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Is there poverty convergence?

Jesús Crespo Cuaresma, Stephan Klasen

and Konstantin M. Wacker

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Johannes Gutenberg University Mainz
Gutenberg School of Management and Economics
Jakob-Welder-Weg 9
55128 Mainz
Germany
wiwi.uni-mainz.de

Contact Details:

Jesús Crespo Cuaresma
Vienna University of Economics and Business
Wittgenstein Centre for Demography and Human Capital
International Institute for Applied Systems Analysis
Austrian Institute of Economic Research

jcrespo@wu.ac.at

Stephan Klasen
University of Göttingen
Department of Economics
Platz der Göttinger Sieben 3
37073 Göttingen Germany

sklasen@uni-goettingen.de

Konstantin M. Wacker
Johannes Gutenberg University of Mainz
Department Law and Economics
Jakob-Welder-Weg 4
55128 Mainz, Deutschland

kwacker@uni-mainz.de

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Jesús Crespo Cuaresma,
Vienna University of Economics and Business,
Wittgenstein Centre for Demography and Human Capital,
International Institute for Applied Systems Analysis,
Austrian Institute of Economic Research
jcrespo@wu.ac.at

Stephan Klasen,
University of Göttingen
sklasen@uni-goettingen.de

Konstantin M. Wacker,
University of Mainz
kwacker@uni-mainz.de

Abstract

Martin Ravallion ("Why Don't We See Poverty Convergence?" *American Economic Review*, 102(1): 504-23; 2012) presents evidence against the existence of proportionate convergence in global poverty rates despite convergence in household mean income levels and the link between income growth and poverty reduction. We show that heterogeneity in this link affects the evidence of poverty convergence and that this result depends on the sample selected, especially on the inclusion of transition economies with poorly measured low poverty incidences. Motivating the poverty convergence equation with an arguably superior semi-elasticity specification, we find robust evidence of convergence in absolute poverty rates.

Keywords: poverty convergence, income inequality, economic growth, poverty trap, transition economies

JEL Classifications: I32, D31, P36

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1. Introduction

In a recent contribution, Martin Ravallion (2012) raises the question of why countries starting out with a high incidence of poverty do not enjoy a higher proportionate rate of poverty reduction. The argument is that one would expect such "poverty converge" to the extent that higher mean household income tends to lower poverty ("*advantages of growth*") and mean household incomes tend to converge across countries ("*advantages of backwardness*").[1] Using a sample of household income data that covers about 90 developing countries between 1977 and 2007[2] and focusing on the conventional poverty headcount ratio at $2/day, Ravallion (2012) finds evidence that both of these individual channels are at work, but that we do not observe proportionate convergence in poverty rates. This seemingly puzzling finding is explained by pointing to the adverse economic effect of poverty on economic growth, so that a high initial poverty rate makes it harder to reduce poverty through growth in mean household income.

In the context of this discussion, we take a closer look at Ravallion's (2012) concept of (proportionate) "poverty convergence", defined as a higher percent reduction of poverty rates in countries starting out with a higher poverty incidence. Based on the seminal work of Bourguignon (2003) on the growth elasticity of poverty reduction, we show that income convergence and the "advantages of growth" for poverty reduction are not sufficient for expecting poverty convergence in the sense of Ravallion (2012). In fact, we show that the growth elasticity of poverty reduction

[1] For the group of countries studied, Ravallion (2012) finds evidence for unconditional as well as conditional cross-country household income convergence, i.e. without and with control variables, with conditional convergence being quantitatively more rapid. He 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 unless the specific dynamics in Eastern European transition economies are controlled for. Results are available upon request.

[2] The poverty and income dataset is obtained from survey data available at *povcal.net*. It has a median interval between surveys of 13 years. About three quarters of household surveys use consumption instead of income data, as is common in the literature. See Ravallion (2012) for more details.

is smaller for more unequal countries and countries that are poorer. This implies that poor countries with high (or rising) income inequality experience less of a (proportionate) decline in poverty during an episode of growth. Thus, the difficulty of poorer countries to converge in poverty rates is analytically related to their lower growth elasticity of poverty reduction. In an empirical specification based on proportionate changes, it can therefore easily happen that one fails to see poverty convergence if the sample includes countries with heterogeneous inequality levels and dynamics, especially when income convergence speed is low. We also show that empirical estimates of the growth elasticity of poverty reduction are heavily influenced by observations with very low poverty incidences where any changes in poverty are very large in proportionate terms. At the same time, such low poverty incidences tend to be poorly measured, so that there is greater uncertainty about these potentially influential observations. Empirically we then show that it is indeed sufficient to control for the specific dynamics of Central Eastern European (CEE) economies, which started at low poverty rates and hence enjoyed high percent reductions in poverty rates after the initial transition collapse, to observe poverty convergence even in the demanding sense of Ravallion (2012).

Given the susceptibility of proportionate rates of poverty reduction to measurement error at low initial poverty rates, we suggest to base the analysis on a growth semi-elasticity of poverty reduction, as proposed by Klasen and Misselhorn (2008). We review the relevant arguments in favor of such an approach, which leaves us with a concept of (absolute) "poverty convergence," i.e. a convergence specification based on untransformed poverty headcount rates (or, alternatively, poverty gaps) across countries. We think such a setting is superior from a policy, welfare, and technical perspective and more intuitive to most observers of the term "poverty convergence." Using an empirical model based on this alternative concept, we find a very robust pattern of poverty convergence in the sample of countries used by Ravallion (2012).

Despite our finding of clear and robust poverty convergence, the pace of poverty convergence appears too slow to predict rapid poverty reduction in poor countries. In this context, our econometric findings show that the observed dynamics of poverty convergence do not appear sufficient to reach the international target of eliminating poverty by 2030, unless one assumes over-optimistic growth assumptions. This highlights the importance of measures aimed at reducing inequality to achieve this goal. Our study is hence also related to the wider literature on the link between key macroeconomic developments (of income and its distribution) and poverty reduction, such as Dollar and Kraay (2002), Bourguignon (2003, 2004), Foster and Székely (2008), Ferreira et al. (2010), Loayza and Raddatz (2010), Ravallion (2013), Dollar et al. (2016), and Bluhm et al. (2016).

The remainder of our paper is organized as follows: in section 2 we review the concept of (proportionate) "poverty convergence" as proposed by Ravallion (2012) and highlight why conventional neoclassical theory does not necessarily imply poverty convergence in that sense. Section 3 takes our conceptual considerations to the data. In section 4, we make a theoretical and empirical case for our alternative concept of (absolute) poverty convergence. Section 5 investigates what both concepts imply for global poverty dynamics and for the discussion of the issue going forward, highlighting the role of income distribution. Section 6 concludes.

2. Revisiting proportionate poverty convergence

Ravallion (2012) motivates the concept of proportionate poverty convergence by the neoclassical argument of convergence of average income (or consumption) levels μ_{it} at time *t* across countries, indexed by *i*, that is, $\beta_i < 0$ in:

$$\Delta \ln \mu_{it} = \alpha_i + \beta_i \ln \mu_{i,t-1} + \varepsilon_{it}, \quad (1)$$

and the "advantage of growth" for poverty reduction, that is, $\eta_i < 0$ in

$$\Delta \ln H_{it} = \delta_i + \eta_i \Delta \ln \mu_{it} + \nu_{it}, \qquad (2)$$

where H_{it} is the (absolute) poverty rate and ε_{it} and ν_{it} are disturbance terms. Ravallion (2012) shows that both of these relationships, income convergence and advantages of growth, are present in the sample of countries used, from which we would assume that $\beta_i^* < 0$ holds in

$$\Delta \ln H_{it} = \alpha_i^* + \beta_i^* \ln H_{i,t-1} + \varepsilon_{it}^*, \quad (3)$$

a concept he refers to as "poverty convergence". Ravallion (2012) however fails to find a significant negative estimate of β_i^* in the data, despite mean income convergence ($\beta_i < 0$) and evidence for the advantages of growth ($\eta_i < 0$).

