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When Do We See Poverty Convergence?*

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Abstract

We show why convergence in mean income levels and the negative relation between mean income growth and poverty changes need not lead to proportionate poverty convergence across countries. We propose an analytical framework that highlights that poverty convergence depends on the speed of income convergence relative to a complex interaction of initial inequality, mean income levels, and inequality dynamics. Our framework allows us to investigate poverty convergence, or the lack thereof, under different plausible dynamics of mean income and inequality.

I. Introduction

Three key economic factors determine trends in poverty rates across the developing world: first, GDP per capita growth lowers poverty rates and has been higher for poorer countries since the mid-1990s (Patel, Sandefur, and Subramanian, 2021). Second, declining income inequality lowers poverty rates for given mean income levels. Empirical evidence of inequality convergence suggests such declines in absolute poverty rates to be faster in economies where income is more unequally distributed (Deininger and Squire, 1996; Ravallion, 2003). Third, the 'growth elasticity of poverty reduction' pins down how mean income growth rates translate into reductions in poverty rates. This elasticity depends itself on income per capita and inequality (Bourguignon, 2003).

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Ravallion (2012) points out that, due to mean income convergence across countries and the negative relationship between mean income and poverty, '*countries starting out with a high incidence of absolute poverty should enjoy a higher subsequent (. . .) proportionate rate of poverty reduction*' (Ravallion, 2012, p. 504). Although Ravallion (2012) finds mean income convergence and a positive relationship between growth and proportionate poverty reduction in a sample of household surveys from some 90 developing countries, he fails to confirm proportionate convergence in the poverty headcount ratio. To explain this seemingly puzzling finding, Ravallion (2012) empirically assesses how initial poverty relates to subsequent growth and finds a negative relationship between initial poverty and subsequent mean income growth. His analysis also finds that the growth elasticity of poverty reduction tends to be lower, in absolute terms, in poorer countries. Both effects, similar in size, tend to cancel the mean income convergence effect, such that one does not observe proportionate poverty convergence in the data.

In this article, we show that mean income convergence and the advantages of growth for poverty reduction are insufficient for ensuring proportionate poverty convergence and that one does not need to rely on a negative relationship between initial poverty and growth, which Ravallion (2012, 2016) posits, to explain the lack of poverty convergence. We show this by combining the growth elasticity of poverty reduction derived by Bourguignon (2003) with the proportionate poverty convergence framework of Ravallion (2012). The former implies that proportionate poverty reduction for a given growth rate is smaller for countries with lower mean income levels. Hence, poor countries may grow faster due to mean income convergence effects but experience a smaller proportionate reduction of poverty from a given growth rate of mean income. This trade-off is the result of an analytical identity and unrelated to the potential detrimental socio-economic consequences of poverty.

By approaching the concept of proportionate poverty convergence through this analytical lens, our paper provides three key contributions. First, we derive a clear-cut analytical solution to the question whether or not one should observe proportionate poverty convergence. Our paper highlights that the answer to this question depends on the speed of mean income convergence, the initial level of income inequality, inequality dynamics, initial mean income, and their mutual interaction. This key point of our paper refines the interpretation of Ravallion (2012, 2016) that the absence of proportionate poverty convergence is a 'paradox' that emerges from poverty impeding growth. Instead, several other factors can impede proportionate poverty convergence in the presence of mean income convergence and the advantages of growth for poverty reduction.

Second, two of those factors that our paper highlights with respect to global poverty dynamics are inequality convergence (Deininger and Squire, 1996; Ravallion, 2003) and the initial correlation between mean income and inequality. These factors should be reflected in ongoing efforts to forecast global poverty dynamics in the context of the Sustainable Development Goal of eliminating extreme poverty by 2030 (e.g. Crespo Cuaresma *et al.*, 2018; Lakner *et al.*, 2020).

Third, our results imply that empirical efforts to address proportionate poverty convergence across a large number of countries or regions are incomplete unless the parameter heterogeneity inherent to the problem is explicitly considered. Recent studies (e.g. Crespo Cuaresma, Klasen, and Wacker, 2017; Ouyang, Shimeles, and

Thorbecke, 2018, 2019) have documented the sensitivity of the evidence for poverty convergence to the sample investigated. Our paper shows that the complex interaction between initial inequality, mean income levels, and subsequent inequality dynamics implies that such empirical evidence on proportionate poverty convergence will necessarily depend on the particular sample of countries employed. This explains the conflicting results found in the empirical literature on poverty convergence (see Crespo Cuaresma *et al.*, 2017; Thorbecke and Ouyang, 2018; Asadullah and Savoia, 2018; Ouyang *et al.*, 2019; Lopez-Calva, Ortiz-Juarez, and Rodríguez-Castelán, 2021).

The remainder of our paper is organized as follows. In section II, we review the concept of proportionate poverty convergence, as proposed by Ravallion (2012), in the context of the wider macroeconomic literature on the link between income, its within-country distribution, and poverty reduction. In section III, we derive an analytical representation of the factors influencing proportionate poverty convergence based on Bourguignon's (2003) growth elasticity of poverty reduction and highlight why conventional neoclassical theory does not necessarily imply poverty convergence in the sense of Ravallion (2012). Section IV investigates how well our extended analytical poverty convergence framework fits the data and illustrates how it can be used to understand proximate sources of poverty dynamics. Section V discusses the implications of our findings and concludes.

II. Poverty convergence: The standard framework

Ravallion (2012) motivates the concept of proportionate poverty convergence by two standard economic arguments. The first one is convergence of mean income (or consumption) levels across countries. Accordingly, one would assume $\beta < 0$ in the standard beta-convergence regression for income levels given by

$$\Delta \ln \mu_{it} = \alpha + \beta \ln \mu_{i,t-1} + \varepsilon_{it}, \tag{1}$$

where μ_{it} is the mean income level of country i at time t and ε_{it} is a random error. In a sample that covers household income data for about 90 developing countries between 1977 and 2007, Ravallion (2012) finds evidence of cross-country convergence in mean household income, as reflected in a negative and statistically significant estimate of β in the regression model given by equation (1). While the existence of unconditional income convergence on a global level is debatable (see, e.g. Johnson and Papageorgiou, 2020; Patel *et al.*, 2021), this finding is in line with studies suggesting the existence of a 'convergence club' among developing economies (see Quah, 1997; Ben-David, 1998).[1]

The second argument in Ravallion (2012) concerns the 'advantage of growth' for poverty reduction, which suggests $\eta > 0$ in

$$lnH_{it} = \delta - \eta \; ln \; \mu_{it} + \nu_{it}, \tag{2}$$

[1]For the group of countries studied, Ravallion (2012) finds evidence for unconditional as well as conditional cross-country mean household income convergence, with a significantly higher speed of conditional convergence. Ravallion (2012) also finds unconditional convergence in consumption per capita data from national accounts data (using the Penn World Table 6.2 as a source). We cannot generally confirm this finding for data sourced from the Penn World Table 9.0 (Feenstra, Inklaar, and Timmer, 2015) unless the specific dynamics in Eastern European transition economies are explicitly controlled for. Results are available upon request.

where H_{it} is the (absolute) poverty rate and ν_{it} is a random error term. Focusing on the poverty headcount ratio at \$2.00/day (at 2005 PPPs) and estimating equation (2) in first differences, Ravallion (2012) empirically confirms that higher mean income growth is associated with faster proportionate poverty reduction. This is in line with the compelling evidence of a very strong correlation between mean income growth and income growth of the poor, which is tantamount to claiming that mean income growth and changes in inequality are not systematically related across countries (Dollar and Kraay, 2002; Dollar, Kleineberg, and Kraay, 2016).

