little difference to the regression coefficient on the poverty rate in the augmented regression; the coefficient on $\ln H_{it-\tau}$ in column (1) in Table 3 becomes -0.018 (t=-3.547).

There is, however, a marked nonlinearity in the relationship, which is being captured by the log transformation of $H_{it-\tau}$ in (4). If one uses $H_{it-\tau}$ rather than $\ln H_{it-\tau}$ on the same sample, the negative effects are still evident but they are much less precisely estimated, with substantially lower t-ratios—a t-ratio of -1.292 for the coefficient on $H_{it-\tau}$—though in both cases the effects come out somewhat more strongly if one adds a squared term in $H_{it-\tau}$ to pick up the nonlinearity, with both the linear and squared terms significant at the 10% level or better. As a simple graphical test for misspecification of the functional form in (4) I plotted $g_i(\mu_{it}) + 0.035 \ln \mu_{it-\tau}$ (from column (1) in Table 3) against $\ln H_{it-\tau}$. The relationship is close to linear in the log poverty rate.[28] The log transformation appears to be the right functional form.

In terms of goodness-of-fit, the more relevant poverty line is that using the $2.00 a day line. On replacing $\ln H_{it-\tau}$ by $\ln F_{it-\tau}(1.25)$ in (4) the poverty rate still has a negative coefficient but it is not significant at the 5% level. I also estimated the following specification:

$$g_i(\mu_{it}) = \alpha + \beta \ln \mu_{it-\tau} + \gamma_1[\ln H_{it-\tau} - \ln F_{it-\tau}(1.25)] + \gamma_2 \ln F_{it-\tau}(1.25)) + \varepsilon_{it} \quad (5)$$

The estimate of $\gamma_1 - \gamma_2$ is -0.010, but it is not significantly different from zero (t=-0.801), suggesting that (4) is the correct specification.

The results are also robust to using the poverty gap index instead of the headcount index; the corresponding version of (4) is similar, with a coefficient on the log of the poverty gap index of -0.011, with t-ratio of -2.338. However, the fit is better using the headcount index.

The subsample of 70 countries with at least three surveys can be used to form inter-temporal averages, to reduce the attenuation biases in the benchmark regression due to measurement error; equation (4) can be re-estimated in the form:

---

28 The working paper version gives the graph (Ravallion, 2009).

$$g_i(\mu_{it}) = \alpha + \beta \ln M_i(\mu_{it-\tau_2}) + \gamma \ln M_i(H_{it-\tau_2}) + \varepsilon_{it} \quad (6)$$

(It will be recalled that $M_i(x_{it-\tau_2}) \equiv (x_{it-\tau_2} + x_{it-\tau_1-\tau_2})/2$.) Column (4) of Table 3 gives the results. The regression coefficients are larger (in absolute value), consistent with the presence of attenuation bias in the earlier regressions. The standard errors also fall noticeably. This strengthens the earlier results based on the benchmark regression (equation (4)).

Another way of using the extra survey rounds is as a source of instrumental variables (IVs). Growth rates between the middle and last survey rounds were regressed on the mean and distributional variables for the middle round but treating the latter as endogenous and retaining the data for the earliest survey round as a source of IVs. Letting τ_i now denote the length of spell *i* (=1,2), the model becomes:

$$g_i(\mu_{it}) = \alpha + \beta \ln \mu_{it-\tau_2} + \gamma \ln H_{it-\tau_2} + \varepsilon_{it} \quad (7)$$

The instrumental variables are $\ln \mu_{it-\tau_1-\tau_2}$, $\ln C_{it-\tau_1-\tau_2}$, $\ln G_{it-\tau_1-\tau_2}$, $\ln F_{it-\tau_1-\tau_2}(z)$ (z=1.25, 2.00) and τ_1. The first-stage regressions for $\ln \mu_{it-\tau_2}$ and $\ln H_{it-\tau_2}$ had R^2=0.884 (F=61.06) and R^2=0.796 (F=31.30) respectively. The corresponding Generalized Methods of Moments (GMM) estimates of (9) are found in Table 3, Column (5). (I also give the corresponding result using national accounts consumption in column (6).) We see that the finding that a higher initial poverty rate implies a lower subsequent growth rate in the mean (at given initial mean) is robust to allowing for the possible endogeneity of the initial mean and initial poverty rate, subject to the usual assumption that the above instrumental variables are excludable from the main regression.

One can also use the subsample to allow for country-fixed effects, which sweep up any confounding latent heterogeneity in growth rates at country level. The main results are <u>not</u> robust to this change. Regressing $g_i(\mu_{it}) - g_i(\mu_{it-\tau_2})$ on $\ln(\mu_{it-\tau_2}/\mu_{it-\tau_1-\tau_2})$ and $\ln(H_{it-\tau_2}/H_{it-\tau_1-\tau_2})$, the coefficient on the former remains significant but the poverty rate ceases to be so.

However, it is hard to take fixed-effects growth regressions seriously with these data. While this specification addresses the problem of time-invariant latent heterogeneity it is unlikely to have much power for detecting the true relationships given that the changes over time in growth rates will almost certainly have a low signal-to-noise ratio. Simulation studies have found that the coefficients on growth determinants are heavily biased toward zero in fixed-effects growth regressions (Hauk and Wacziarg, 2009).[29] I suspect that the problem of time-varying measurement errors in both growth rates and initial distribution is even greater in the present data set, possibly reflecting survey comparability problems over time.