At this point, it is important to stress that the absence of poverty convergence in the sense put forward above does not mean that poverty rates across countries would not converge in a conventional sense (a fact also mentioned in Ravallion, 2012), i.e. that a country with a higher poverty incidence would experience higher absolute (percentage point) reductions in poverty than a country with low poverty incidence. Rather, $\beta_i^* < 0$ in equation (3) demands that, for example, a country starting out with a poverty level of 60 percent should be more likely to reduce poverty to 30 percent in the same time as another country reduces poverty from 10 to 5 percent, since both are 50 percent reductions in the headcount ratio. While such a demanding concept appears neither very intuitive nor particularly appealing, there are at least two good reasons for using it. One reason is the evident analogy to the macro literature on income convergence, where econometric specifications relate growth rates of income per capita to the log of initial income. The other reason is the fact that equation (3) follows straight from two concepts that are well-established in the literature: the mentioned income convergence (1) and what is usually referred to as the "growth elasticity of poverty reduction" (Bourguignon, 2003) in equation (2), which shows the percentage change in the headcount poverty rate as a function of the growth rate in average income. However, this approach also has several shortcomings.

The first shortcoming of the proportionate approach to poverty convergence has to do with its welfare implication, as large changes in the dependent variable of equation (3), $\Delta\ln H_{it}$, will not imply an equally large change in welfare over the range of $H_{i,t-1}$ as the above example of a 50 percent reduction in the headcount rate for two countries with different initial poverty levels easily highlights.[3] For a given population, one would usually like to give equal welfare weight to each percentage point of poverty reduction, no matter if we start at an initial poverty rate of 60 or 10 percent,[4] which would call for a dependent variable such as the change in the (untransformed) headcount ratio, ΔH_{it}.

Second, and most importantly, previous research on the "growth elasticity of poverty reduction" (Bourguignon, 2003), which is captured by the parameter η_i in equation (2), has highlighted that the relationship between percent changes in the headcount poverty rate and the growth rate in average income is highly heterogeneous across countries. In fact, it is linked by a (non-linear) analytical identity. Assuming log-normally distributed incomes,[5] this elasticity is given by

$$\varepsilon := \frac{\Delta H_{it}}{\Delta\ln(\mu_{it})H_{i,t-1}} = \frac{1}{\sigma}\lambda\left[\frac{\ln(z/\mu_{i,t-1})}{\sigma} + \frac{1}{2}\sigma\right], \qquad (4)$$

where z is some poverty line (such as \$2/day) in relation to mean income μ, σ is the standard deviation of log income, a measure for relative income inequality, and $\lambda(\cdot)$

[3] Note that this reverses the implicit welfare concept of the macro literature on income convergence, where the logarithm scales down income growth at high income levels, which would be in line with the neoclassical concept of decreasing marginal utility of income.
[4] If anything, the welfare gain of an individual moving out of poverty should even be larger at high poverty rates if poverty has negative external effects, as Ravallion (2012) suggests.
[5] Whether or not incomes are indeed log-normally distributed is beyond the topic of this paper and is unlikely to substantially influence the key insight of our main point about the non-linearity and the opposing effects of inequality and initial income in the proportionate poverty convergence framework. Results in section 3 and by Bourguignon (2003) suggest it is at least a meaningful approximation.

is the hazard rate of the standard normal distribution (i.e. the ratio of its density to the cumulative function). Equation (4) is helpful beyond highlighting that the log-linearity assumed in equation (2) is worrisome, as it highlights that the proportionate poverty reduction a country achieves with a given growth rate of mean income necessarily increases with the development level $\mu_{i,t}/z$ (i.e. a lower initial level of poverty) and decreases with income inequality, σ. The opposing effects of initial income and inequality for poverty convergence become especially apparent if one substitutes $\Delta \ln \mu_{it}$ from equation (1) into equation (4) and re-arranges to obtain

$$\Delta \ln H_{it} \approx \frac{\Delta H_{it}}{H_{i,t-1}} = \frac{1}{\sigma}\lambda\left[\frac{\ln(z/\mu_{i,t-1})}{\sigma} + \frac{1}{2}\sigma\right](\alpha_i + \beta_i \ln \mu_{i,t-1}). \qquad (5)$$

Equation (5) highlights the essential analytical point of our paper: the positive effect of income convergence on proportionate poverty reduction under $\beta_i < 0$ is moderated by the fact that lower-income economies experience a lower growth elasticity of poverty reduction stemming from the first term, $\ln(z/\mu_{i,t-1})$ in the hazard function. The total poverty convergence effect will then depend on the (absolute) size of β_i, the (inverse) development level $z/\mu_{i,t}$, and the level (and change) of income inequality σ. In a poor country with high (and rising) inequality, income convergence may then lead to a pace of poverty reduction that is lower than in a less poor (but more equal) country that might grow slower (in view of income convergence) but gets a higher elasticity of poverty reduction out of this growth rate. Thus, we might fail to see proportionate poverty convergence. Note that this has, so far, nothing to do with possible detrimental socio-economic effects of poverty on growth but at this point is a simple analytical identity, highlighting that the absence of proportionate poverty convergence is not at odds with standard neoclassical concepts of income convergence and average advantages of growth for poverty reduction. Rather, whether or not we see poverty convergence is an empirical question depending on the parameters β_i, $z/\mu_{i,t}$, and levels (and changes) of σ for the investigated sample, thus also highlighting the importance of the characteristics of the sample being investigated.[6]

Figure 1 illustrates our point graphically. Here, we assume that countries at each (inverse) initial development level $z/\mu_{i,t-1}$ converge in mean incomes μ at the speed implied by the sample of Ravallion (2012). We then calculate (based on the analytical results in Bourguignon, 2003) the corresponding proportionate reduction in poverty headcount rates, $\Delta\ln H_{it}$, they would achieve from the resulting growth rate, depending on their initial income inequality (and assuming no distributional changes). Moving along the three curves from left to right (that is, increasingly towards poorer countries) for a given inequality level σ thus captures the tradeoff entailed in our equation (5): increasing mean income growth (due to convergence) but a decreasing growth elasticity of poverty reduction. As Figure 1 illustrates, if all countries had a given inequality level, we would not see proportionate poverty convergence. This reflects that the empirical mean income convergence effect is too low and outweighed by the growth elasticity of poverty reduction that increases with the development level. We would hence observe proportionate poverty divergence.[7] This would be the case, for example, if the sample only consisted of Mauritania and Tunisia, which both started out at an initial inequality level close to σ=0.8 (and assuming no distributional changes). Another finding would occur if the sample consisted of Brazil, Tunisia, and Egypt, for example. Since among those countries, initial poverty and inequality are inversely related, poorer countries would still enjoy a relatively high growth elasticity of poverty reduction, which—together with mean income convergence—would lead to proportionate poverty convergence. In the absence of any systematic relationship between (inverse) development level $z/\mu_{i,t}$ and inequality σ, however, whether we see proportionate