Given mean income convergence and advantages of growth (that is, growth in mean incomes implying poverty reduction), Ravallion (2012) posits that $\beta^* < 0$ should hold for the relationship

$$\Delta \ln H_{it} = \alpha^* + \beta^* \ln H_{i,t-1} + \varepsilon^*_{it}, \tag{3}$$

since $\alpha^* = -\alpha\eta - \beta\delta, \beta^* = \beta, \varepsilon^*_{it} = -\eta\varepsilon_{it} + \nu_{it} - (1+\beta)\nu_{i,t-1}$, meaning that mean income convergence ($\beta < 0$) implies (proportional) poverty convergence ($\beta^* < 0$).[2] Ravallion (2012), however, fails to find a significant negative estimate of β^* in cross-country data, despite mean income convergence ($\beta < 0$) and evidence for the advantages of growth ($\eta > 0$).[3] He explains this seemingly puzzling finding by presenting evidence of an (indirect) adverse effect of initial poverty on economic growth and a direct 'poverty elasticity effect' of initial poverty, lowering the growth elasticity of poverty reduction.[4] The evidence is based on regression estimates after including the initial poverty rate in the model for the growth rate of mean income, indicating a sizeable negative impact at any given initial mean income level. The analysis in Ravallion (2012) proceeds by showing, in a reduced-form analysis, that both of these poverty effects almost exactly cancel out the mean convergence effect, thus explaining why proportionate poverty convergence is not actually observed in the data.

It is important to understand that the direct 'poverty elasticity effect' linking mean income with poverty rates, which is log-linearly approximated by Ravallion (2012) in equation (2), is actually governed by a highly nonlinear relationship. In the next section, we analyze the form of this relationship in detail using the framework provided by Bourguignon (2003), and provide insights about the role played by mean income convergence and its interaction with income inequality dynamics as a determinant of poverty convergence.

[2]Note that the absence of proportionate poverty convergence in the sense of equation (3) does not mean that poverty across countries would not converge in absolute headcount ratios. Proportionate poverty convergence demands that, for example, a country starting out with a poverty level of 60% should be more likely to reduce poverty to 30% in the same time as another country reduces poverty from 10% to 5%, since both are 50% reductions in the headcount ratio. Alternatively, absolute poverty convergence - in the sense that a country with a higher poverty incidence would experience higher absolute (percentage point) reductions in poverty than a country with low poverty incidence - could be motivated with a growth semi-elasticity of poverty reduction (Klasen and Misselhorn, 2008), see Crespo Cuaresma *et al.* (2017).

[3]Ravallion (2012) uses a model setting that suggests country-specific speeds of convergence but estimates a global coefficient common to all countries in spite of the potential econometric problems associated with this type of specification (see Bliss, 1999). Our analytical contribution highlights the importance of heterogeneity in the parameter η in equation (2) and hence of β^* in equation (3).

[4]In other words, $\ln H_{i,t-1}$ enters equation (1) as an additional driver of changes in (log) mean income, with a negative parameter, leading to a higher value of β^* in equation (3).

III. Extending the poverty convergence framework

Under the assumption of log-normally distributed incomes,[5] Bourguignon (2003) shows that this so-called 'growth elasticity of poverty reduction', which captures the relationship between percent changes in the poverty headcount ratio and the growth rate in mean income takes the form

$$\eta^* = \left| \frac{\Delta H_{it}}{\Delta \ln (\mu_{it}) H_{i,t-1}} \right| = \frac{1}{\sigma} \lambda \left(\frac{\ln (z/\mu_{i,t-1})}{\sigma} + \frac{1}{2}\sigma \right), \tag{4}$$

where z is some poverty line (such as \$2.00/day), μ is mean income, σ is the standard deviation of log income, a measure for relative income inequality, and $\lambda(\cdot)$ is the ratio of the density to the cumulative distribution function of the standard normal distribution. Note that this representation assumes a constant inequality parameter σ, which simplifies the exposition. Equation (4) highlights that the proportionate poverty reduction a country achieves with a given growth rate of mean income is positive but depends on the initial levels of mean income and inequality. Ravallion's (2012) reduced-form estimation under a homogeneous parameter assumption may thus be too restrictive to account for the inherent cross-country heterogeneity of the growth elasticity of poverty reduction implied by equation (4).

The heterogeneity in the growth elasticity of poverty reduction implies that whether we observe proportionate poverty convergence in the data depends on the relationship between the speed of mean income convergence, initial inequality and its relation to mean income, as well as on inequality dynamics. Accordingly, the composition of the sample of countries under scrutiny plays a crucial role when it comes to evaluating the existence of poverty convergence. This could explain why empirical studies following up on Ravallion (2012) arrive at different conclusions concerning the existence of convergence in poverty headcounts.

The growth elasticity of poverty reduction under log-normally distributed incomes given by equation (4) summarizes the relationship between percent changes in the poverty headcount ratio and the growth rate in mean income. By assuming common parameters for the full sample of countries, Ravallion's (2012) reduced-form estimation framework does not reflect that this elasticity depends on initial levels of mean income and inequality in a highly nonlinear way. To understand the implications for the concept of proportionate poverty convergence, it is instructive to use a dynamic representation of the growth and inequality elasticities of poverty reduction (see Bourguignon, 2003: equation (2)) and to relate it to the proportionate poverty convergence framework:

$$\begin{aligned} \Delta \ln H_{it} \approx & -\lambda \left(\tfrac{\ln(z/\mu_{i,t-1})}{\sigma_{i,t-1}} + \tfrac{1}{2}\sigma_{i,t-1} \right) \tfrac{1}{\sigma_{i,t-1}} \Delta \ln \mu_{i,t} + \\ & + \lambda \left(\frac{\ln (z/\mu_{i,t-1})}{\sigma_{i,t-1}} + \frac{1}{2}\sigma_{i,t-1} \right) \left(\frac{1}{2}\sigma_{i,t-1} - \frac{\ln (z/\mu_{i,t-1})}{\sigma_{i,t-1}} \right) \Delta\sigma_{it} = \\ = & -\eta_{i,t-1} \Delta \ln \mu_{i,t} + \xi_{i,t-1} \Delta\sigma_{it}, \end{aligned} \tag{5}$$