The problem of noise in the changes in growth rates can be illustrated if we consider the relationship between the two measures of the mean used in this study, namely that from the surveys (μ_{it}) and that from the private consumption component of domestic absorption in the national accounts (C_{it}). Using a log-log regression in the levels gives an elasticity of μ_{it} to C_{it} of 0.75 (R^2=0.82) for the latest survey rounds. Using a country-fixed effects specification in the levels, the elasticity drops to 0.51 (R^2=0.21). However, when one also includes fixed-effects in the growth rates in the mean (using the subsample with at least three surveys) the elasticity drops to 0.09 (R^2=0.07), which must be considered an implausibly low figure, undoubtedly reflecting substantial attenuation bias due to measurement error in the changes in growth rates.

6. Initial poverty and the growth elasticity of poverty reduction

We have seen that countries starting with a higher poverty rate tend to see slower growth at a given initial mean consumption. Now I turn to the second channel—how the growth elasticity of poverty reduction depends on initial distribution. This can be thought of as the direct effect of the initial distribution on the pace of poverty reduction, as distinct from the indirect effect via the rate of growth in the mean. Again I focus on the $2 line, although the $1.25 line gives similar results.

For any given relative distribution, the elasticity of the poverty rate to mean consumption is simply (one minus) the elasticity of the poverty rate with respect to the poverty line.[30] This can be calculated at any given poverty line. The interaction effect between this elasticity and the growth rate in the mean is then an obvious predictor of the rate of poverty reduction.[31] On calculating the elasticity for the $2 a day poverty line using the initial survey for each country, and denoting that elasticity by $\eta_{it-\tau}$, one finds that the regression coefficient of $\ln(H_{it} / H_{it-\tau})$ on

---

29 This point is illustrated well by the Monte Carlo simulations found in Hauk and Wacziarg (2009).

30 This follows immediately from the aforementioned fact that the poverty rate is homogeneous of degree zero in the poverty line and the mean for a given Lorenz curve.

31 On exploiting this fact in a decomposition analysis for a panel of countries (using an earlier version of the same data set used here) Kraay (2006) concludes that the bulk of the variance in rates of poverty reduction is due rates of growth. Note that this can be true and yet there is a large difference in the rates of poverty reduction at a given rate of growth between countries with different initial distributions; see Ravallion (2007).

$\eta_{it-\tau} \ln(\mu_{it} / \mu_{it-\tau})$ is not significantly different from unity; the coefficient is 1.062 with a standard error of 0.198 and R^2=0.389. Of course there are also changes in relative distribution, which presumably account for the bulk of the remaining variance in rates of poverty reduction. Consistently with past findings in the literature,[32] the changes in relative distribution are virtually orthogonal to rates of growth and (hence) the above regression coefficient is very close to unity. (If higher growth is systematically associated with worsening distribution then the regression coefficient would be biased downward, and so below unity.) However, there may well be relevant correlations with the properties of the initial distribution. Additionally, the elasticity is itself a function of the initial mean and initial distribution. These observations motivate a reduced form model in which the rate of poverty reduction depends on both the rate of growth and its interaction effects with relevant aspects of the initial distribution.

Table 5 gives regressions of the annualized change in the log of the $2 a day poverty rate against both the annualized growth rate in the mean and its interaction with the initial poverty rate. Columns (1) and (2) give unrestricted estimates of an encompassing test:

$$g_i(H_{it}) = \delta_0 + \delta_1 \ln H_{it-\tau_2} + (\eta_0 + \eta_1 H_{it-\tau_2}) g(\mu_{it}) + \upsilon_{it} \qquad (8)$$

Results are given for both OLS and IVE; the IVE method uses the growth rate in private consumption per capita from the national accounts as the instrument for the growth rate in the survey mean. Following Ravallion (2001), this IV allows for the possibility that a spurious negative correlation exists due to common measurement errors (given that the poverty measure and the mean are calculated from the same surveys).

The results in Table 5 indicate that the (absolute) growth elasticity of poverty reduction tends to be lower in countries with a higher initial poverty rate. There is no sign of conditional convergence in poverty; the null that $\delta_1 = 0$ is easily accepted. Table 5 also gives homogeneity tests for the null $\eta_0 + \eta_1 = 0$; the tests pass comfortably, indicating that the relevant growth rate is the "poverty-adjusted rate," as given by the growth rate in the mean *times* one minus the poverty rate. At an initial poverty rate of 10% (about one standard deviation below the mean) the elasticity is about -3 while it falls to about -0.7 at a poverty rate of 80% (about one standard deviation above the mean). I also used the subsample with three survey rounds to implement an IVE using the same instruments as before. Again, the homogeneity restriction is easily accepted

[32] For a recent overview see Ferreira and Ravallion (2009).

(t=-0.447). The IVE of the regression coefficient of $g_i(H_{it})$ on $(1-H_{it-\tau_2})g_i(\mu_{it})$ is -3.478 (t=-3.092).