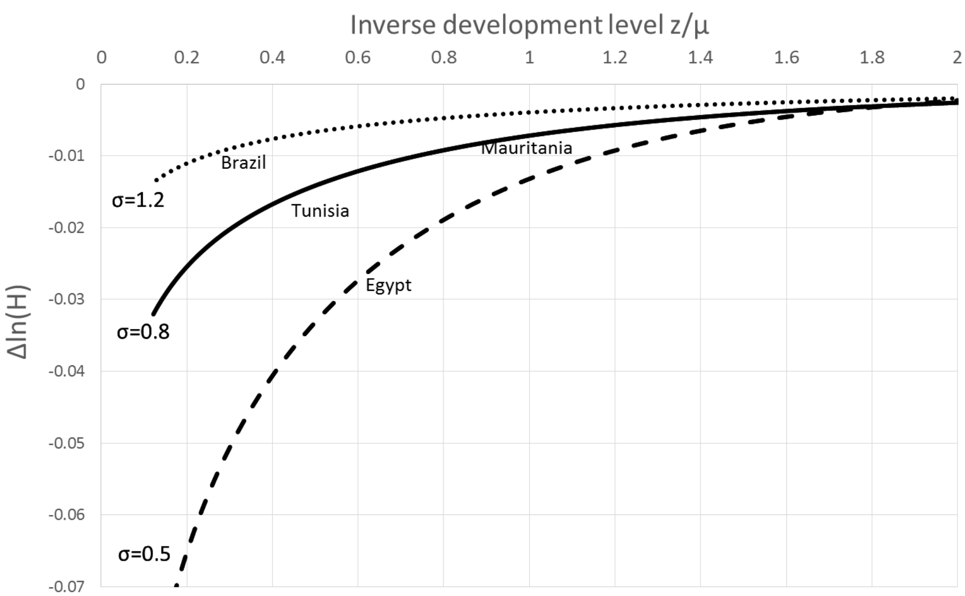
[6] This problem is exacerbated if convergence speeds differ by initial income level, e.g. in the case of club convergence (see Quah, 1997, or Canova, 2004, for example). We demonstrate the susceptibility of the Ravallion (2012) result to sample selection in section 3.

[7] This raises the question at which mean income convergence speed we would observe proportionate poverty convergence for a given inequality level. An example is given in Figure B.4 in Appendix B.2, showing that even quite fast income convergence only implies proportionate poverty convergence for some part of the sample distribution.

poverty convergence or not will simply depend on the chosen sample.

A third shortcoming of the proportionate approach to poverty convergence is the little policy relevance of proportionate changes in the poverty headcount rate, as opposed to absolute percentage point changes. Policy-makers tend to care about percentage point changes in poverty, not the percent reductions (Klasen and Misselhorn, 2008).

Figure 1: Dependence of proportionate poverty convergence on distribution



Note: Figure 1 shows proportionate changes in poverty headcount rates, ΔlnH, in dependence of (inverse) initial development level z/μ_{t-1}, assuming that mean incomes μ converge with $\Delta \ln \mu_{it} = 1.08 - 0.014 \ln \mu_{i,t-1}$, the speed in the sample of Ravallion (2012). The effect is shown for different inequality levels, where σ is the standard deviation of the log-normal distribution.

Finally, inference based on proportional changes in the poverty headcount rate is highly sensitive to low initial poverty incidences, where percent changes are particularly large and influential for the regression results. This can lead to potentially large biases in empirical estimates of the poverty convergence speed, as measurement error may be an important problem when low initial poverty incidence observations are present in the data.[8]

In short, the heterogeneity of the growth elasticity of poverty reduction, combined with the high sensitivity to poorly measured low poverty incidences, can easily lead to the finding of no proportionate poverty convergence, purely for mathematical and statistical reasons, and unrelated to any substantive issue related to poverty reduction in poor countries.

3. What do the data really say?

In this section, we revisit the data set presented by Ravallion (2012) in the context of our analytical considerations presented above.[9] We start with the baseline case of an unconditional proportionate poverty convergence regression, as presented by Ravallion (2012), in the first column of Table 1. As one can see, no proportionate poverty convergence appears to be present in the data, which instead delivers a positive and statistically insignificant estimate of β^* . Variation in the initial poverty levels are also not able to explain much variation in proportionate poverty changes, as indicated by the low R-squared.

[8] Even rounding issues introduce substantial measurement error at low levels of poverty incidence. For example, if poverty incidence fell from 4.4 to 1.6%, this is a decline of 64%. If rounded to 4 and 2% it is a decline of 50%. Similar rounding errors are much smaller at higher levels of poverty incidence. When using percentage point changes, such rounding errors introduce the same bias at all levels of poverty. Note that Bourguignon (2003) dropped all observations from low poverty incidence countries (mostly transition countries) for that reason in his empirical analysis of the drivers of the growth elasticity of poverty reduction.

[9] Ravallion (2012) offers a detailed description of the data set. The only change we perform in the data set is deleting the erroneous observation for Indonesia. 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) and an income level of $2005 per month in 1984 for Indonesia is simply implausible and can only be considered a mistake.

Table 1: Proportionate poverty convergence results

	(1)	(2)	(3)
Depentent variable:	$\Delta\ln(H_{\$2})$	$\Delta\ln(H_{\$2})$	$\Delta\ln(H_{\$2})$
Log initial poverty	0.00608		0.00282
$ln(H_{i,t-1})$	(0.0100)		(0.00430)
Theoretical prediction of $\Delta\ln(H_{\$2})$		0.824***	0.822***
based on Bourguignon (2003: 2')		(0.117)	(0.118)
Constant	-0.0404	-0.0125***	-0.0222
	(0.0410)	(0.00351)	(0.0172)
Observations	88	88	88
R-squared	0.008	0.793	0.795

Notes: OLS results with heteroscedasticity robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data from Ravallion (2012) with the Indonesia observation deleted.

Following our argument from the previous section, observed growth rates in income per capita, changes in inequality and development levels ($\mu_{i,t}/z$) should be able to explain the proportionate poverty changes, in line with Bourguignon (2003). We thus construct "theoretical predictions" for $\Delta\ln H_{it}$ based on (a variant of) equation (4)[10] and use these to predict the actual poverty changes. As the second column in Table 1 demonstrates, variation in these expected proportional changes in poverty based on the theoretical growth elasticity of poverty reduction explains almost 80 percent of the actual proportionate poverty changes, highlighting that under the framework of Bourguignon (2003) there is not much in the cross-country variation of poverty data that would appear particularly puzzling. The failure to find poverty convergence in the specification presented in column 1 of Table 1 thus appears to be due to the reasons stated above and related to the heterogeneity of the growth elasticity of poverty reduction.

[10] See equation (2') in Bourguignon (2003).

If Ravallion's (2012) argument on the causal effect of poverty levels on poverty reduction through growth beyond a mere arithmetic identity holds and hence high levels of poverty prevent poverty convergence, the initial poverty headcount would have an additional effect on subsequent proportionate changes in poverty conditional on the theoretical predictions. As one can see in the third column of Table 1, the insignificant parameter for initial poverty in this specification indicates that this is not the case.[11]

Finally, equation (5) raises questions on the robustness of the results of Ravallion (2012) to the composition of the particular sample of countries employed, as it highlights that proportionate poverty convergence depends on the realized levels of income inequality relative to the income convergence speed. This argument is particularly pervasive in the presence of a sample of countries with low initial poverty rates as any subsequent *absolute* (percentage point) changes in the headcount rate will translate into large *proportionate* (percent) changes that might drive the results. As argued above, these large proportionate changes in poverty are prone to be poorly measured (even due to simple rounding issues). In the sample data, this notably concerns Central and Eastern European (CEE) transition economies.[12] Contrary to most other developing countries in the sample, these economies already started out at high development levels with low poverty incidences in the period studied by Ravallion (2012). This is visible on the horizontal axis of Figure 2, which essentially is a reproduction of Figure 1 in Ravallion (2012), where CEE observations are far off the sample mean,[13] thus also

[11] Our analytical representation in equation (5) also allows us to assess by how much mean income convergence has to speed up in order to see proportionate poverty convergence (assuming log-normality of income and no changes in distribution). This exercise is described in more detail in Appendix B.1. A reduction in the income half-life from currently 50 years to 3 years would be needed given the observed parameters in the sample. This would imply an enormous acceleration in the convergence speed of mean income as compared to historical estimates.