[5]Without loss of generality, we maintain the assumption of log-normally distributed income throughout our paper for ease of exposition and due to the evidence that it provides a reasonable approximation when analyzing poverty dynamics (see Bourguignon, 2003; Lopez and Serven, 2006; Klasen and Misselhorn, 2008; Bergstrom, 2020).

where $\xi_{i,t-1}$ denotes the terms preceding $\Delta\sigma_{it}$. Substituting equation (1) into equation (5) yields

$$\Delta \ln H_{it} = -\eta_{i,t-1}\left(\alpha + \beta \ln \mu_{i,t-1} + \varepsilon_{it}\right) + \xi_{i,t-1}\Delta\sigma_{it}, \tag{6}$$

which allows for an intuitive interpretation of why mean income convergence and the advantages of growth for poverty reduction do not necessarily imply proportionate poverty convergence. Although lower initial mean income has a positive correlation with subsequent poverty reduction via the convergence term $\beta < 0$, it is unclear whether this effect balances out the negative relation taking place through a lower growth elasticity η. Since $\partial\eta/\partial\mu < 0$ (see equation (5)), the terms in equation (6) embody a negative relationship with initial mean income via $-\eta\alpha$ (since α is assumed positive) and a positive relationship via $-\eta\beta$ (since β is assumed negative).

More formally, differentiating both sides of equation (6) with respect to $\ln H_{i,t-1}$, noting that $H_i(\mu_i) = \Phi(\ln(z/\mu_i)/\sigma_i + \sigma_i/2)$ and that $\eta_{i,t-1}$ and $\xi_{i,t-1}$ are functions of $\ln\mu_{i,t-1}$, yields:

$$\frac{\partial\Delta\ln H_{it}}{\partial\ln H_{i,t-1}} = \frac{\partial\ln\mu_{it-1}}{\partial\ln H_{i,t-1}}\left(\frac{\partial\eta_{i,t-1}}{\partial\ln\mu_{i,t-1}}\Delta\ln\mu_{i,t} + \frac{\partial\xi_{i,t-1}}{\partial\ln\mu_{i,t-1}}\Delta\sigma_{it} - \beta\eta_{i,t-1}\right). \tag{7}$$

Equation (7) highlights the complex nonlinear dependence of percent changes in poverty on initial poverty and makes evident that simple convergence regressions with constant parameters across countries such as the one in equation (3) are not necessarily an adequate description of the link between initial poverty and its subsequent change.[6] Particularly, it is evident from equation (7) that $\beta < 0$ is not sufficient to observe proportionate poverty convergence since $-\beta\eta_{i,t-1} > 0$ and $\partial\eta_{i,t-1}/\partial\ln\mu_{i,t-1} < 0$.

The remaining part of this section shows how proportionate poverty convergence depends on the parameters in equations (5)–(7). We discuss this relationship first with a simple simulation under the assumption of a stable income distribution (i.e. σ not changing over time), before gauging the role of inequality dynamics in this context.

The case of constant income inequality

We start by analysing the implications of equations (5)–(7) for countries starting out at low mean income levels and hence higher poverty levels, under the assumption of constant inequality. Assuming positive growth in mean incomes, since $-\beta\eta_{i,t-1} > 0$ and $\left(\partial\eta_{i,t-1}/\partial\ln\mu_{it-1}\right)\Delta\ln\mu_{i,t} < 0$, the sign of $\partial\Delta\ln H_{it}/\partial\ln H_{it-1}$, and thus the convergence parameter in the proportionate poverty convergence equation, could be positive or negative. It should be noted that this is independent of the assumption of log-normally distributed income. The standard neoclassical theory of mean income convergence and advantages of growth for poverty reduction, therefore, does not necessarily imply proportionate poverty convergence in the sense of Ravallion (2012). Even in the presence of a globally homogeneous parameter β in equation (1), whether

[6]Note that equations (5)–(7) can accommodate the indirect adverse economic effect of initial poverty on economic growth that is essential in the framework of Ravallion (2012: equations 10.2 and 11). However, to keep our exposition focused, we refrain from this extension.

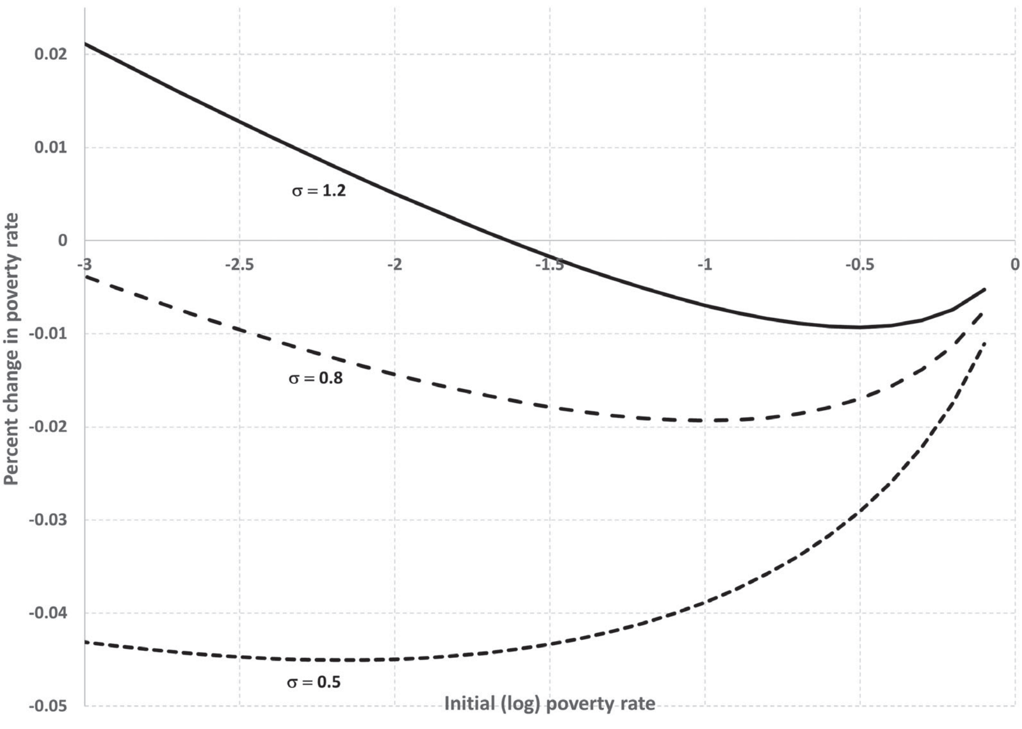

Figure 1. Dependence of proportionate poverty changes on the initial poverty level and inequality
Notes: This figure shows proportionate changes in poverty headcount ratios, ΔlnH, in dependence of the initial (log) level of poverty, as described by equation (7), assuming that the dynamics of mean income is given by $\Delta \ln \mu_{it} = 0.076 - 0.013 \ln \mu_{i,t-1}$. The effect is shown for different inequality levels, where σ is the standard deviation of the log-normal distribution of income

we observe proportionate poverty convergence depends on the (absolute) size of β, the development level $\mu_{i,t}$, and the level (and change) of income inequality as measured by σ.