There is also a strong interaction effect with the size of the middle-class:

$$g_i(H_{it}) = \underset{(-1.749)}{-0.011} + (\underset{(0.221)}{0.043} - \underset{(-4.818)}{0.029} MC_{it-\tau})g_i(\mu_{it}) + \hat{\upsilon}_{it} \quad R^2=0.539,\ n=91 \qquad (9)$$

At the lower mode for $MC_{it-\tau}$ of around 15% (Figure 2), equation (9) implies a growth elasticity of -0.39 (t=-3.13) while at the upper mode, around 75%, it is -2.13 (t=-7.15). However, this interaction effect is largely attributable to $H_{it-\tau}$. Letting $H_{it-\tau}$ and $F_{it-\tau}(13)$ enter separately (recalling that $MC_{it} = F_{it}(13) - H_{it}$) only $H_{it-\tau}$ is significant:

$$g_i(H_{it}) = \underset{(-1.939)}{-0.011} + (\underset{(0.039)}{0.167} - \underset{(-0.631)}{0.030} F_{it-\tau}(13) + \underset{(3.638)}{0.029} H_{it-\tau})g_i(\mu_{it}) + \hat{\upsilon}_{it} \quad R^2=0.539,\ n=91 \quad (10)$$

One cannot reject the null hypotheses that the interaction effect with $F_{it-\tau}(13)$ has no impact, though nor can one reject the null that the coefficients on the two interaction effects add up to zero (F=0.001), implying again that it is the population share of the middle class (by developing country standards) that matters.

Statistically it is a dead heat then between a model in which it is a larger middle class that determines how much impact a given rate of growth has on poverty and a model in which it is the initial poverty rate that matters. However, given that the main way people in developing countries enter the middle class is by escaping poverty—recall that 80% of the variance in changes in the size of the middle class is accountable to changes in the poverty rate—it seems more reasonable to think of poverty as the relevant primary factor.

I also did an encompassing test with extra interaction effects with $G_{it-\tau}$, the partial elasticity of poverty reduction ($\eta_{it-\tau}$), the primary school enrollment rate, life expectancy, the price of investment goods and regional dummy variables for SSA and East Asia. (Growth elasticities of poverty reduction are significantly lower in SSA, but this is entirely due to the region's above-average poverty incidence.) These are individually and jointly insignificant (the joint F-test accepted the null with prob.=0.199).

Does the relationship differ according to whether growth is positive or negative? The survey mean decreased over time for about 30% of the spells; the mean $I[g_i(\mu_{it})] = 0.687$ where $I[x]$ is the indicator function ($I[x]=1$ if x>0 and $I[x]=0$ otherwise). On stratifying the parameters according to whether the mean is increasing or not, and re-estimating specification (3) in Table 5 one obtains:

$$\begin{aligned} g_i(H_{it}) &= \underset{(-1.628)}{-0.013} + (\underset{(4.246)}{2.869} H_{it-\tau} - \underset{(-5.046)}{3.117}) I[g_i(\mu_{it})] g_i(\mu_{it}) \\ &+ (\underset{(3.709)}{2.218} H_{it-\tau} - \underset{(-5.717)}{1.984})(1 - I[g_i(\mu_{it})]) g_i(\mu_{it}) + \hat{\upsilon}_{it} \end{aligned} \qquad R^2=0.552,\ n=91 \quad (11)$$

The positive interaction effect is found during spells of contraction in the mean ($I[g_i(\mu_{it})] = 0$) as well as expansions ($I[g_i(\mu_{it})] = 1$); the homogeneity restriction passes in both cases (the t-test for contractions is 1.143, versus 1.425 for expansions). Nor can one reject the null that the coefficients are the same for expansions versus contractions (F=2.978, prob.=0.062).

So the key proximate determinant of the rate of poverty reduction is the "poverty adjusted growth rate" ($(1 - H_{it-\tau}) g_i(\mu_{it})$) rather than the ordinary growth rate ($g_i(\mu_{it})$). The regression coefficient of the rate of poverty reduction ($g_i(H_{it})$) against the poverty-adjusted growth rate in the survey mean is almost twice as high as for the ordinary growth rate.[33] Allowing for initial poverty rate adds 17 percentage points to the share of the variance in the rate of poverty reduction that can be explained by the rate of growth in the mean.

7. So why don't we see poverty convergence?

Recall that the speed of poverty convergence, $\partial g_i(H_{it}) / \partial \ln H_{it-\tau}$, is close to zero (section 4). We can now combine the main results from the last two sections to explain why. Based on the various encompassing tests in sections 5 and 6, my empirically-preferred model takes the form:

$$g_i(H_{it}) = \eta(1 - H_{it-\tau}) g_i(\mu_{it}) + \upsilon_{it} \qquad (12.1)$$

$$g_i(\mu_{it}) = \alpha + \beta \ln \mu_{it-\tau} + \gamma \ln H_{it-\tau} + \varepsilon_{it} \qquad (12.2)$$

The regressors in (12.2) are not, of course, independent; as we also saw in Section 3, countries with a higher initial mean tend to have a lower poverty rate.[34] I shall allow for this by assuming that $\ln H_{it-\tau}$ varies linearly as a function of $\ln \mu_{it-\tau}$ consistently with the data. We can then derive the following three-way decomposition of the poverty convergence elasticity:

---

[33] Recall that the regression coefficient of $g_i(H_{it})$ on $g_i(\mu_{it})$ is -1.372 (t=-5.948; R^2=0.363). The regression coefficient of $g_i(H_{it})$ on $(1 - H_{it-\tau}) g_i(\mu_{it})$ is -2.613 (t=-7.273; R^2=0.535).