[12] The 11 Central and Eastern European countries in the sample, with their corresponding time spans, are Poland (1996-2005), Ukraine (1996-2005), Belarus (2000-2005), Latvia (1998-2004), Romania (1998-2005), Russia (1993-2005), Albania (1996/97-2005), Estonia (1995-2004), Lithuania (1996-2004), Moldavia (1997-2004), and Macedonia (1998-2003).

[13] The mean initial poverty headcount in the CEE subsample is 5.6%, compared to 30.6% in the

implying that they get a high leverage in the corresponding least-squares regression (see also Figure B.1 in Appendix B.2). Together with the fact that their proportionate poverty dynamics as the dependent variable constitute outliers as their low initial levels translated into high percent changes, those countries drive the main results in Ravallion (2012). Once one controls for their specific development experience which, in the words of Ravallion (2012: 509) "is clearly not typical of the developing world", we observe proportionate poverty convergence. [14] This result is shown in Table 2 (and by the dashed line in Figure 2). In addition, Table B.2 in Appendix B.2 demonstrates that proportionate poverty convergence once one controls for CEE dynamics is robust to adding further control variables to the model and to using different measures of poverty. Thus our second argument, the sensitivity to poorly measured low poverty incidence countries as a second reason for failing to find poverty convergence is also confirmed by the data.

overall sample of Ravallion (2012).

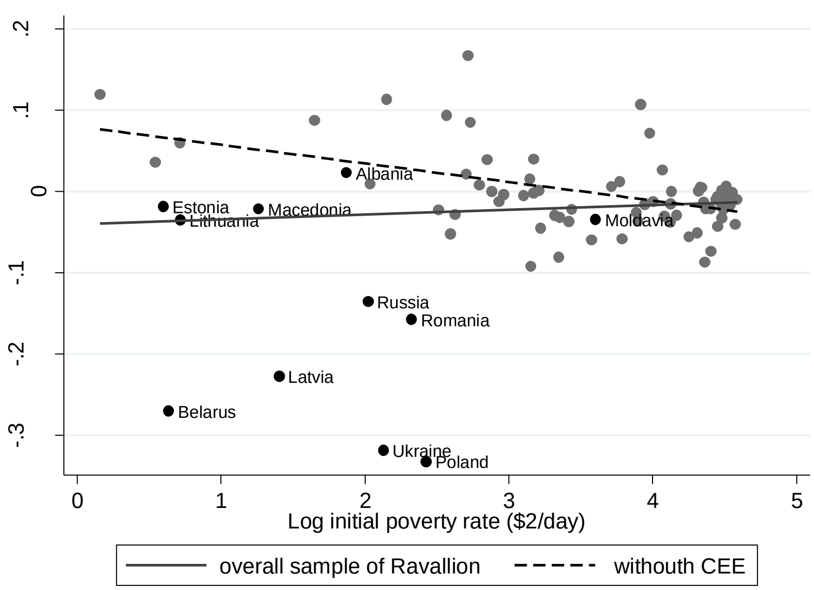
[14] In particular, it is sufficient to take out the observations of Poland, Ukraine, Belarus, and Latvia, which are the most outlying points, to obtain poverty convergence at the 5 percent level of statistical significance. Excluding Romania and Russia in addition leads to poverty convergence at the 1 percent significance level (results not reported but available on request). Furthermore, it is worth mentioning that there are no significantly different convergence dynamics within the CEE group, as indicated by a statistically insignificant CEE-specific convergence parameter (results not reported but available on request).

Table 2: Sensitivity of proportionate poverty convergence to transition economies

	(1)	(2)
Dependent variable:	$\Delta\ln(H_{\$2})$	$\Delta\ln(H_{\$2})$
Note:	w/o CEE	w/ CEE dummy
Log initial poverty	-0.0227***	-0.0218***
$ln(H_{i,t-1})$	(0.00465)	(0.00635)
CEE dummy		-0.178***
		(0.0421)
Constant	0.0800***	0.0768***
	(0.0196)	(0.0250)
Observations	77	88
R-squared	0.227	0.420

Notes: OLS results with heteroscedasticity robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data from Ravallion (2012) with the Indonesia observation deleted.

Figure 2: Proportionate poverty convergence



Data source: Ravallion (2012), including Indonesia observation.

A detailed analysis of CEE poverty dynamics is beyond the scope of this paper.[15] What is more relevant in our context is the question why there is proportionate poverty convergence outside of CEE countries in the first place, despite the demanding convergence concept of Ravallion (2012) and the large heterogeneity of the growth elasticity of poverty reduction. [16] This appears to be driven mainly by two different factors. First, mean income convergence in this sample has been remarkably quick by historical standards,[17] adding favorably to the last term in equation (5). Second, inequality convergence has taken place in the developing world and in the data set (see Figure B.2 and table B.3 in Appendix B.2 and Ravallion, 2003). This implies that considering two countries with the same development level and the same rate of mean income growth, the country starting out at higher initial poverty levels (due to higher inequality) will reduce poverty faster due to the higher reduction in inequality, an effect that is captured in the first

[15] The two most promising channels to explain the specific CEE dynamics appear to be cyclical reversion effects for the mean income growth rate and unique distributional effects that influence the growth elasticity of poverty reduction. First, prior to the sample period, CEE transition economies suffered severe shocks to their output level. Most neoclassical convergence models suggest that such countries, which are far off their steady state, should see higher subsequent growth ('cyclical reversion'). Indeed, CEE countries saw significantly higher mean income growth rates than implied by a simple mean income convergence regression (results are available upon request). Second, inequality levels increased substantially during the initial output collapse in transition economies, with a positive relationship between the size of the output collapse and the increase in inequality (see Ivashenko, 2003; Grün and Klasen, 2001). In subsequent years (which are those included in the sample) there was some decline of inequality in countries like Russia, Ukraine, and Belarus, moderating the massive inequality shock experienced earlier. As a result, the unconditional poverty elasticity of growth was larger in those countries, due to this decline in inequality. On the issue, also see Milanovic (1996).

[16] It seems worth noticing in this context that dropping the 5 or 10 percent of Ravallion's (2012) sample that had the lowest initial poverty incidence, as is usual in many empirical assessments of the growth elasticity, does not lead to observing proportionate poverty convergence in the sense of equation (3). This suggests that the absence of proportionate poverty convergence cannot exclusively be explained by the susceptibility of the growth elasticity of poverty reduction at low initial rates.

[17] Using the national account consumption data from Penn World Tables (PWT) 6.2, Ravallion (2012: table 1) finds an unconditional convergence coefficient of -0.007*. Using the PWT9.0 we find an insignificant parameter of -0.004 when not controlling for transition economies and -0.01** when controlling for them. Looking at the PWT9.0 consumption data by decade since 1970 for 'developing countries' (defined as countries below the median consumption per capita in 2010), we find that the only decade of statistically significant convergence were the 1990s, which largely overlap with the Ravallion (2012) sample (median first survey year: 1991, median end survey year: 2004). Considering all countries, there are broader convergence trends, but again the strongest patterns are found for the 1980s and 1990s. Results are available upon request.

term of equation (5).

Summing up our results thus far, there appears to be nothing puzzling in the absence of proportionate poverty convergence in the developing world in the sense of Ravallion (2012) and conventional theoretical settings explain the observed dynamics quite well. They further suggest that whether we observe proportionate poverty convergence depends on the importance of levels and trends of income inequality relative to mean income convergence and thus on the sample investigated, as demonstrated for the case of dropping the observations of CEE transition economies.