Figure 1 illustrates the quantitative implications of equation (7) for poverty changes under different mean income and initial distributional conditions. The horizontal axis plots the (log) initial poverty rate. For a given income inequality level, there is a one-to-one correspondence between this poverty rate H and a mean income level μ, given log-normally distributed incomes, as defined right above equation (7). Using the framework of mean income convergence, we estimate mean income growth using the point estimates obtained with the sample in Ravallion (2012) for equation (1), given by $\Delta \ln \mu_{it} = 0.076 - 0.013 \ln \mu_{i,t-1}$. These growth rates can then be used to calculate implied proportionate changes in the poverty headcount ratio (on the vertical axis of Figure 1) based on equation (6) above. We perform this calculation for three different levels of inequality ($\sigma = 0.5, 0.8, 1.2$). Under the assumption of log-normally distributed incomes, the link between σ and the Gini index is given by $\sigma = \sqrt{2}\Phi^{-1}\left(\frac{\text{Gini}+1}{2}\right)$, and these levels of inequality correspond to Gini coefficients of 27.6, 42.8, and 60.4, respectively. We assume no changes in inequality for all calculations.

The resulting relationship between initial poverty and subsequent proportionate poverty reduction is depicted in Figure 1. The first key takeaway from Figure 1 is that the relationship between the initial (log) poverty rate and subsequent percent changes in the poverty rate for a given inequality level is non-monotonic. Proportionate poverty convergence (that is, a negative slope in the relationship between the initial poverty rate and its subsequent percent change) is only present up to a certain level of the initial poverty rate. For those countries with a relatively low level of initial poverty, the growth elasticity of poverty reduction is high. Up to a certain level of initial poverty, mean income convergence dynamics hence translates into proportionate poverty convergence. But for initially poorer countries, the declining growth elasticity of poverty reduction ($\partial\eta/\partial\mu < 0$) increasingly dominates the benefits of mean income convergence, leading to proportionate poverty divergence. This is reflected in an increasing upward slope in the right part of Figure 1.

For a given initial poverty rate, countries with higher income inequality experience lower mean income growth[7] and a lower percent reduction in the poverty rate from a given growth rate because their growth elasticity is smaller ($\partial\eta/\partial\sigma < 0$). Countries with high inequality (e.g. $\sigma = 1.2$ in Figure 1) and high initial mean income levels accordingly observe increases in the poverty headcount ratio: mean income convergence predicts a decline of mean income in those countries. Although such a result is theoretically supported by the analysis, the sample of countries used in Ravallion (2012) only has eight economies whose initial level of income would imply a decrease in mean income through convergence dynamics.[8] Moreover, the dependence of the growth elasticity on inequality is reflected in the different slopes and inflection points of the curves depicted in Figure 1.[9]

A second implication of Figure 1 is that, if one does not account for unobserved cross-country heterogeneity, the sample correlation between the initial poverty rate (or mean income) and inequality affects our inference concerning poverty convergence. Suppose we observe two countries with inequality levels of $\sigma = 0.5$ and $\sigma = 1.2$, respectively. For the low-inequality country, the proportionate poverty reduction will always be larger, but proportionate poverty convergence between the two countries will only be observed if it starts out at a higher initial poverty rate than the country with $\sigma = 1.2$. Controlling for cross-country heterogeneity, for example, by panel fixed effects as in Ouyang *et al.* (2018), can thus lead to very different conclusions as compared with merely exploring cross-country variation (as in Ravallion, 2012).[10]

Absence of proportionate poverty convergence is hence not at odds with standard neoclassical concepts of mean income convergence and advantages of growth for poverty reduction. Rather, whether we see proportionate poverty convergence is an empirical question and depends on the interaction between the overall speed of mean income

[7] Due to the fact that $H_i = \Phi\left(\ln\left(z/\mu_i\right)/\sigma_i + \sigma_i/2\right)$, for countries with the same initial poverty level H, the country with higher inequality σ needs to also have a higher mean income level μ to obtain the same initial poverty level. Via mean income convergence, this higher mean income level translates into lower subsequent mean income growth.

[8] In the context of conditional convergence, adjustments towards a country-specific equilibrium that imply a reduction in the capital-to-effective-labour ratio (and thus a reduction of income per unit of effective labour) are empirically very relevant (see Cho and Graham, 1996).

[9] Inequality enters the results depicted in Figure 1 in two ways. First, η, which is part of equation (7) that pins down the vertical axis of Figure 1, depends on σ (for any given inequality level). Second, identical initial poverty levels for different σ imply different initial μ and hence different growth rates.

[10] This finding suggests that the sample correlation between initial mean income and inequality may play an important role for proportionate poverty convergence (or lack thereof). A simulation study to explore this possibility is reported in Online Appendix S1 and suggests that one cannot easily explain observed poverty dynamics with sample means or correlations of initial mean income and inequality.

convergence and the mean income and inequality levels of the countries in the sample.[11] In other words, sample composition will have an important effect on proportionate poverty dynamics and thus implications for proportionate poverty convergence.

Proportionate poverty convergence: The case of inequality convergence

The results presented above and summarized in Figure 1 are obtained under the assumption that within-country inequality remains stable. Studies such as Deininger and Squire (1996) or Ravallion (2003), however, provide evidence for convergent income inequality dynamics across countries. To incorporate income inequality dynamics in our analysis, we alter our simulation setting by assuming inequality to converge according to the law of motion given by $\Delta \ln \text{Gini}_{it} = 0.17 - 0.045 \ln \text{Gini}_{i,t-1}$, which is the inequality convergence equation implied by the sample in Ravallion (2012). Such a specification for the dynamics in income inequality implies convergence to a steady-state Gini coefficient of 43.7, slightly above earlier findings in Ravallion (2003), and can be used to compute expected changes in inequality and to predict proportionate changes in poverty, making use of equation (5).

Figure 2 illustrates the results obtained from the simulation assuming both mean income and inequality convergence. The incorporation of inequality dynamics further increases the complexity of the assessment of poverty convergence. At relatively high development levels (on the left part of Figure 2), countries starting out at the same initially low inequality level would still experience proportionate poverty convergence. For them, mean income convergence is the dominating force, given that the growth elasticity of poverty reduction is high at low levels of inequality ($\partial\eta/\partial\sigma < 0$). On the other hand, for countries starting out at high initial inequality (e.g. $\sigma = 1.2$), we would observe proportionate poverty divergence. The quantitative effect of inequality changes on proportionate poverty changes depends on a complex interaction between initial inequality and initial mean income (see equation (5)). In countries with high initial inequality, declining inequality reduces poverty proportionately faster at lower initial poverty levels (equivalent to higher initial mean income). This outweighs the effect from slower mean income convergence and is reflected in the upward slope of the solid line for $\sigma = 1.2$ in Figure 2.

