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Why We Don't See Poverty Convergence: The Role of Macroeconomic Volatility[*]

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Abstract

Martin Ravallion ("Why Don't We See Poverty Convergence?" *American Economic Review*, 102(1): 504-23; 2012) presents evidence against the existence of poverty convergence in aggregate data despite the conditional convergence of per capita income levels and the close linkage between growth and poverty reduction in standard neoclassic growth theory and associated empirics. In this contribution we address this puzzle. After showing some evidence of regional convergence, we demonstrate that macroeconomic volatility prevents countries with a higher incidence of poverty from converging in poverty levels to those with less poverty on a global scale. Once volatility is controlled for, the relevant convergence parameter shows the expected negative sign and is robust to various estimation techniques and model specifications. Only if a country's volatility exceeds a relatively high threshold level, it no longer converges. Similarly, initial poverty only exercises a negative impact on mean (income) convergence in countries where macroeconomic volatility is high.

Keywords: poverty convergence, macroeconomic volatility

JEL Classifications: I32, D31, E32

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1. Introduction

Despite the sharp reductions in extreme poverty in all developing regions in recent years (see for instance World Bank, 2012), more than one billion people continue to live on less than $1.25 a day and another billion live on an income between $1.25 and $2 a day. Furthermore, the achievement of the United Nations' "Millenium Development Goal" of halving world poverty can be attributed to overachievement in a limited group of populous countries, including particularly China and India, while the performance of some other regions (in particular Sub-Saharan Africa) is much less promising (see Sala-i-Martin, 2006, World Bank, 2013). More specifically, Ravallion (2012) shows that countries with the highest incidence of poverty tended to achieve relatively less progress in fighting poverty, thereby starting a debate concerning why we do not see "poverty convergence".

From a theoretical point of view, the combination of convergence in mean consumption (as implied by standard neoclassical growth models under the assumption of a common steady state for all countries) and strong linkage between growth in mean consumption and absolute poverty reduction implies that we should see such poverty convergence in the data. As argued by Ravallion (2012, 504), "*countries starting out with a high incidence of absolute poverty should enjoy a higher subsequent growth rate in mean consumption and (hence) a higher proportionate rate of poverty reduction*". The empirical results of such an analysis, however, offer "*little or no sign of poverty convergence*" (Ravallion 2012, 504), and the conclusion of the study is that "*clearly something important is missing from the story*" (Ravallion 2012, 504). He suggests that this is related to the fact that countries with higher initial absolute poverty (also potentially linked to higher initial inequality and the size of the middle class) achieve both lower growth and lower poverty reduction given growth; the precise mechanisms for why this is the case remaining unclear.

In this paper we aim to provide an explanation by highlighting a "missing part" which appears essential to understand why we do not observe unconditional poverty convergence: the role played by macroeconomic volatility.

In section 2 we review Ravallion's (2012) arguments for poverty convergence and provide arguments concerning why macroeconomic volatility could impede this process. Section 3 describes the data and sets up our econometric model. We replicate the results of Ravallion (2012) in section 4 and show that the absence of poverty convergence is not particularly robust. In section 5, we show empirically that macroeconomic volatility hampers poverty convergence. Section 6 concludes.

2. Poverty convergence and its barriers

2.1 Why do we expect poverty convergence?

The argument presented by Ravallion (2012) starts from a standard income convergence specification, given by

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

where μ_{it} denotes mean consumption (income) in country i and period t and ε_{it} is a standard disturbance term assumed to fulfill the usual assumptions of the error term in linear regression models. Equation (1) summarizes the neoclassical assumption of "advantages of backwardness", concerning the fact that the further a country lags behind in terms of income, the easier it is to catch up. Such dynamics are motivated by the existence of diminishing returns to capital and the ability to replicate technologies used in more advanced economies. Accordingly, β_i is expected to be negative, i.e. the further away a country is from its steady state, the faster the rate of growth in mean consumption. Ravallion (2012) finds convincing evidence of such a pattern in his dataset.