4. An alternative approach: absolute poverty convergence

Given the shortcomings of the concept of the growth elasticity of poverty reduction, Klasen and Misselhorn (2008) suggest the use of a semi-elasticity instead, which would imply rewriting equation (2) as

$$\Delta H_{it} = \delta_i^* + \eta_i^* \Delta \ln \mu_{it} + \nu_i^*. \qquad (6)$$

Note that the difference is the absolute (instead of proportionate) percentage point change on the left-hand-sided variable. This approach has several conceptual advantages. First, it does not suffer the same sensitivity to observations with low initial poverty incidence, as the percentage point changes in the headcount rate are no longer divided by the (low) initial poverty rates. Second, policymakers are usually interested precisely in those *percentage point*, not percentage changes of the poverty rate. Third, this approach also seems more suitable from a welfare perspective as each percentile lifted out of poverty is attributed the same change in the variable of interest. Fourth, the semi-elasticity provides an arguably superior linear approximation of poverty dynamics.[18]

Combining equation (6) with the mean income convergence equation (1) leads to an (absolute) poverty convergence equation:

$$\Delta H_{it} = a_i^* + b_i^* H_{i,t-1} + e_{it}^*. \qquad (7)$$

Note that equation (7) implies a conventional concept of convergence in the sense that for $b_i^* < 0$, poverty headcounts rate tend to converge in absolute values across countries. It is also important to highlight that equations (3) and (7) are related in the sense that $\beta_i^* \leq 0 \rightarrow b_i^* < 0$. Estimating equation (7) making use of the data in Ravallion (2012) reveals highly significant convergence dynamics in poverty headcount rates, as illustrated in the first column of Table 3. As columns 2-4 of Table 3 indicate, this finding is robust to the inclusion of the control variables proposed by Ravallion (2012), and to alternative measures of poverty such as the poverty gap and even for the headcount ratio at the lower $1.25/day line, where the problem of initially low and imprecisely measured poverty rates is more severe.[19]

Figure 3, which provides a scatter plot of the key result, also highlights that CEE transition economies no longer drive the outcome. They are still grouped far off the sample mean of initial poverty rates but their subsequent poverty dynamics no longer drive the result when measured in percentage point (as opposed to percent) changes. Although their poverty dynamics are still significantly different, whether they are included in the sample or not no longer influences the key conclusion concerning absolute poverty convergence (as also indicated by the regression lines depicted in Figure 3). This reflects the fact that the semi-elasticity approach

[18] This is partly shown in Figures A.1 and A.2 and Table A.1 in the Appendix. Those results show a better fit and higher explanatory power of the growth semi-elasticity (6) compared to the elasticity in equation (2).

[19] Similarly, the estimation results based on these alternative poverty measures are robust to the inclusion of the control variables mentioned above. In all cases, the absolute poverty convergence parameter remains negative and statistically significant at the 1% level (results available upon request).

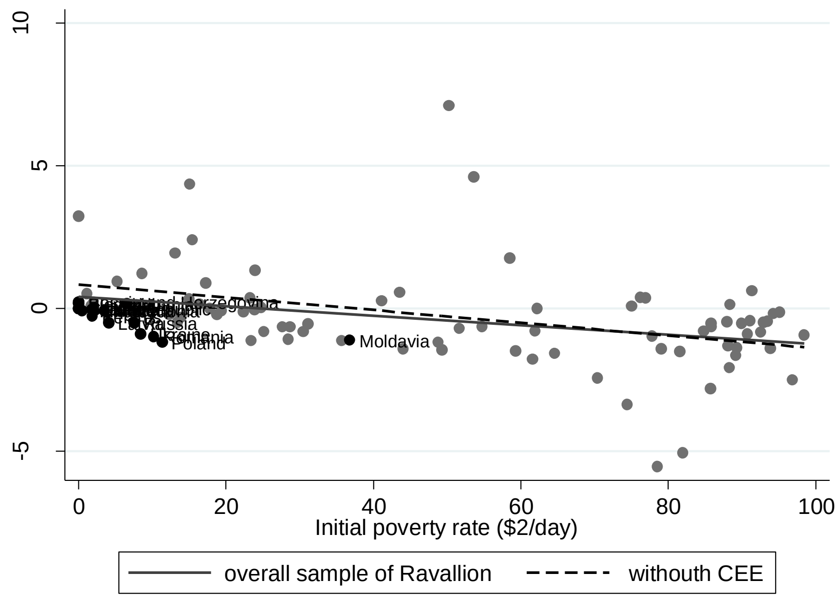
proposed by Klasen and Misselhorn (2008) is less susceptible to (sometimes arbitrary or poorly measured) developments at the very left tail of the income distribution.

Table 3: Absolute poverty convergence results

	(1)	(2)	(3)	(4)
Dependent variable:	$\Delta(H_{\$2})$	$\Delta(H_{\$2})$	$\Delta(H_{\$1.25})$	$\Delta(PG_{\$2})$
Note:	Semi-elasticity Headcount $2	Semi-elasticity Headcount $2	Semi-elasticity Headcount $1.25	Semi-elasticity Poverty gap 2$
Initial poverty	-0.0158***	-0.0330***	-0.0293***	-0.0264***
$H_{i,t-1}$	(0.00373)	(0.00681)	(0.00464)	(0.00479)
Log primary		-0.408		
schooling		(0.421)		
Log life expectancy		-4.178**		
		(1.794)		
Log relative price of		0.477**		
investment goods		(0.200)		
Constant	0.375*	18.03**	0.298**	0.365*
	(0.206)	(7.924)	(0.138)	(0.215)
Observations	88	87	88	88
R-squared	0.105	0.361	0.257	0.200

Notes: The 'initial poverty' measure in columns (3)-(4) is the respective initial level corresponding to the dependent variable (i.e. the initial headcount at $1.25/day and the initial poverty gap at $2/day, respectively). OLS results, heteroscedasticity robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data from Ravallion (2012) excluding the Indonesia observation.

Figure 3: Absolute poverty convergence



Data source: Ravallion (2012), including Indonesia observation.

Overall, the theoretical considerations and empirical evidence presented in this section provide strong arguments to look at convergence dynamics in poverty measures through the lens of a growth semi-elasticity and an according absolute concept of poverty convergence. As we discuss in the next section, however, showing absolute poverty convergence says little about the speed of this convergence and the corresponding policy implications.

5. Will poverty be eradicated by 2030? A policy discussion

How confident do our results of absolute poverty convergence make us concerning the achievement of the global community's goal of eradicating extreme poverty by 2030? [20] To illustrate potential poverty dynamics going forward, we start with an initial poverty rate of 23 (15) percent, which is the sample mean (median) for the 1.25$ headcount rate in 2004 (the median year of the second survey). Taking convergence speeds implied by the parameters in column 3 of Table 3, this would imply an extreme poverty headcount rate of 16.1 (12.4) percent in 2030, far off the target of the international community. For countries with initial poverty rates above the mean (median), the headcount ratio would be accordingly higher, notably countries in Sub-Saharan Africa.

Of course, higher growth can make some difference. Therefore, let us assume one moves the average sample mean income growth rate of 1.3 % p.a. to the 75th percentile of 3.5 % p.a., a remarkable increase. This would increase the annual percentage point reduction of poverty for the mean (median) country from 0.52 (0.46) to 1.31 (1.26) percentage points—still too low for many developing countries to reduce poverty fast enough, although the 2030 goal would be within reach for the large majority of them.[21]

A similar result can be deduced from the exercise of Ravallion (2012) which is essentially—as our contribution pointed out—about the *speed* of poverty convergence. From a specification that explains proportionate poverty changes with initial poverty levels, growth, and an interaction thereof (and controls for CEE

[20] Note that technically speaking, "eradicating" poverty in the context of the Sustainable Development Goals means a headcount rate below 3 percent.