[34] Nonetheless, as we have also seen, the differences across countries in initial distributions entail that $\ln \mu_{it-\tau}$ and $\ln H_{it-\tau}$ are not so highly correlated as to prevent disentangling their effects.

$$\frac{\partial g_i(H_{it})}{\partial \ln H_{it-\tau}} = \eta\beta(1-H_{it-\tau})\left(\frac{\partial \ln H_{it-\tau}}{\partial \ln \mu_{it-\tau}}\right)^{-1} + \eta\gamma(1-H_{it-\tau}) - \eta g_i(\mu_{it})H_{it-\tau} \qquad (13)$$

(Mean convergence effect) (Direct effect of poverty) (Poverty elasticity effect)

On evaluating all variables at their sample means and using the estimates in column (1) of Table 4 and column (5) from Table 5, and using the OLS elasticity of elasticity of the initial headcount index with respect to the initial survey mean of -1.305, one finds that the mean convergence effect is -0.038, while the direct effect of poverty is 0.024 and the poverty elasticity effect is 0.0195. The mean convergence effect is almost exactly cancelled by the combination of the two "poverty effects," which are roughly equal in size.

Naturally, different data points and parameter estimates give different magnitudes for this decomposition, though all share the feature that the two poverty effects work in opposition to the (conditional) mean convergence effect. Evaluating the decomposition at a higher initial headcount index increases the poverty elasticity effect while reducing the other two components. The estimates using only the consumption surveys give a higher direct effect of poverty, as do the estimates from the subsample with three surveys; in the latter case the poverty convergence elasticity is larger due to both a lower mean convergence component and the higher direct effect.

8. Conclusions

The most interesting thing about the fact that we do not see poverty convergence in the developing world is what it tells us about the underlying process of economic growth and its impact on poverty. The lack of poverty convergence—despite mean convergence and that growth generally reduces poverty—suggests that something about the initial distribution is offsetting the "advantage of backwardness."

That something turns out to be poverty itself. The paper's findings point to three distinct consequences of being a poor country for subsequent progress against poverty. The usual neoclassical convergence effect entails that countries starting with a lower mean, and so (typically) a higher poverty rate, grow faster and (hence) enjoy faster poverty reduction than otherwise similar countries. Against this, there is an adverse direct effect of poverty on growth, such that countries with a higher initial incidence of poverty tend to experience a lower rate of growth, controlling for the initial mean. Additionally a high poverty rate makes it harder to achieve a given proportionate impact on poverty through growth in the mean. (By the same token, the proportionate impact of economic contraction on poverty tends to be smaller in countries with a higher poverty rate.)

The two "poverty effects" work against the mean convergence effect, leaving little or no correlation between the initial incidence of poverty and the subsequent rate of progress against poverty. In terms of the pace of poverty reduction, the "advantage of backwardness" for countries starting with a low capital endowment (given diminishing returns to aggregate capital) is largely wiped out by the high level of poverty that tends to accompany a low initial mean. This dynamic "disadvantage of poverty" appears to exist independently of other factors impeding growth and poverty reduction, including human underdevelopment and policy distortions.

The evidence is mixed on the role played by other aspects of distribution. A larger middle class—by developing-country (but not Western) standards—makes growth more poverty-reducing. But this effect is largely attributable to the lower poverty rate associated with a larger middle class. Controlling for the initial incidence of poverty, there is no sign that a higher overall level of initial inequality, as measured by the Gini index, inhibits the pace of poverty reduction via either the rate of growth or the growth elasticity of poverty reduction. Of course, initial inequality can still matter via its bearing on the initial incidence of poverty. If high inequality comes with low absolute poverty at a given mean then it does not imply worse longer-term prospects for growth and poverty reduction.

Knowing more about the "reduced form" empirical relationship between growth, poverty reduction and the parameters of the initial distribution will not, of course, resolve the policy issues at stake. The policy implications of distribution-dependent poverty reduction depend on why countries starting out with a higher incidence of poverty tend to face worse growth prospects and enjoy less poverty reduction from a given rate of growth. The initial level of poverty may well be picking up other factors, such as the distribution of human and physical capital; indeed, the underlying theories point more to "wealth poverty" than consumption or income poverty. The control variables used here for schooling, life-expectancy and the price of investment goods do not "knock out" the effect of poverty, either on growth or poverty reduction at a given rate of growth. However, the cross-country empirical relationships reported here do point to the importance in future work of better understanding the handicaps faced by poor countries in their efforts to become less poor.

References

Acemoglu, Daron and Fabrizio Zilibotti, 1997, “Was Prometheus Unbound by Chance?” *Journal of Political Economy* 105(4): 709-751.