Hypothesizing "advantages of growth" for poverty reduction, he specifies he following equation

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

where H is the (absolute) poverty rate and it is reasonable to assume $\eta_i < 0$, i.e. higher average income translates into lower incidence of poverty. Ravallion (2012) also finds empirical evidence that this channel is present in the data. Assuming that (1) and (2) hold, it can be shown that[1]

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

follows, with $\beta_i^* = \beta_i < 0$. We should hence see poverty convergence in the data if (1) and (2) are fulfilled. Ravallion (2012: 505), however, finds that "*there is little or no systematic effect of starting out poor on the proportionate rate of poverty reduction*" and identifies two channels that work against the convergence effect. On the one hand, high initial poverty has an adverse direct effect on growth, and on the other hand high initial poverty makes it harder to achieve any given proportionate impact on poverty through growth in the mean. The conclusion is therefore that poverty itself is the root cause of the lack of convergence, by offsetting both the 'advantage of backwardness' and the 'advantage of growth'.[2] This conclusion, while highlighting the complexity and sustainment of poverty, does not provide an explanation about what hides behind poverty persistence and thus offers no policy guidance concerning how to effectively fight poverty. As Ravallion (2012: 521)

[1] See Appendix A for the detailed derivation.

[2] Although the size of the middle class might as well determine how much impact a given rate of growth has on poverty, Ravallion (2012) argues that the main way to enter the middle class is by escaping poverty, which makes these two explanations somewhat tantamount. This is supported empirically by the extremely high correlation between the size of the middle class and the poverty rate in the data.

himself put it, "*[t]he policy implications of (…) poverty reduction depend on why countries starting out with a higher incidence of poverty tend to face worse growth prospects and enjoy less poverty reduction from a given rate of growth*". The aim of our contribution is to add to the understanding of the specific constraints faced by countries with a high poverty headcount in their efforts to reduce poverty. In this context, we highlight the role of (macroeconomic) volatility which we consider – among other potential factors – an essential variable that might be central to shaping the transformation of growth into poverty alleviation.

2.2 Barriers to poverty convergence: The role of volatility

Following the line of reasoning put forward above, there might be two main channels that prevent poverty convergence: 'initial conditions' associated with high poverty might retard convergence or they might impede the poor to benefit from growth. While there are several potential candidates for such social barriers that could be derived from the pro-poor growth literature (see Klasen, 2007), such as lacking capacity to absorb new technologies because of educational or health constraints; legal, social, or geographic rigidities; or lack of redistribution and institutional shortcoming, we focus on the role of (macroeconomic) volatility. On the one hand, macroeconomic fluctuations might hamper mean convergence via negative effects of uncertainty on growth.[3] On the other hand, volatility might constitute an important barrier for the poor to reap the 'advantages of growth'. Ravallion (2009), for example, relates the poverty incidence to the minimum level of wealth needed to stop being liquidity-constrained in investment choices. For any given income level, however, this liquidity constraint will depend directly on volatility because larger expected fluctuations will require setting aside more savings that, in turn, cannot be used for investment. While these investments (e.g. in schooling or fertilizer) could lift people out of poverty, there is ample evidence that especially poor household cannot make them under high uncertainty simply because a minimum subsistence consumption has to be ensured to stay alive and hence poorer households will be more likely to opt for a "safe strategy" (e.g. Mordoch, 1995; Moser and Barrett, 2006; Tanaka et al., 2010; Dercon and Christiaensen, 2011).[4] For the same reason, volatility-induced uncertainty might also delay the adjustment of labor input into growing sectors and regions because of absent opportunities for risk insurance, especially for the poor (Dixit and Rob, 1994).

While these argument highlight why increased macroeconomic volatility may reduce the demand for poverty-alleviating investments, volatility may also have a negative effect on the availability of capital to the poor, thereby worsening their credit constraints. Economic instability might induce capital flight, thereby limiting the amount of credit available and substituting it more to secure assets, hence away from the poor. Furthermore, uncertainty can be interpreted as a limited liability for the debtors resulting in credit constraints that, according to Mookherjee and Ray (2002), create poverty traps with no interclass-mobility, an argument why poverty convergence is less likely in volatile environments.

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[3] That countries with higher volatility have in fact lower growth has been documented, among others, by Ramey and Ramey (1995), Aghion et al. (2010) and Hnatkovska and Loayza (2005).