[21] These calculations are based on the parameters in Appendix Table A.3, column 1, re-estimated for the 1.25$ headcount rate (results are available upon request). Note that it is not at odds with theory that the initial poverty parameter is no longer statistically significant in column 1 of Table A.3 as the convergence effect is expected to run through mean income convergence (which is explicitly controlled for in this specification). More importantly, column 2 of Table A.3 highlights that the growth semi-elasticity does no longer depend on initial poverty, as opposed to the semi-elasticity used in column 3.

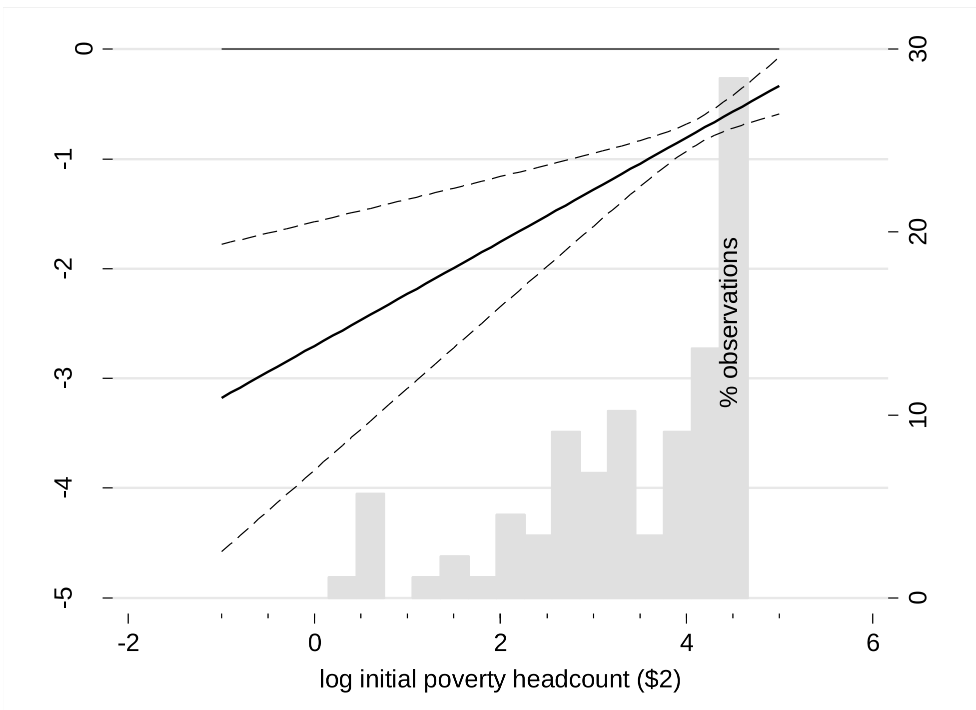
dynamics; see Appendix Table A.3, column 3), we can calculate the growth elasticity of poverty reduction by initial income level. This captures the effect of one percent growth on proportionate changes in the poverty headcount rate and is depicted in Figure 4. As Bourguignon (2003) and our contribution point out, this elasticity is increasing (in absolute terms) in the development level and hence decreases with poverty. What is more important, however, is that most developing countries currently stand at a poverty rate that translates into a low growth elasticity of poverty reduction, as depicted by the shaded histogram in Figure 3. This means they obtain a rather low proportionate poverty reduction out of growth. Again, for an initial mean (median) poverty rate of 23 (15) percent at 1.25$ in 2004, one would observe a 4.5 (4.3) percent p.a. reduction in the headcount rate given at the mean income growth rate of 1.3 %.[22] Until 2030, that would lead to a 1.25$ headcount rate of 7.4 (4.9) percent. Only if growth would increase to the 75th percentile of 3.5 % p.a., that representative mean (median) country would manage to bring down the extreme poverty rate below 3 percent by 2026 (2021).

Despite some numerical differences, both of these exercises suggest that achieving the global target of eliminating poverty by 2030 will be extremely unlikely even for countries at current average poverty rates and requires growth rates that countries cannot sustain based on historical experience (see also Pritchett and Summers, 2015).[23] This also reflects that inequality, despite slowly converging, is still very persistent in the developing world. Higher poverty reduction can thus only be achieved if inequality is also reduced which, as shown by Bourguignon (2003) and Klasen and Misselhorn (2008), not only reduces poverty directly, but also increases the growth elasticity (and semi-elasticity) of poverty reduction and might even,

[22] We use the model presented in the third column of Table A.3 but for the 1.25$ headcount rate. Regression results are available upon request.
[23] Ravallion (2012) additionally raises the point that initial log poverty may have a negative effect on growth (significant at the 1% level in Ravallion, 2012: Table 2, model 1). We cannot confirm this finding using his data set after deleting the observation for Indonesia and adding a CEE dummy. However, Wacker (2016) provides similar evidence.

following Deininger and Squire (1998), increase growth. Going forward, this suggests that more work along the lines of Bourguignon (2002, 2003, 2004), Foster and Székely (2008), and Dollar and Kraay (2002) analyzing in more detail how poverty, inequality, and growth are systematically related and how pro-poor distributive policies can maintain solid growth rates seems imperative.

Figure 4: Growth elasticity of poverty reduction at 2$ by initial poverty level



Note: Figure 4 displays the implied effect through the interaction between log initial poverty and mean income growth on log changes in poverty as estimated in Appendix table A.3, column 3.

6. Conclusion

In this paper, we demonstrate that whether we should see proportionate poverty convergence in the data analytically depends on the speed of income convergence relative to other parameters, including the income level and levels and changes in income inequality. From that angle, there is nothing surprising in the results of Ravallion (2012) that poverty has not converged (in the proportional sense) over the last decades. In fact, the correlations in the data by Ravallion (2012) are largely consistent with theory and no detrimental effect of initial poverty beyond what is expected from theory can be found. We further highlight that his concept of proportionate poverty convergence contains the problems of the growth elasticity of poverty reduction, including the susceptibility to observations with low initial poverty incidence. This is made apparent by showing that one observes proportional poverty convergence after controlling for the specific dynamics of CEE transition economies. We propose an alternative concept of absolute poverty convergence based on the semi-elasticity considerations by Klasen and Misselhorn (2008) and present robust evidence of absolute convergence in different poverty measures across the developing world using such a framework. However, convergence appears too slow to achieve the global goal of eradicating poverty by 2030 by most realistic assumptions in the absence of significant efforts targeted at reducing inequality.