Aghion, Philippe and Patrick Bolton, 1997, “A Theory of Trickle-Down Growth and Development,” *Review of Economic Studies* 64: 151-172.

Aghion, Philippe, Eve Caroli and Cecilia Garcia-Penalosa, 1999, “Inequality and Economic Growth: The Perspectives of the New Growth Theories”, *Journal of Economic Literature* 37(4): 1615-1660.

Aghion, Philippe, Abhijit Banerjee and Thomas Piketty, 1999, “Dualism and Macroeconomic Volatility,” *Quarterly Journal of Economics* 114(4): 1359-1397.

Alesina, Alberto and Dani Rodrik, 1994, “Distributive Politics and Economic Growth”, *Quarterly Journal of Economics* 108: 465-90.

Azariadis, Costas, 2006, “The Theory of Poverty Traps: What Have we Learned?,” in Samuel Bowles, Steven Durlauf and Karla Hoff (eds) *Poverty Traps*, Princeton: Princeton University Press.

Banerjee, Abhijit and Esther Duflo, 2003, “Inequality and Growth: What Can the Data Say?” *Journal of Economic Growth* 8(3): 267-99.

Bardhan, Pranab, Samuel Bowles and Herbert Ginitis, 2000, “Wealth Inequality, Wealth Constraints and Economic Performance,” in A.B. Atkinson and F. Bourguignon (eds) *Handbook of Income Distribution Volume 1*, Amsterdam: North-Holland.

Barro, Robert, 2000, “Inequality and Growth in a Panel of Countries,” *Journal of Economic Growth* 5(1): 5-32.

Barro, Robert and Xavier Sala-i-Martin, 1992, “Convergence,” *Journal of Political Economy* 100(2): 223-251.

Beck, Thorsten, Asli Demirguc-Kunt and Ross Levine, 2007, “Finance, Inequality and the Poor,” *Journal of Economic Growth* 12: 27-49.

Bénabou, Roland, 1996, “Inequality and Growth”, in Ben Bernanke and Julio Rotemberg (eds) *National Bureau of Economic Research Macroeconomics Annual*, Cambridge: MIT Press.

Birdsall, Nancy, Carol Graham and Stefano Pettinato, 2000, “Stuck in the Tunnel: Is Globalization Muddling the Middle Class?” Center on Social and Economic Dynamics, Working Paper 14, Brookings Institution, Washington DC.

Birdsall, Nancy, D. Ross and R. Sabot, 1995, “Inequality and Growth Reconsidered: Lessons from East Asia”, *World Bank Economic Review* 9(3): 477-508.

Bourguignon, François, 2003, “The Growth Elasticity of Poverty Reduction: Explaining Heterogeneity across Countries and Time Periods,” in T. Eicher and S. Turnovsky (eds) *Inequality and Growth: Theory and Policy Implications*, Cambridge: MIT Press.

Chen, Shaohua and Martin Ravallion, 2010, “The Developing World is Poorer than we Thought, but no less Successful in the Fight against Poverty,” *Quarterly Journal of Economics,* in press.

Clarke, George R.G., 1995, “More Evidence on Income Distribution and Growth”, *Journal of Development Economics* 47: 403-428.

Cunha, Flavio and James Heckman, 2007, “The Technology of Skill Formation,” *American Economic Review, Papers and Proceedings,* 97(2): 31-47.

Dasgupta, Partha and Debraj Ray, 1986, “Inequality as a Determinant of Malnutrition and Unemployment”, *Economic Journal* 96: 1011-34.

Deininger, Klaus and Lyn Squire, 1998, “New Ways of Looking at Old Issues: Inequality and Growth,” *Journal of Development Economics* 57(2): 259-87.

Doepke, Matthias and Fabrizio Zilibotti, 2005, “Social Class and the Spirit of Capitalism,” *Journal of the European Economic Association* 3(2-3): 516-524.

Easterly, William, 2001, “The Middle Class Consensus and Economic Development,” *Journal of Economic Growth* 6(4): 317-335.

______________ 2009, “How the Millennium Development Goals are Unfair to Africa,” *World Development* 37(1): 26-35.

Fields, Gary, 2001, *Distribution and Development*. New York: Russell Sage Foundation.

Ferreira, Francisco and Martin Ravallion, 2009, “Poverty and Inequality: The Global Context”, in Wiemer Salverda, Brian Nolan and Tim Smeeding (eds), *The Oxford Handbook of Economic Inequality*, Oxford: Oxford University Press.

Forbes, Kristin J., 2000. “A Reassessment of the Relationship Between Inequality and Growth,” *American Economic Review* 90(4): 869-87.

Galor, Oded, and Joseph Zeira, 1993, “Income Distribution and Macroeconomics.” *Review of Economic Studies* 60(1): 35–52.

Hauk, William R. and Romain Wacziarg, 2009, "A Monte Carlo Study of Growth Regressions," *Journal of Economic Growth* 14(2): 103-147.

Hoff, Karla, 1996, "Market Failures and the Distribution of Wealth: A Perspective from the Economics of Information," *Politics and Society* 24(4): 411-432.

Kraay, Aart, 2006, "When is Growth Pro-Poor? Evidence from a Panel of Countries," *Journal of Development Economics* 80: 198-227.