[4] The argument has also conceptual and empirical links to the work on consumption smoothing (Deaton, 1991,1992; Rosenzweig and Wolpin, 1993; Townsend 1994).

Overall, these arguments highlight that the ely in volatile environmentrgument why poverty convergence is lewidespread poverty and high volatility, at least over the medium run. This is the case because the cheap availability of technology would be hampered by low demand for such investment and diminishing returns to capital would not lead to more supply of finance for the poor. Accordingly, the speed of convergence might be influenced by macroeconomic volatilities.

3. Econometric model and data

3.1 Dataset

The basic dataset used to test the hypothesis that macroeconomic volatility explains the lack of convergence in poverty rates across countries comes from Ravallion (2012). The poverty and income dataset is obtained from survey data taken from *povcal.net*, covering about 90 developing countries between 1977 and 2007 with a median interval between surveys of 13 years. It includes, inter alia:

- the proportion H_{it} of the population in country i at time t living in households with consumption (income) p.c. below the poverty line of $2.00 per person per day at 2005 PPP.

- the overall mean consumption (income) μ_{it} in the sample.

To this dataset, we add as our measure for macroeconomic volatility, which is the standard deviation of (log) GDP per capita evaluated in the period spanning five years prior to the corresponding survey for which poverty data are available. The GDP per capita data are sourced from the Penn World Table 7.1 (Heston et al. 2012). Furthermore, we also collect data on the countries' *population* from the World Bank WDI and on the *number of surveyed households* from *povcal.net*, which are used for the estimates based on weighted least square methods.[5]

3.2 Econometric models: Weighting and interactions

Ravallion (2012) estimates the reduced form model (3) in order to carry out inference about poverty convergence, but also investigates the channels by estimating equations (1) and (2), adding supplementary control variables as well. The unit of observation in our context is a country but any model taking into account poverty and inequality necessarily involves surveys of individuals or households. This raises a set of econometric concerns.

First, it is individuals that escape the relevant definition of poverty (i.e. living from below $2.00 a day), not countries. However, if most of the poor converge in poverty but happen to live in a large country, they will be underrepresented in the overall cross-country sample relative to the poor in smaller countries. If the latter do not happen to converge in

[5] Data about the number of surveyed individuals are not available for all surveys. If possible, we took the average over both survey rounds. If only one of the surveys included information on the sampling size, we used this figure.

poverty, their relevance for the world population of poor will be overestimated. A simple way to assess this problem is to estimate equation (3) by weighted least squares (WLS) instead of OLS and use the country population as weights.

On the other hand, the sample designs and time periods between the used samples differ across countries. This affects the overall reliability of the data and raises the question whether one is willing to rely as much on a poverty measure which is retrieved from a sample covering 1% of the population as on a sample covering 20% of the population. To address this issue, we consider regressions estimated using WLS with weights based on sample size.[6]

Ravallion (2012) argues that the time periods between surveys barely correlate with other measures of the initial distribution. If there is poverty convergence, however, it is most likely that it takes place over the long run and that such a process is polluted by short-term fluctuations over short time spans. Therefore, one would typically want to rely more on data that covers a longer time period between samples. WLS estimation taking the time period between the relevant surveys as weights might provide a more reliable and robust assessment.[7]

Another potential shortcoming concerns regional heterogeneity. In fact, equation (3) is a dynamic model and could lead to inconsistent and potentially misleading estimates of the convergence coefficient if it suffers from parameter heterogeneity across economies (see e.g. Pesaran and Smith, 1995; Phillips and Sul, 2003). Income convergence, which is relevant for poverty convergence via equation (1), has been shown not hold for all regions (see Azariadis, 2006), so accordingly we also consider a simple generalization of model (3) which allows for continent-specific parameters,

$$\Delta \ln H_{it} = \sum_{j=1}^{4} \mathbf{1}_{(j)} \alpha_j^* + \sum_{j=1}^{4} \mathbf{1}_{(j)} \beta_j^* \ln H_{i,t-1} + \varepsilon_{it}^*, \qquad (4)$$

where the sample is split into J=4 different regions (Africa, Americas, Asia and Europe, according to the United Nations regional definition) and $\mathbf{1}_{(j)}$ is an indicator variable equal 1 if country i falls into region j, and 0 otherwise.[8]