Compared with Figure 1, the case with inequality convergence implies that countries with lower initial inequality observe more positive proportionate poverty changes. This results from the fact that inequality convergence leads to substantial poverty declines in countries with high initial inequality but to high proportionate poverty increases in low-inequality countries (at least at low levels of poverty). Figure 2 also reveals that empirical assessments of proportionate poverty convergence will be highly dependent on the inclusion or exclusion of countries with low initial poverty levels. Given that expected percent changes in poverty rates are largest for those countries, their leverage in a linear regression setting will be important and is likely to dominate the relationship between

[11] This problem is exacerbated if mean income convergence speeds differ by initial mean income level, for example, in the case of club convergence (see, e.g. Quah, 1997, or Canova, 2004). We show the sensitivity of the results in Ravallion (2012) to the choice of country subsamples in Crespo Cuaresma *et al.* (2017).

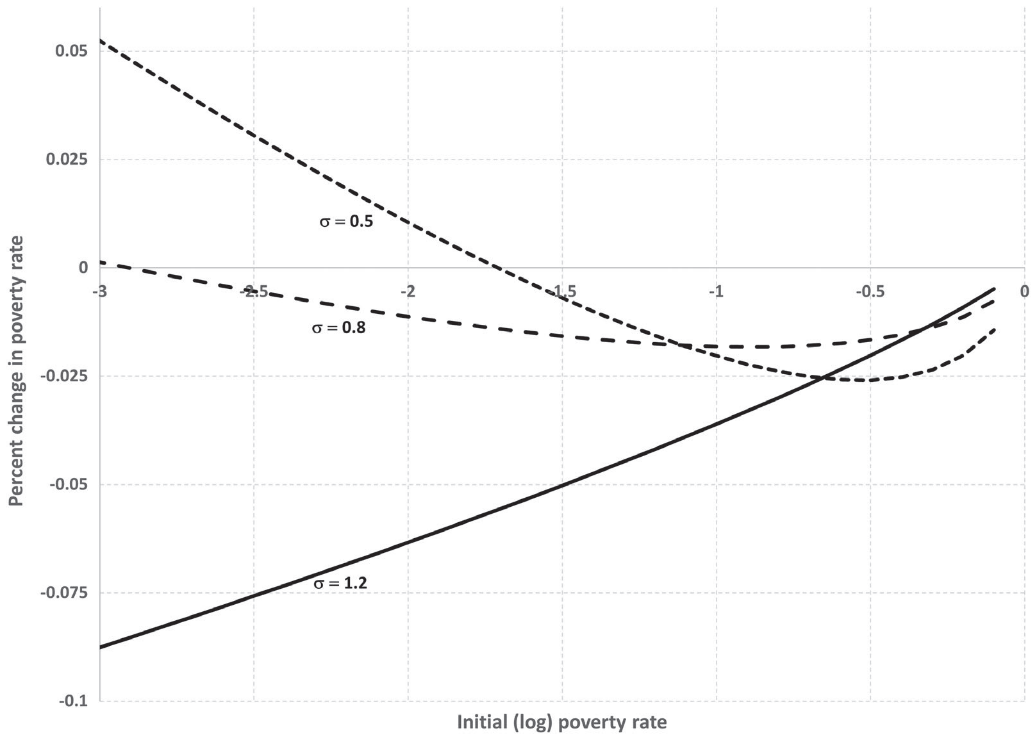

Figure 2. Proportionate poverty changes in the presence of mean income and inequality convergence
Notes: This figure shows proportionate changes in poverty headcount ratios, ΔlnH, in dependence of the initial (log) level of poverty, assuming that the dynamics of mean income and inequality are given by $\Delta \ln \mu_{it} = 0.076 - 0.013 \ln \mu_{i,t-1}$ and $\Delta \ln Gini_{it} = 0.17 - 0.045 \ln Gini_{i,t-1}$, respectively. The effect is shown for different inequality levels, where σ is the standard deviation of the log-normal distribution of income

proportionate poverty changes and development levels when they are part of the sample together with countries at higher initial poverty levels.

In summary, our analysis based on Bourguignon's (2003) growth elasticity of poverty reduction reveals that the existence of proportionate poverty convergence depends on the speed of mean income convergence relative to a complex interaction of initial inequality, development levels, and inequality dynamics. Even in the presence of mean income convergence, we have highlighted that proportionate poverty convergence may not be present for reasonable values of those variables. Moreover, the evidence for or against poverty convergence is susceptible to the selection of countries in the sample, especially if economies at relatively low initial poverty levels are included. In the next section, we illustrate the relevance of these analytical results for the empirical assessment of the evidence concerning proportionate poverty convergence.

IV. Bringing the poverty convergence framework to the data

So far, we have analyzed the theoretical predictions of the poverty convergence framework under the assumptions of log-normally distributed incomes, mean income convergence, and inequality convergence. How well does this framework fit actual poverty trends? In this section, we demonstrate that our analytical approximation based on Bourguignon (2003) fits observed poverty data extremely well but that various factors beyond convergence dynamics affect the observed changes of mean income and inequality across countries. We further illustrate how this setting can be used to decompose poverty changes into their contributing factors.

Data

The main dataset we use comes from Ravallion (2012).[12] The consumption and income variables are based on household surveys available from PovcalNet. As is common in the literature, consumption data have been used where available, while about a quarter of the observations rely on income data. To compute changes in poverty headcount ratios, at least two surveys per country are necessary. The median interval between surveys is 13 years (1991–2004) and the sample covers about 90 developing countries between 1977 and 2007 with small variations depending on the availability of control variables. As in Ravallion (2012), we focus on the poverty headcount ratio at \$2.00/day based on 2005 PPPs. The only change we perform in the data set is to delete an erroneous observation for Indonesia.[13] All changes in the data are annualized.

How well does the poverty convergence framework fit the data?

We first see how well the assumption that incomes are log-normally distributed fits the data. In particular, this assumption implies that observed changes in the poverty headcount ratio should be given by equation (5). Using observed growth rates in mean incomes, changes in inequality, and (inverse) development levels ($z/\mu_{i,t}$), we construct 'theoretical predictions' for $\Delta \ln H_{it}$ based on equation (5). We then regress our theoretical predictions on observed changes in poverty. Results are reported in the first column of Table 1 and show that the predictions based on the theoretical growth elasticity of poverty reduction explain almost 80% of the variation in actual proportionate poverty changes across countries. This result supports the approximation of incomes by the log-normal distribution and the applicability of the framework of Bourguignon (2003) to approximate cross-country proportionate poverty dynamics.

In column (2) of Table 1, we use equation (6) to construct our theoretical predictions for $\Delta \ln H_{it}$. That is, we replace actual mean income developments $\Delta \ln \mu_{it}$i in equation (5) by convergence equation (1), estimated from the Ravallion (2012) sample: $\Delta \ln \mu_i = 0.076 - 0.013 \ln \mu_{i,t-1}$ (and set the error terms equal to zero, their assumed conditional expected value).[14] Although mean income convergence is present in the data, it seems to describe overall dynamics in mean income growth and associated poverty poorly: variation in the predictions based on equation (6) explain merely 5.5% of the variation

[12] See Ravallion (2012) for a detailed description of the data set.