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Appendix

Figure A.1: Poverty elasticity of growth

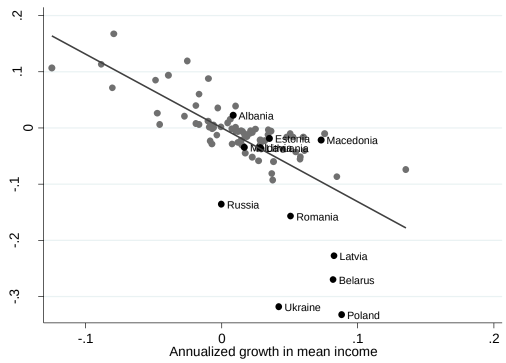


Figure A.2: Poverty semi-elasticity of growth

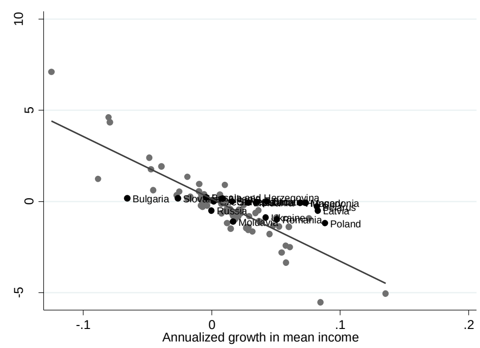


Table A.1: Growth elasticity vs. semi-elasticity of poverty reduction

	(1)	(2)
VARIABLES	$\Delta\ln(H_{\$2})$	$\Delta(H_{\$2})$
Mean income growth	-1.312***	-34.19***
	(0.217)	(4.492)
Constant	0.000163	0.148
	(0.00496)	(0.115)
Observations	88	88
R-squared	0.461	0.704

Data source: Ravallion (2012), Indonesia observation deleted. OLS results, heteroscedasticity robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.2: Robustness of log poverty convergence specification with CEE dummy

	(1)	(2)	(3)	(4)
VARIABLES	$\Delta\ln(H_{\$2})$	$\Delta\ln(H_{\$2})$	$\Delta\ln(H_{\$1.25})$	$\Delta\ln(PG_{\$2})$
Note:	\$2 a day (headcount) w/o CEE	\$2 a day (headcount)	\$1.25 a day (headcount)	Poverty gap (\$2 a day)
Log initial poverty	-0.0358***	-0.0313***	-0.0208*	-0.0245***
	(0.00631)	(0.00965)	(0.0113)	(0.00517)
CEE dummy		-0.173***	-0.184***	-0.184***
		(0.0440)	(0.0671)	(0.0392)
Log primary schooling	-0.0205	-0.0287		
	(0.0156)	(0.0174)		
Log life expectancy	-0.112**	-0.0727		
	(0.0422)	(0.0614)		
Log relative price of	0.00377	0.0109		
investment goods	(0.00654)	(0.0110)		
Constant	0.657***	0.487*	0.0481	0.0576***
	(0.197)	(0.293)	(0.0412)	(0.0181)
Observations	76	87	81	88
R-squared	0.434	0.486	0.188	0.361

Notes: The 'log initial poverty' measure is the respective initial level corresponding to the dependent variable (i.e. the initial log headcount at \$2/day, at \$1.25/day, and the log initial poverty gap at \$2/day, respectively). OLS results, heteroscedasticity robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data source: Ravallion (2012), Indonesia observation deleted.

Table A.3: Effects of initial poverty on the poverty (semi-)elasticity of growth

	(1)	(2)	(3)
VARIABLES	$\Delta(H_{\$2})$	$\Delta(H_{\$2})$	$\Delta\ln(H_{\$2})$
Initial poverty	-0.000973	0.00113	
	(0.00310)	(0.00350)	
Log(initial poverty)			-0.0103***
			(0.00379)
Mean income growth	-36.75***	-27.80***	-2.704***
	(4.690)	(7.304)	(0.687)
Initial poverty ×		-0.178	
Mean income growth		(0.121)	
Log(initial poverty) ×			0.474***
Mean income growth			(0.165)
CEE dummy	1.114**	0.747*	-0.0686*
	(0.433)	(0.425)	(0.0407)
Constant	0.0936	0.0851	0.0380**
	(0.151)	(0.146)	(0.0157)
Observations	88	88	88
R-squared	0.756	0.771	0.692

Data source: Ravallion (2012), Indonesia observation deleted. OLS results, heteroscedasticity robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix B.

B.1 Simulation exercise

Bourguignon (2003) derives the proportionate change in the poverty headcount under the assumption of a log-normal income distribution as

$$\frac{\Delta H_{it}}{H_{i,t-1}} = \lambda\left[\frac{\ln(z/\mu_t)}{\sigma} + \frac{1}{2}\sigma\right]\left[-\frac{\Delta\ln(\mu_t)}{\sigma} + \left(\frac{1}{2} - \frac{\ln(z/\mu_t)}{\sigma^2}\right)\Delta\sigma\right]. \qquad \text{(B.1)}$$

We parameterize (B.1) with the values observed in the sample of Ravallion (2012), keeping distribution constant ($\Delta\sigma = 0$). Furthermore, we note that the mean growth rate $\Delta\ln(\mu_t)$ can be written as: $\alpha_i + \beta_i \ln\mu_{i,t-1}$ and replace it with a simulated one, based on different values β_i. We can then use the simulated value of $\frac{\Delta H_{it}}{H_{i,t-1}}$ to run the proportionate poverty convergence regression (3). This allows us to investigate which speed of income convergence would be needed to obtain proportionate poverty convergence given the other sample moments. We start with values of $\alpha = 1.08$, $\beta = -0.0137$, which corresponds to the sample values and then change β, leaving α unchanged. The results are summarized in table B.1.

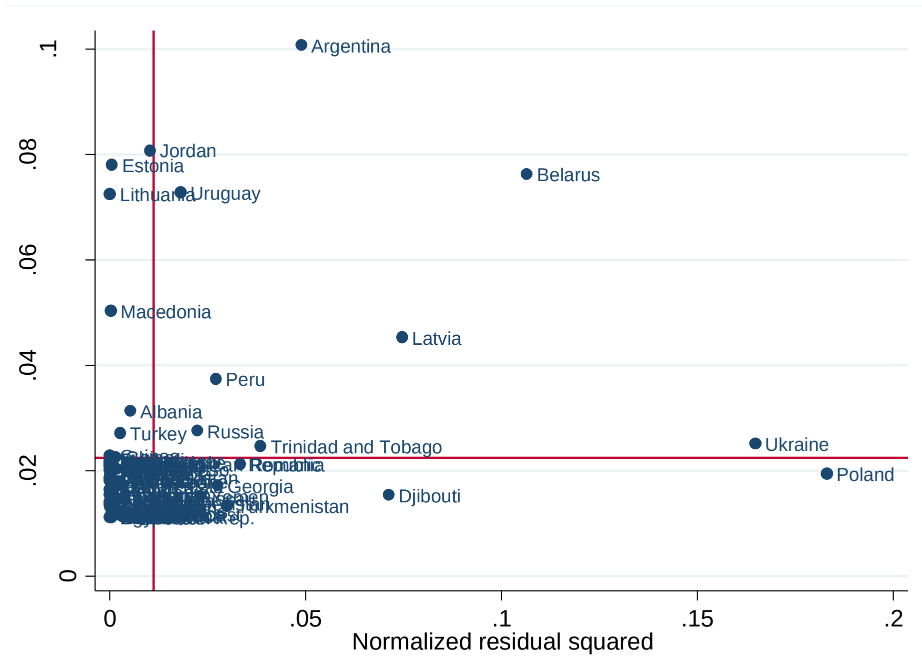
Table B.1: Poverty convergence for simulated income convergence speeds

Mean income convergence parameter β_i	Implied income half-life (years)	Resulting proportionate poverty convergence parameter β_i^*
-0.0137	50.4	0.0089***
-0.100	6.6	0.0045***
-0.15	4.3	0.0020***
-0.20	3.1	-0.0006***

For the baseline case, $\beta = -0.0137$, which means that it needs about 50 years for incomes across countries to close half of the existing gaps ('half-life'), we do not find proportionate poverty convergence but divergence. This is also true for even much faster convergence speeds. Only once β approaches 0.2, which implies a half-life of 3 years, do we find slow proportionate poverty convergence.