In addition to the weighting of the least squares minimization problem in the regression model and the potential regional heterogeneity, one has to consider how barriers to poverty convergence operate in the framework put forward above. Factors affecting poverty

[6] For calculating the sampling weights, we took the average over both included surveys, where available, or simply the one sample size available. Following this approach, data for 78 countries was easily available. We could successfully collect data on the sample size from other sources, increasing our sample to 83 countries. The Belarus 2000 survey size is based on individuals and in order to obtain the household equivalent we divided by 2.6 (the average household size in 1999). The six remaining countries for which we could not find information on the sample size for any of the two surveys included are Iran, Macedonia, Russia, Thailand, Tunisia, and Uzbekistan.

[7] One may argue that these statistical considerations about sampling weights cannot explain the puzzling finding of Ravallion (2012) that we observe the ‘advantage of backwardness’ and the ‘advantage of growth’ in the sample but no poverty convergence. While this is true to some extent, it might still be the case that poverty convergence takes longer than convergence in mean, which would suggest a stronger focus on the long run.

[8] Ravallion (2012) also notes that the growth literature has found differential regional effects for Sub-Saharan Africa (negative) and East Asia (positive). He hence includes two dummy variables to his estimation model of *means*-convergence given by equation (1), but finds no significant effect.

convergence enter the model by changing the terms α_i, δ_i or as interactions with β_i and/or η_i in equations (1) and (2). Let us denote the potential barrier as B_i. Making the corresponding parameters in equations (1) and (2) depend (linearly) on B_i implies enlarging the model by the following equations,

$$\alpha_i \coloneqq z_i + \theta_{1i} B_i, \quad (5a)$$
$$\delta_i \coloneqq d_i + \theta_{2i} B_i, \quad (5b)$$
$$\eta_i \coloneqq h_i + \theta_{3i} B_i, \quad (5c)$$
$$\beta_i \coloneqq p_i + \theta_{4i} B_i. \quad (5d)$$

Note that assuming that (5a), (5b) or (5c) hold implies that a linear term containing the poverty barrier variable would enter equation (3). Assuming (5d) would lead to the poverty barrier entering also as an interaction term with $\ln H_{i,t-1}$.[9] Intuitively, an interaction with $\ln H_{i,t-1}$ means that we move away from the assumption of a homogeneous speed of convergence across economies and instead allow the speed of convergence to depend on some additional covariate. Ravallion (2012) generally controls for a set of promising variables in his study but does not take into account interaction terms, thus avoiding specifications where convergence in (average) income is shaped by third factors.

Allowing for the barrier B_i to operate through all different channels outlined above, the reduced form model (3) boils down to the form

$$\Delta \ln H_{it} = a_i + b_i \ln H_{i,t-1} + \omega_i B_i + \theta_{4i} B_i \ln H_{i,t-1} + e_{it}, \quad (6)$$

where any redefinitions in (5a)-(5c) would be reflected in a_i and $\omega_i B_i$ (and the variance of e_{it}), while the redefinition in (5d) would affect the term $\theta_{4i} B_i \ln H_{i,t-1}$.

4. How robust is the lack of poverty convergence?

Using the data used by Ravallion (2012),[10] we are able to replicate the results reported in the study. Column 1 in Table 1 reports the main result in Ravallion (2012), i.e. the estimates of equation (3) using OLS and shows a positive estimate for the convergence parameter, indicating (statistically insignificant) divergence.[11] The model has an R-squared of 8 % and thus very limited explanatory power for explaining differences in poverty dynamics across economies.

Weighting the observations by population size to give more weight to larger countries does not change the finding qualitatively (see column 2 in Table 1), nor does correcting for the statistical reliability of the different observations using weights based on survey size (see columns 3 and 4). Finally, we also weight the observations by the years between the two survey rounds. The results are reported in column 5 and show a negative and insignificant

[9] See Appendix B.
[10] The data can be downloaded from http://www.aeaweb.org/articles.php?doi=10.1257/aer.102.1.504.
[11] This result matches Figure 1 in Ravallion (2012), although the paper does not show this particular result in a table. The slope estimate and the t-ratio are mentioned in the text (Ravallion, 2012, p. 504) and are identical to the results we find.

parameter estimate. Overall, we conclude from this exercise that the lack of (unconditional) poverty convergence is robust to several estimation techniques that take into account the statistical reliability, longer-run effects or population size.