Kraay, Aart and Claudio Raddatz, 2007, "Poverty Traps, Aid and Growth," *Journal of Development Economics* 82(2): 315-347.

Knowles, Stephen, 2005, "Inequality and Economic Growth: The Empirical Relationship Reconsidered in the Light of Comparable Data," *Journal of Development Studies* 41(1): 135-159.

Levine, Ross and D. Renelt, 1992, "A Sensitivity Analysis of Cross-Country Growth Regressions," *American Economic Review* 82: 942-963.

Li, Hongyi and Heng-fu Zou, 1998, "Income Inequality is not Harmful to Growth: Theory and Evidence," *Review of Development Economics* 2(3): 318-334.

Lind, Jo Thori and Karl Moene, 2010, "Miserly Developments," mimeo, Department of Economics, University of Oslo.

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

______________ and __________, 2009, "Too Poor to Grow," Policy Research Working Paper 5012, World Bank, Washington DC.

Murphy, Kevin, Andrei Schleifer and Robert Vishny, 1989, "Industrialization and the Big Push," *Journal of Political Economy* 97(5): 1003-1026.

Perotti, R., 1996, "Growth, Income Distribution and Democracy: What the Data Say," *Journal of Economic Growth,* 1(2): 149-187.

Persson, Torsten and Guido Tabellini, 1994, "Is Inequality Harmful for Growth?" *American Economic Review* 84: 600-621.

Ravallion, Martin, 1995, "Growth and Poverty: Evidence for Developing Countries in the 1980s," *Economics Letters,* 48, 411-417.

______________, 1997, "Can High Inequality Developing Countries Escape Absolute Poverty?" *Economics Letters,* 56, 51-57.

_______________, 1998, “Does Aggregation Hide the Harmful Effects of Inequality on Growth?” *Economics Letters*, 61(1): 73-77.

_______________, 2001, “Growth, Inequality and Poverty: Looking Beyond Averages,” *World Development*, 29(11): 1803-1815.

_______________, 2007, “Inequality is Bad for the Poor,” in J. Micklewright and S. Jenkins (eds.), *Inequality and Poverty Re-Examined.* Oxford: Oxford University Press.

_______________, 2009, “Why Don’t we see Poverty Convergence?” Policy Research Working Paper 4974, World Bank, Washington DC (http://econ.worldbank.org/docsearch).

_______________, 2010, “The Developing World’s Bulging (but Vulnerable) ‘Middle Class’”, *World Development*, 38(4): 445-454.

Ravallion, Martin, Shaohua Chen and Prem Sangraula, 2009, “Dollar a Day Revisited,” *World Bank Economic Review* 23(2): 163-184.

Sridharan, E., 2004, “The Growth and Sectoral Composition of India’s Middle Class: Its Impact on the Politics of Economic Liberalization,” *India Review* 3(4): 405-428.

Voitchovsky, Sarah, 2005, “Does the Profile of Income Inequality Matter for Economic Growth?” *Journal of Economic Growth* 10: 273-296.

World Bank, 1990, *World Development Report: Poverty*, New York: Oxford University Press.

___________, 2000, *World Development Report: Attacking Poverty*, New York: Oxford University Press.

___________, 2006, *World Development Report: Equity and Development*, New York: Oxford University Press.

___________, 2008, *Global Purchasing Power Parities and Real Expenditures. 2005 International Comparison Program*, Washington DC: World Bank.

Figure 1: The lack of poverty convergence amongst developing countries: Growth in the poverty rate plotted against its initial value