[13] The data for the two surveys (\$2005 in 1984 and \$85 in 2005) do not correspond to the data in his three-survey file (\$38.26 for 1984). A mean income level of \$2005 per month in 1984 for Indonesia is implausible and must be due to a coding mistake.

[14] Note that a similar convergence equation could be used to model changes in inequality. We revert to this aspect at the end of section IV but disregard it for the moment to keep the exposition focused.

TABLE 1

Relationships between actual and predicted poverty changes (and levels)

Variables	(1) $\Delta ln(H_{\$2})$	(2) $\Delta ln(H_{\$2})$	(3) $\widehat{\Delta ln(H_{\$2})}$ based on equation (6) ($\beta = -0.013$)	(4) $\widehat{\Delta ln(H_{\$2})}$ based on equation (6) ($\beta = -0.009$)	(5) $\Delta ln(H_{\$2})$
Theoretical prediction of $\Delta \ln(H_{\$2})$	0.824***	0.512			
based on equations (5) [column 1] and (6) [column 2]	(0.117)	(0.362)			
Log initial poverty $\ln(H_{i,t-1})$			−0.00997*	0.0128**	0.00608
			(0.00523)	(0.00498)	(0.0100)
Constant	−0.0125***	−0.0160*	0.0266	−0.0812***	−0.0404
	(0.00351)	(0.00809)	(0.0210)	(0.0199)	(0.0410)
Observations	88	88	88	88	88
R-squared	0.793	0.055	0.107	0.180	0.008

Notes: The dependent variables are log-changes in poverty rates for columns (1), (2) and (5). The explanatory variable in columns (1) and (2) are the predictions of log-changes in poverty rates based on equations (5) and (6), respectively. The dependent variables in columns (3) and (4) are predicted log-changes in poverty rates based on equation (6) with $\beta = -0.013$ (column (3)) and $\beta = -0.009$ (column (4)). OLS estimates with heteroscedasticity robust standard errors in parentheses.
$^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$. Data from Ravallion (2012) excluding the observation for Indonesia.

in actual proportionate poverty changes across countries. In that sense, Ravallion (2012: 504) is certainly correct to state that 'something important is missing from the story' if our aim is to describe actual developments in proportionate poverty rates.[15] Our aim, however, is to illustrate the implications of mean income convergence for proportionate poverty convergence.

If we assume that mean income dynamics are indeed governed by convergence patterns, as we assume for prediction of $\Delta \ln H_{it}$ based on equation (6), what would be the implications for proportionate poverty dynamics? To pursue this issue, we regress our predictions of $\Delta \ln H_{it}$ from equation (6) (setting initial inequality levels equal to the actual values in the sample and assuming $\Delta\sigma = 0$) on the log initial poverty level. Results are reported in column (3) and in the left panel of Figure 3: indeed, under the empirical mean income convergence speed from the Ravallion (2012) sample, our extension of the poverty framework by Bourguignon (2003) suggests proportionate poverty convergence – poor countries grow faster, which translates into faster proportionate changes in poverty headcount ratios. This differs from the pattern in the actual data, where no relationship is found between log initial poverty levels and subsequent proportionate poverty reduction (column 5 in Table 1).

Note, however, that our parameterization of $\beta = -0.013$ is just one point estimate from the particular sample of Ravallion (2012). Neoclassical models do not pin down the

[15]One aspect that needs to be taken into account is the particular characteristics of poverty levels and changes in Central-Eastern-European transition countries, which are discussed more extensively in Crespo Cuaresma *et al.* (2017) and Kuschnig, Zens, and Cuaresma (2021). Another (possibly related) aspect is that the residuals from equation (1) are indeed negatively correlated with initial poverty rates (although the correlation coefficient is only −0.12), the key point stressed by Ravallion (2012). Our paper highlights that such a negative correlation is not necessary for the absence of proportionate poverty convergence despite mean income convergence.

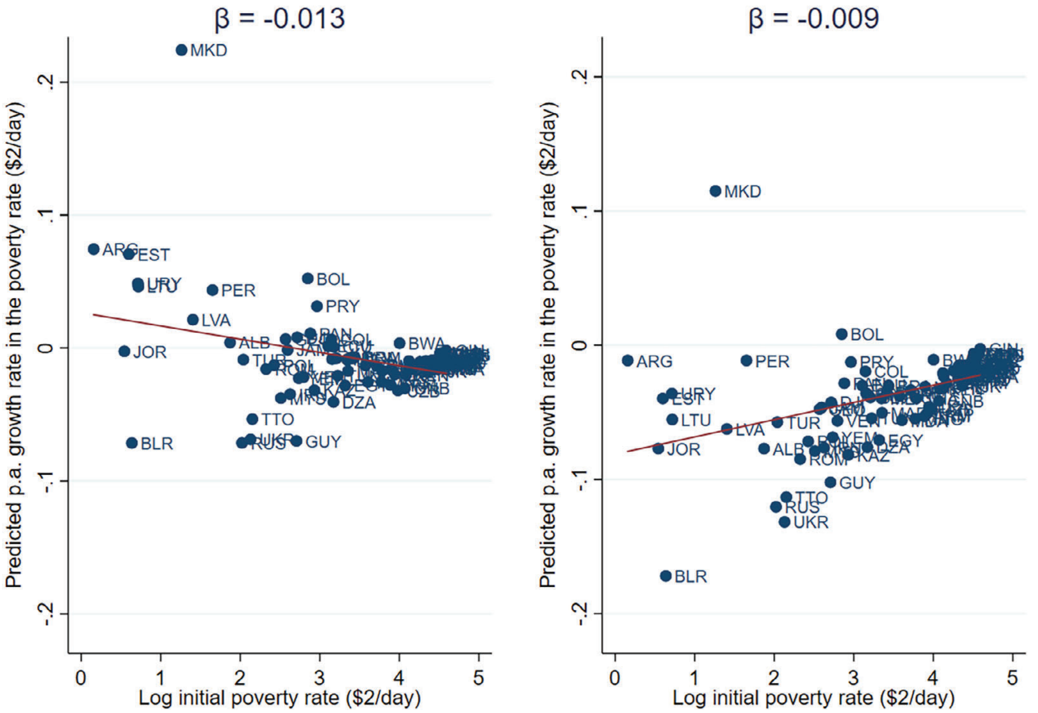

Figure 3. Poverty dynamics simulated based on equation (6)

speed of mean income convergence at a fixed parameter value (see also Patel *et al.*, 2021 for empirical estimates). If one adds one standard error ($\text{SE}(\widehat{\beta}) = 0.004$) to the estimate $\widehat{\beta}$ and hence sets $\beta = -0.009$, one obtains a completely different picture of (statistically significant) proportionate poverty divergence in our sample of countries. This is reported in column 4 of Table 1 and depicted in the right panel of Figure 3.