B.2 Additional material

Figure B.1: Leverage vs. Residual Plot



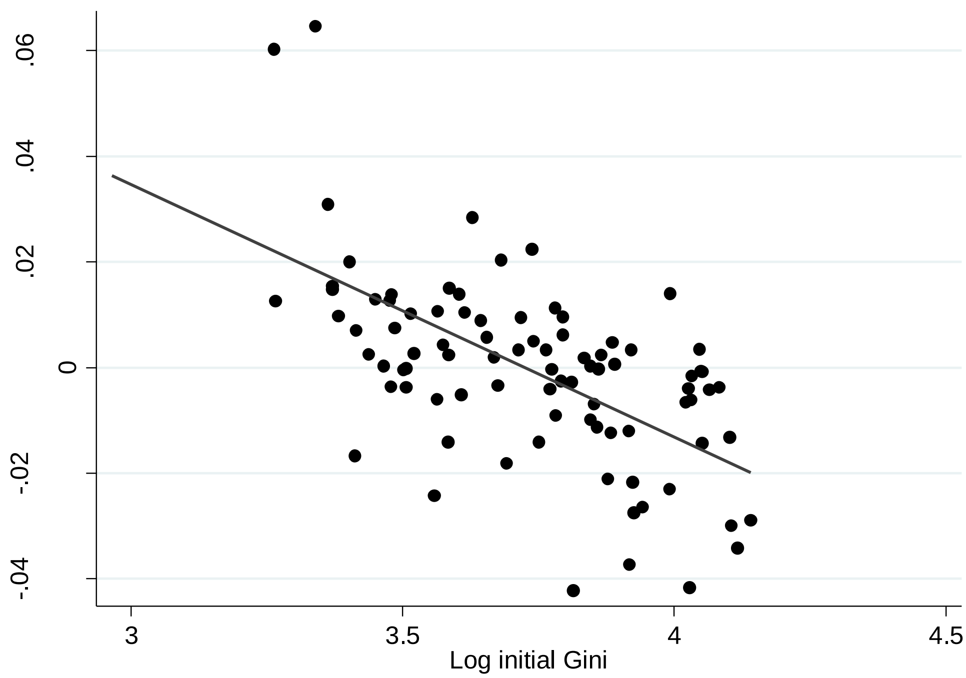
Note: Figure B.1 plots the observations' leverage in the proportionate poverty convergence regression (without Indonesia) against the residual. As one can observe, several CEE observations are problematic because they obtain both, a high residual ('outlier') and a high leverage in the regression, rendering the latter worrisome.

Table B.2: Robustness of proportionate poverty convergence with CEE dummy

	(1)	(2)	(3)	(4)
VARIABLES	$\Delta\ln(H_{\$2})$	$\Delta\ln(H_{\$2})$	$\Delta\ln(H_{\$1.25})$	$\Delta\ln(PG_{\$2})$
Note:	$2 a day (headcount) w/o CEE	$2 a day (headcount)	$1.25 a day (headcount)	Poverty gap ($2 a day)
Log initial poverty	-0.0358***	-0.0313***	-0.0208*	-0.0245***
	(0.00631)	(0.00965)	(0.0113)	(0.00517)
CEE dummy		-0.173***	-0.184***	-0.184***
		(0.0440)	(0.0671)	(0.0392)
Log primary schooling	-0.0205	-0.0287		
	(0.0156)	(0.0174)		
Log life expectancy	-0.112**	-0.0727		
	(0.0422)	(0.0614)		
Log relative price of	0.00377	0.0109		
investment goods	(0.00654)	(0.0110)		
Constant		0.488*	0.0484	0.0577***
		(0.293)	(0.0411)	(0.0181)
Observations	0.657***	0.487*	0.0481	0.0576***
R-squared	(0.197)	(0.293)	(0.0412)	(0.0181)

Notes: The 'log initial poverty' measure is the respective initial level corresponding to the dependent variable (i.e. the initial log headcount at $2/day, at $1.25/day, and the log initial poverty gap at $2/day, respectively). OLS results, heteroscedasticity robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Data of Ravallion (2012) excluding the Indonesia observation.

Figure B.2: Inequality convergence



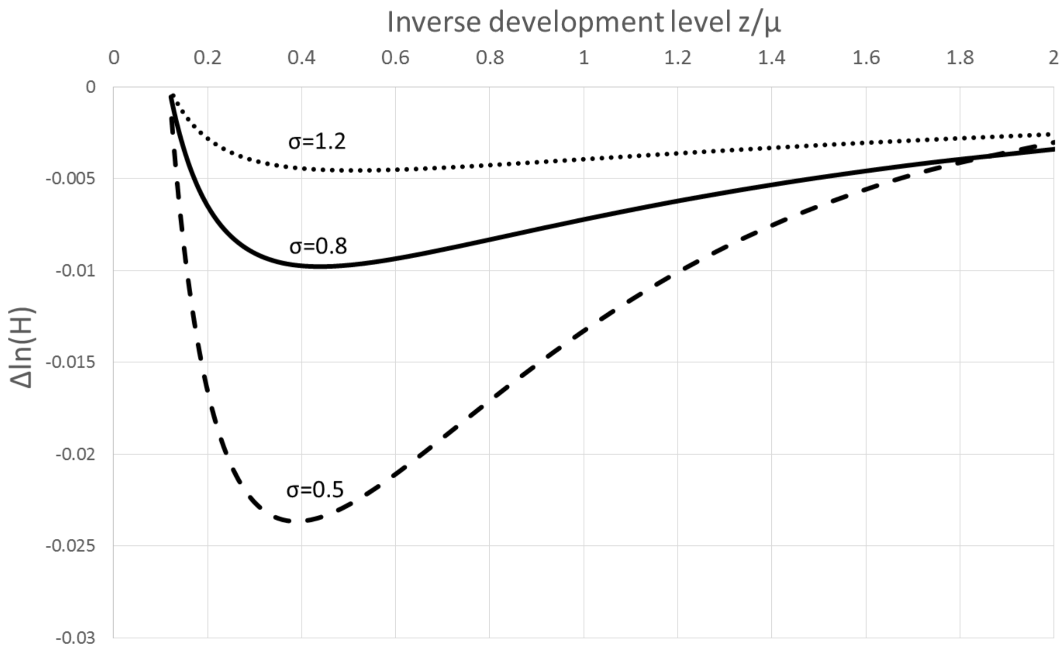
Note: Figure B.3 depicts the result from the third column of table B.3

Table B.3: Inequality Convergence

	(1)	(2)	(4)	(6)
VARIABLES	ΔGini	ΔGini	Δln(Gini)	Δln(Gini)
Initial Gini	-0.0433***	-0.0457***		
	(0.00720)	(0.00726)		
Log initial Gini			-0.0446***	-0.0473***
			(0.00808)	(0.00799)
CEE dummy		-0.189		-0.00468
		(0.213)		(0.00630)
Constant	1.790***	1.916***	0.166***	0.176***
	(0.307)	(0.311)	(0.0305)	(0.0302)
Observations	88	88	88	88
R-squared	0.343	0.349	0.340	0.347

Data source: Ravallion (2012), Indonesia observation deleted. OLS results, heteroscedasticity robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure B.4: Dependence of proportionate poverty convergence on distribution



Note: Figure B.4 shows proportionate changes in poverty headcount rates, ΔlnH, in dependence of (inverse) initial development level z/μ_{t-1}, assuming that mean incomes μ converge with $\Delta \ln \mu_{it} = 3 - 0.48 \ln \mu_{i,t-1}$ and hence much faster than in the sample of Ravallion (2012). The effect is shown for different inequality levels, where σ is the standard deviation of the log-normal distribution. Under this assumption of relatively fast mean income convergence, we would see proportionate poverty convergence for a given inequality level up to an (inverse) initial development level z/μ_{t-1} around 0.4, which covers about 40 % of the countries in the sample of Ravallion (2012).