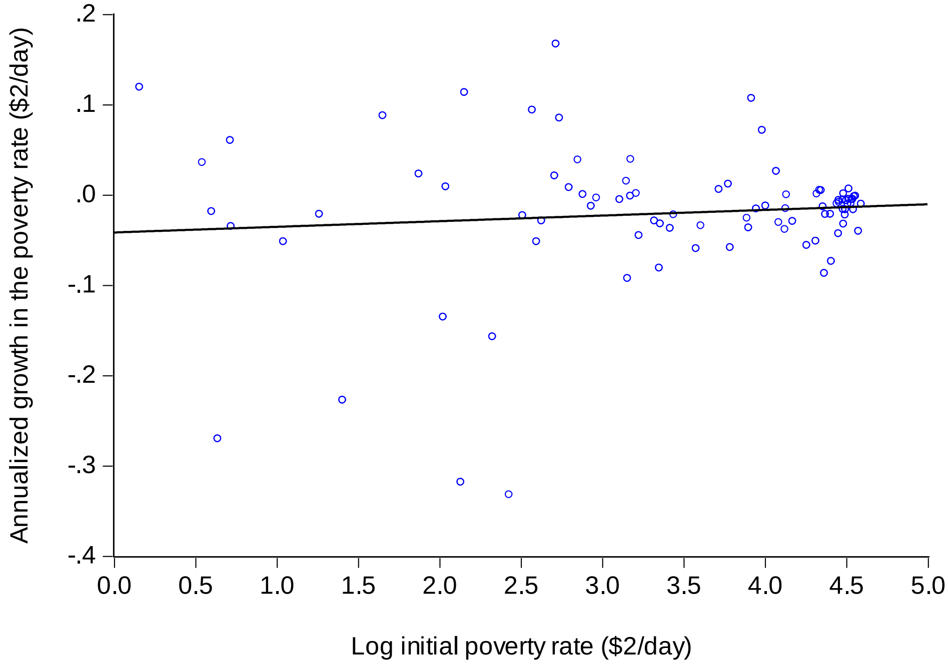

Figure 2: Densities of middle-class population shares

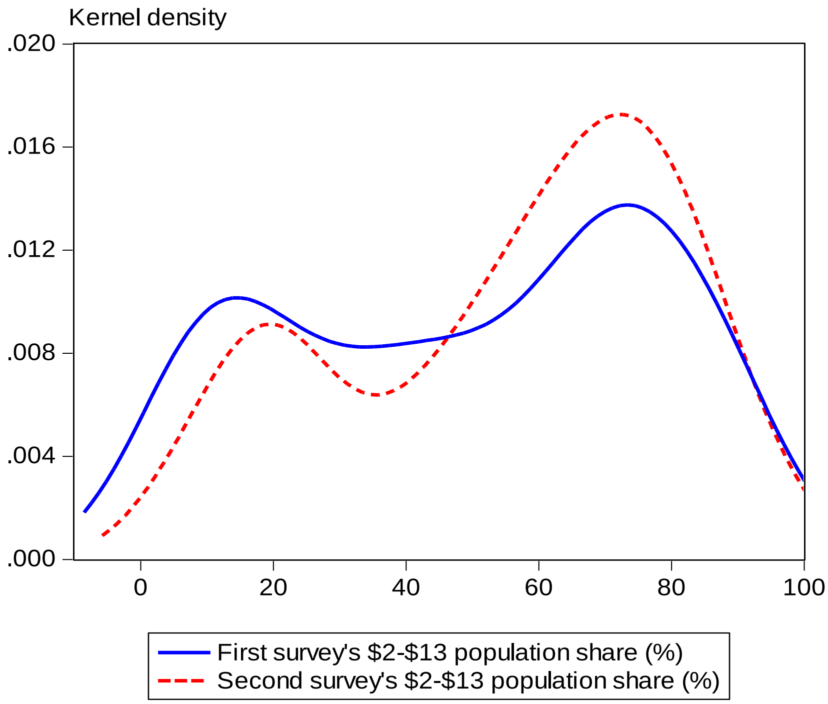

Table 1: Convergence tests for mean consumption

	(1) Surveys means (full sample)	(2) Surveys means (consumption surveys only)	(3) Consumption per capita from national accounts
Unconditional	-0.013**	-0.010	-0.007
	(-3.413; n=99)	(-1.882; n=74)	(-1.743; n=92)
Conditional	-0.042**	-0.040**	-0.026**
	(-7.435; n=90)	(-4.928; n=68)	(-4.431; n=90)

Note: The table gives $\hat{\beta}$ in the regression $g_i(\mu_{it}) = \alpha + \beta \ln \mu_{it-\tau} + \gamma X_{it-\tau} + \varepsilon_{it}$ where μ_{it} denotes the surveys mean (Columns 1 and 2) or consumption from the national accounts (column 3). T-ratios based on White standard errors (corrected for heteroskesdicity). The conditional estimates include controls (all for earliest survey date) comprising log mean consumption per capita from national accounts (for the survey means), log primary school enrollment rate; log life expectancy; log relative price index of investment goods.

Table 2: Convergence tests for the poverty rate

	(1) Headcount index ($2.00 a day)	(2) Headcount index ($1.25 a day)
Unconditional	0.005	-0.005
	(0.542; n=91)	(-0.393; n=79)
Conditional	-0.015	-0.028
	(-1.035; n=86)	(-1.734; n=79)

Note: The table gives $\hat{\beta}$ in the regression $g_i(H_{it}) = \alpha + \beta \ln H_{it-\tau} + \gamma X_{it-\tau} + \varepsilon_{it}$ where H denotes the poverty rate. T-ratios based on White standard errors (corrected for heteroskesdicity). The conditional estimates include controls (all for earliest survey date) comprising log mean consumption per capita from national accounts, log primary school enrollment rate; log life expectancy; log relative price index of investment goods.

Table 3: Alternative estimates of the regression of growth rates on initial mean and initial headcount index of poverty

	(1)	(2)	(3)	(4)	(5)	(6)
	Sample with two surveys:				Sample with three surveys:	
	Full sample	Consumption surveys only	National accounts consumption per capita	Means from first two surveys used as initial conditions	GMM estimator with IVs from earliest survey rounds	As for (5) but using national accounts consumption instead of survey means
Intercept	0.234**	0.300**	0.151**	0.235**	0.175*	0.177**
	(5.183)	(5.850)	(3.705)	(4.569)	(2.772)	(3.517)
Log initial mean	-0.035**	-0.044**	-0.020**	-0.029**	-0.019	-0.014
	(-5.131)	(-5.318)	(-3.037)	(-3.264)	(-1.469)	(-1.804)
Log initial headcount index	-0.017**	-0.025**	-0.011**	-0.022**	-0.020**	-0.026**
	(-3.626)	(-4.845)	(-2.711)	(-6.305)	(-3.090)	(-4.468)
R^2	0.147	0.201	0.128	0.133	n.a.	n.a.
N	92	70	81	77	64	59

Notes: The dependent variable is the annualized change in log survey mean ($g_i(\mu_{it})$ for (1), (2), (4) and (5) and annualized change in log private consumption per capita from national accounts ($g_i(C_{it})$) for (3) and (6). The initial mean corresponds to the same measure used for the growth rate in each regression. The poverty rate is $2.00 for survey means and $1.25 for national accounts consumption (column 2). The t-ratios in parentheses are based on robust standard errors; * denotes significant at the 5% level; ** denotes significant at the 1% level.