Figure 3 simulates percent changes in the poverty rate from equation (6) under different values for β and plots them (on the vertical axis) against the actual log initial poverty rate. A negative relationship indicates proportionate poverty convergence.

Using plausible empirical parameter values from the sample of Ravallion (2012) we have hence shown that mean income convergence may, but need not, imply proportionate poverty convergence, which adds empirical plausibility to our simulated results in section III.

Understanding the proximate sources of poverty dynamics

Despite the poor performance of the proportionate poverty convergence framework to predict actual dynamics of poverty headcount ratios (see Table 1, column 2), our analytical extension of the framework facilitates its use as a stylized neoclassical reference model to study the proximate sources of observed poverty dynamics. For example, our discussion above highlighted the susceptibility of proportionate poverty convergence to the speed of mean income convergence. If countries and time periods are characterized by different mean income convergence speeds, as Patel *et al.* (2021) document, it is straightforward

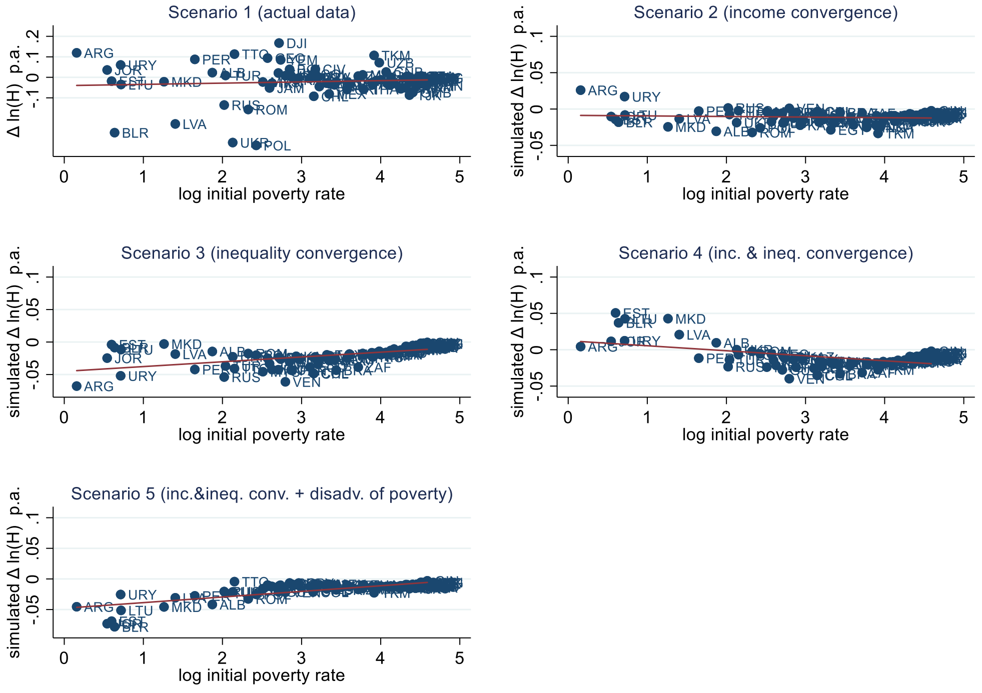

Figure 4. Poverty dynamics simulated based on equation (6)

to analyse the implications for poverty dynamics. For the remainder of this section, we illustrate how different growth and inequality dynamics can be applied to study poverty dynamics in the proportionate poverty convergence framework.

We start with the actual data from Ravallion (2012) that we aim to explain through the lens of the poverty convergence framework. These are plotted in the top left panel of Figure 4. We first obtain the changes in poverty rates that would be implied by equation (6) in the presence of mean income convergence ($\Delta \ln \mu_i = 0.076 - 0.013 \ln \mu_{i,t-1}$) but with no changes in inequality ($\Delta\sigma = 0$). The results are reported in the upper right panel of Figure 4 (Scenario 2, see also Table A1) and show slight proportionate poverty convergence, with a regression slope, which is far from being significantly different from zero.

On the other hand, if mean incomes had not converged across the developing world (and had instead grown at the average sample growth rate of 1.5% p.a.) and inequality had converged following the estimated dynamics given by $\Delta \ln \sigma_i = 0.03 - 0.04 \ln \sigma_{i,t-1}$, proportionate poverty would have significantly diverged (Scenario 3; middle left panel of Figure 4). Although initial inequality and poverty levels are positively correlated, the impetus of inequality convergence at that rate seems too slow for poorer countries to make up for their lower growth elasticity of poverty reduction, resulting in proportionate divergence.[16] Mean income and inequality convergence combined, however, result in

[16] In spite of the positive correlation between initial inequality and poverty, several countries with high initial poverty headcount ratios have low levels of inequality. Inequality convergence dynamics lead to an increase in inequality and thus the poverty headcount ratio in these economies, which also works against poverty convergence.

clear proportionate poverty convergence, as depicted in the middle right panel of Figure 4 (Scenario 4).

Figure 4 simulates percent changes in the poverty rate from equation (6) under different values for β and plots them (on the vertical axis) against the actual log initial poverty rate. A negative relationship indicates proportionate poverty convergence.

How can we reconcile the finding of empirical mean income and inequality convergence with proportionate poverty divergence? As highlighted by Ravallion (2012), the missing link is the negative association between initial poverty and subsequent growth. For Scenario 5, we model mean income growth as $\Delta \ln \mu_i = 0.216 - 0.033 \ln \mu_{i,t-1} - 0.016 \ln H_{i,t-1}$, which corresponds to the empirical estimates from the sample. In this case, we observe proportionate poverty divergence at a similar rate as in the actual Ravallion (2012) sample, as depicted in the last panel of Figure 4 (and column 5 of Table A1).

In other words, under the empirically observed mean income and inequality convergence speed in the Ravallion (2012) sample, proportionate poverty divergence requires the negative correlation of initial poverty with growth that Ravallion (2012) stresses. However, we have also shown that this is by no means a necessity: one can observe proportionate poverty divergence with reasonable mean income and inequality convergence speeds and with no detrimental effect of initial poverty for growth. Previous empirical findings in Crespo Cuaresma *et al.* (2017) and Ouyang *et al.* (2019) have further highlighted that the peculiarities of the Ravallion (2012) sample are not necessarily characteristic of the developing world.

A final observation from Figure 4 is that all simulated scenarios 2–5 provide a rather poor fit for the actual proportionate changes in the poverty rate (see Table A2 and Figure A1). Our result in column 1 of Table 1 suggests that this is not driven by a deviation from the log-normality assumption in the framework of Bourguignon (2003). Rather, various factors beyond convergence dynamics are present in the observed changes of mean income and inequality across countries.[17] The extension of the proportionate poverty convergence framework presented here can nevertheless be a useful reference point to study those deviations and how they impact poverty dynamics, as furthered in Hartmann and Wacker (2020).

V. Conclusion

In this article, we show analytically that the existence of proportionate poverty convergence in cross-country data depends on the speed of mean income convergence relative to other parameters, including the mean income level, income inequality, and its change over time. From that angle, there is nothing surprising in the results of Ravallion (2012) that poverty rates have not converged across countries (in a proportional sense) over the last decades, despite reasonable mean income convergence.