Table 1: Poverty Dynamics: Statistical Robustness and Sample Weights

	Original results in Ravallion (2012)	Population weighting	Survey sample size weighting	Relative survey sample size weighting	Weighting based on period length between survey
	(1)	(2)	(3)	(4)	(5)
Log initial headcount index	0.00590 (0.0100)	0.0204 (0.0157)	0.00392 (0.0130)	-0.00559 (0.0121)	-0.00342 (0.00817)
Intercept	-0.0400 (0.0409)	-0.115* (0.0672)	-0.0423 (0.0537)	0.0231 (0.0556)	-0.00573 (0.0330)
Estimation method	OLS	WLS	WLS	WLS	WLS
Weight	-	Population	Survey sample size	Survey sample size divided by population	Years between surveys
Observations	89	89	83	83	89
R-squared	0.008	0.093	0.003	0.005	0.004

The dependent variable is the annualized change in log poverty rate for $2 a day. Heteroscedasticity robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

In order to address the potential concern of parameter heterogeneity, we allow for continent-specific convergence speeds and steady state poverty levels by estimating equation (4). By doing so, we concentrate on within-continent poverty convergence dynamics. Column 1 of Table 2 shows the results of a simple OLS regression based on the specification given by equation (4). The results suggest that poverty convergence is the rule for all regions, although the estimated convergence parameter is only statistically significantly different from zero for American and Asian economies. Having in mind that American countries started with a relatively low poverty headcount initially while observing very strong convergence, this is an important piece to the puzzle of overall lacking poverty convergence: convergence seems to take place within (certain) regions but as the regions with relatively less poverty converge faster, overall convergence is blurred.

When using WLS with the number of surveyed households relative to population size as weights (as in column 4 of Table 1), the estimated convergence parameters for African countries turns statistically significant as well and is very large (see column 2 in Table 2). This effect is not driven by the slightly reduced sample size, as the comparison to an unweighted OLS estimation based on the smaller set of observations shown in column 3 of Table 2 suggests.

Table 2: Regional Poverty Convergence

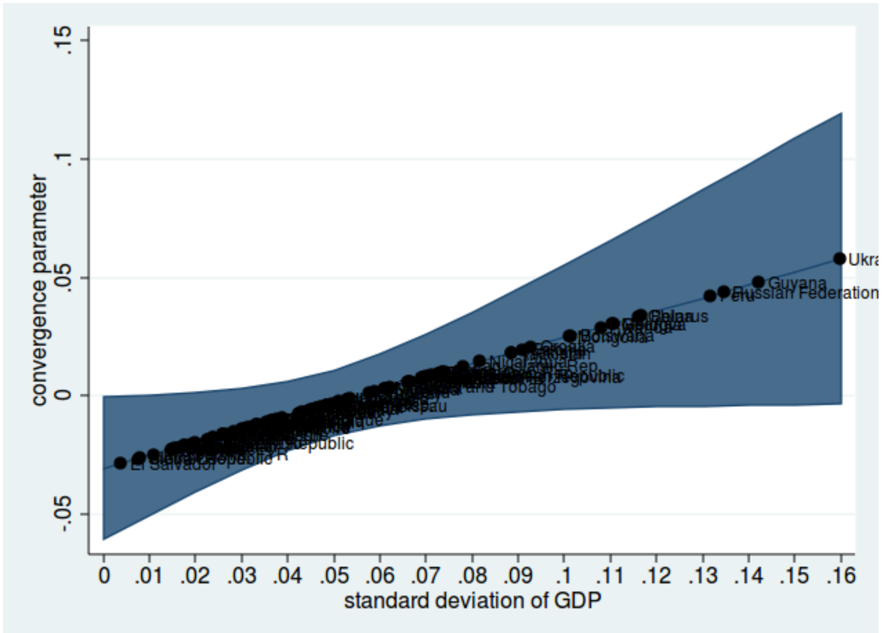
	OLS, region-specific parameters (1)	WLS, region-specific parameters (2)	OLS, region-specific parameters, reduced sample (3)
Log initial headcount index (America)	-0.0458***	-0.0416***	-0.0458***
	(0.00622)	(0.00907)	(0.00624)
Log initial headcount index (Africa)	-0.0297	-0.103***	-0.0380
	(0.0254)	(0.00914)	(0.0257)
Log initial headcount index (Asia)	-0.0179**	-0.0202**	-0.0207***
	(0.00687)	(0.00947)	(0.00753)
Log initial headcount index (Europe)	-0.0143	-0.0260	-0.00796
	(0.0454)	(0.0423)	(0.0471)
America Dummy	0.0667*	0.0362	-0.0238
	(0.0356)	(0.0478)	(0.114)
Africa Dummy	0.0540	0.353***	
	(0.114)	(0.0537)	
Europe Dummy	-0.178**	-0.163*	-0.292**
	(0.0877)	(0.0821)	(0.143)
Asia Dummy			-0.0790
			(0.116)
Intercept	0.0637**	0.0805**	0.154
	(0.0284)	(0.0386)	(0.112)
Estimation	OLS	WLS	OLS
Weight	-	Survey sample size divided by population	-
Observations	89	83	83
R-squared	0.459	0.692	0.495