Table 4: Regressions for consumption growth rates on the initial poverty rate augmented with extra control variables

	(1)	(2)	(3)	(4)
	Growth rates based on:			
	Survey Means	Consumption from national accounts	Survey Means	Consumption from national accounts
	Complete specification:		Dropping weak predictors:	
Intercept	0.466	0.441	0.26	-0.275
	(0.845)	(0.971)	(1.279)	(-1.914)
Initial mean ($\ln \mu_{it-\tau}$ for (1) and (3) and $\ln C_{it-\tau}$ for (2) and (4))	-0.071**	-0.033**	-0.060**	-0.030**
	(-4.111)	(-4.526)	(-6.912)	(-3.764)
Poverty rate ($\ln H_{it-\tau}$)	-0.033**	-0.015**	-0.027**	-0.014**
	(-4.542)	(-2.844)	(-5.750)	(-3.024)
Gini index ($\ln G_{it-\tau}$)	-0.023	-0.060	-	-
	(-0.463)	(-1.297)		
Income share of middle three quintiles ($\ln MQ_{it-\tau}$)	-0.099	-0.170*	-0.091**	-
	(-1.170)	(-2.351)	(-3.985)	
Share of population in Western middle class ($1-F_{it-\tau}(13)$)	-0.078	-0.141*	-0.110**	-0.133**
	(-1.471)	(-2.339)	(-2.432)	(-3.691)
The miser index	0.018	-0.019		
	(0.979)	(-1.440)		
Primary school enrolment rate (log)	0.007	0.003	-	-
	(0.704)	(0.270)		
Life expectancy (log)	0.114**	0.177**	0.129**	0.139**
	(2.712)	(4.173)	(3.068)	(3.665)
Price of investment (log)	-0.014**	-0.014**	-0.014**	-0.017**
	(-2.751)	(-2.413)	(-2.698)	(-3.434)
N	0.438	0.484	0.430	0.453
R^2	88	84	88	87

Notes: The dependent variable is the annualized change in log mean ($g_i(\mu_{it})$ for (1) and (3) and $g_i(C_{it})$ for (2) and (4)). The initial mean corresponds to the same measure used for the growth rate in each regression. The share of the Western middle class is not logged given that 11 observations are lost because of zeros. The t-ratios in parentheses are based on robust standard errors; * denotes significant at the 5% level; ** denotes significant at the 1% level. The hyphen indicates that the variable is dropped.

Table 5: Regressions for proportionate change in poverty rate as a function of the growth rate and initial poverty rate

	(1) OLS	(2) IVE	(3) OLS	(4) IVE	(5) OLS	(6) IVE
	Complete specification:		Dropping initial poverty rate:		Imposing homogeneity:	
Intercept	0.002	0.008	-0.012	-0.005	-0.012**	-0.008
	(0.078)	(0.267)	(-1.908)	(0.607)	(-2.175)	(-1.365)
Initial poverty rate ($\ln H_{it-\tau}$)	-0.004	0.008	-	-	-	-
	(-0.792)	(0.267)				
Growth rate (annualized change in log survey mean, $g_i(\mu_{it})$)	-2.674**	-3.564**	-2.615**	-3.323**	-	-
	(-6.660)	(-4.325)	(-6.608)	(-4.560)		
Growth rate interacted with initial poverty rate ($g_i(\mu_{it}).H_{it-\tau}$)	2.780**	3.492**	2.621**	3.101**	-	-
	(5.206)	(3.650)	(4.915)	(3.746)		
(1-Poverty rate) *times* growth rate ($g_i(\mu_{it}).(1-H_{it-\tau})$)	-	-	-	-	-2.613**	-3.294**
					(-7.273)	(-4.585)
N	91	86	91	86	91	86
R^2	0.537	0.439	0.535	0.458	0.535	0.466
Homogeneity test	0.673	-0.215	0.037	-0.620	n.a.	n.a.

Notes: The dependent variable is the annualized change in log poverty rate for $2 a day ($g_i(H_{it})$); t-ratios based on robust standard errors in parentheses; * denotes significant at the 5% level; ** denotes significant at the 1% level. The homogeneity test is the t-test for the sum of the coefficients on the growth rate $g_i(\mu_{it})$ and the growth rate interacted with initial poverty rate $g_i(\mu_{it})H_{it-\tau}$; if the relationship is homogeneous then the coefficients sum to zero and the regressor becomes $g_i(\mu_{it}).(1-H_{it-\tau})$. The hyphen indicates that the variable is dropped.