Our analysis casts doubt on the results of linear, reduced-form regression analysis of proportionate poverty convergence. Our results rather highlight the importance of

[17]The R-squared statistics for the mean income and inequality convergence regressions are 0.07 and 0.35, respectively.

simultaneously analysing the systematic interactions between mean income convergence, inequality convergence, and the relation between poverty, inequality, and growth. Some studies have investigated specific aspects of this link (see Herzer and Vollmer, 2011; Brueckner, Norris, and Gradstein, 2015; Berg *et al.*, 2018; Brueckner and Ledermann, 2018; Gründler and Scheuermeyer, 2018, and Scholl and Klasen, 2018, on inequality and growth; Ravallion, 2003, and Lin and Huang, 2011, for inequality convergence, and the extensive literature on income convergence), but their simultaneous interactions and implications for poverty dynamics have not been studied systematically yet. A rigorous quantitative assessment of the structural linkages among poverty, inequality, and growth appears particularly important for poverty projections towards the Sustainable Development Goal of ending poverty by 2030. We have illustrated how sequential analyses of mean income and inequality convergence, their interaction and relationship with initial conditions can provide a useful reference framework to study poverty dynamics.

Appendix A

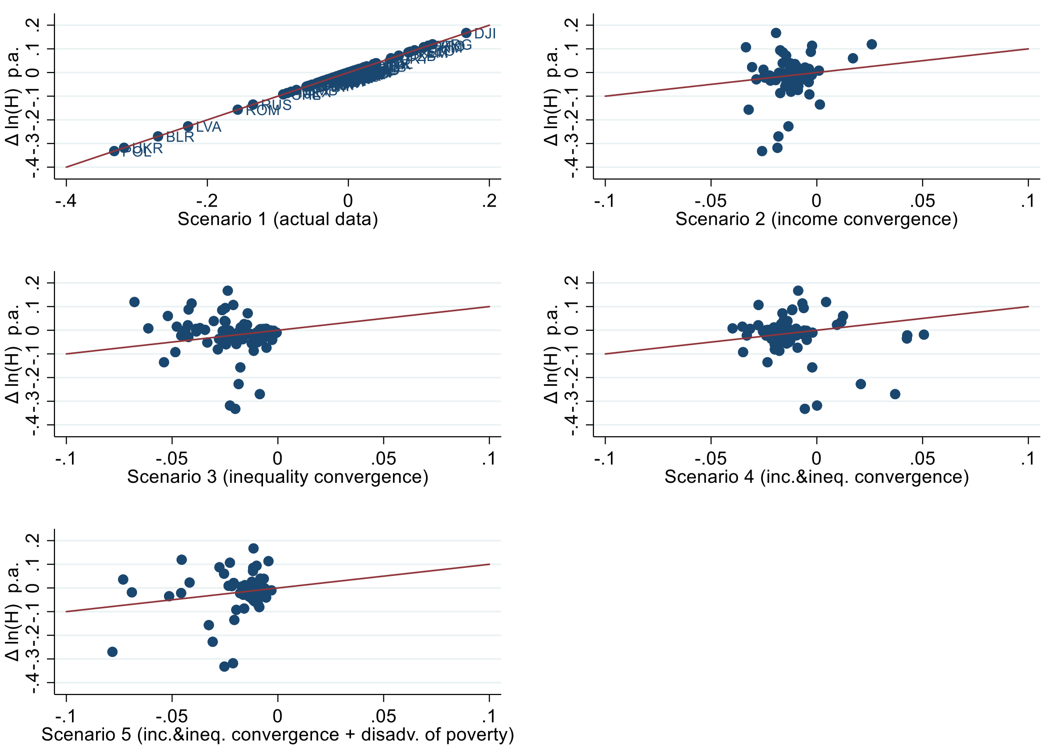

Figure A1. Actual versus predicted proportionate changes in the poverty rate

TABLE A1

Poverty convergence regressions for different scenarios

	(1)	(2)	(3)	(4)	(5)
	Scenario 1	*Scenario 2*	*Scenario 3*	*Scenario 4*	*Scenario 5*
Variables	*Predicted $\Delta ln(\mathrm{H}_{\$2})$*				
Log initial poverty $\ln(H_{i,t-1})$	0.00608	−0.000806	0.00739***	−0.00689***	0.00919***
	(0.0100)	(0.00132)	(0.00183)	(0.00183)	(0.00147)
Constant	−0.0404	−0.00863*	−0.0451***	0.0124*	−0.0479***
	(0.0410)	(0.00511)	(0.00721)	(0.00714)	(0.00577)
Observations	88	88	88	88	88
R-squared	0.008	0.011	0.314	0.266	0.583

Notes: The dependent variables are predicted log-changes in poverty rates for the different scenarios described in the text. Scenario 1 uses the actual data for log-changes in poverty. Scenario 2 assumes mean income convergence but no change in income inequality. Scenario 3 assumes no convergence in income but convergence in income inequality. Scenario 4 assumes mean income and income inequality convergence. Scenario 5 assumes the effects of initial poverty on mean income growth, coupled with mean income and income inequality convergence. OLS estimates with heteroscedasticity robust standard errors in parentheses.
***$P < 0.01$,
**$P < 0.05$,
*$P < 0.1$.

TABLE A2

Fit of different scenarios

	(1)	(2)	(3)	(4)	(5)
	Scenario 1	*Scenario 2*	*Scenario 3*	*Scenario 4*	*Scenario 5*
Variables	$\Delta ln(\mathrm{H}_{\$2})$	$\Delta ln(\mathrm{H}_{\$2})$	$\Delta ln(\mathrm{H}_{\$2})$	$\Delta ln(\mathrm{H}_{\$2})$	$\Delta ln(\mathrm{H}_{\$2})$
Predicted $\Delta\ln(H_{\$2})$ based on respective scenario	1	2.126*	−0.743	−0.917	1.153
	(0)	(1.163)	(0.454)	(0.677)	(0.915)
Constant	0	0.00446	−0.0346***	−0.0298**	−0.000562
	(0)	(0.0108)	(0.0106)	(0.0136)	(0.0129)
Observations	88	88	88	88	88
R-squared	1.000	0.059	0.022	0.034	0.044

Notes: The dependent variable is actual log-changes in poverty rates; the explanatory variable is a prediction of log-changes in poverty rates based on different scenarios. Scenario 1 uses the actual data for log-changes in poverty. Scenario 2 assumes mean income convergence but no change in income inequality. Scenario 3 assumes no convergence in income but convergence in income inequality. Scenario 4 assumes mean income and income inequality convergence. Scenario 5 assumes the effects of initial poverty on mean income growth, coupled with mean income and income inequality convergence. OLS estimates with heteroscedasticity robust standard errors in parentheses.
***$P < 0.01$,
**$P < 0.05$,
*$P < 0.1$.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Online Appendix S1