The dependent variable is the annualized change in log poverty rate for $2 a day. Heteroscedasticity robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

5. Poverty convergence and volatility

Among the models estimated in Ravallion (2012), one of them adds an interaction term between initial poverty and growth to the set of standard regressors. The results of the estimation of this model are presented in column 1 of Table 3 and make Ravallion (2012) conclude that the impediment to poverty convergence is "*poverty itself*" (Ravallion, 2012, p. 521). We assess the role of macroeconomic volatility by expanding the econometric specification chosen by Ravallion (2012). When controlling for macroeconomic volatility and its interaction with the initial poverty rate, our results indicate that the volatility variable is able to explain the differences in poverty dynamics across countries (see column 2 of Table 3). Figure 1 depicts the (conditional) elasticity of poverty changes with respect to the initial poverty rate for different volatility levels. It reveals negative convergence parameters for countries with macroeconomic volatility below 0.06 and that the majority of countries experienced volatility below this threshold: for a subsample of 56 of 88 countries poverty convergence trends took place on average over the period considered. On the other hand, some countries experienced a large degree of volatility that translates to a large positive convergence parameter and thus blurs the overall picture concerning poverty convergence on an aggregate scale.

Figure 1: Effect of initial poverty on poverty reduction with respect to volatility (incl. 95% confidence interval)



In columns 3 to 5 of Table 3 we show that the interaction effect of initial poverty with volatility remains significant even after controlling for growth and its interaction with initial poverty (as suggested by Ravallion, 2012) in various specifications. In all of these combinations the interaction of growth and initial poverty remains statistically significant (together with the interaction with volatility) but so does the negative convergence parameter.

Model 4, which adds the volatility variable and its interaction with initial poverty to the initial model of Ravallion (2012) in column 1, outperforms the latter by standard model selection criteria (AIC, BIC) and rejects the null hypothesis that the reduced model (1) provides the same fit as our extended model (4) at the 1 % level of statistical significance using a standard likelihood ratio test. This suggests that the role played by macroeconomic volatility as a barrier to poverty convergence is qualitatively important. In the last column of Table 3 we show that our result is also robust to WLS estimation using the ratio of survey sample size to population as weights.

Table 3: Poverty Convergence Equations with Interaction Terms

	Model in Ravallion (2012) (1)	Model with volatility and interaction (2)	Expanded model with volatility and interaction (3)	Expanded model with volatility and interactions (4)	Model with volatility (5)	Model with volatility and interaction terms (6)	WLS model (7)
Log initial headcount index	-0.00529	-0.0308**	-0.0225*	-0.0295***	-0.00930**	-0.00967**	-0.0145*
	(0.00498)	(0.0153)	(0.0120)	(0.00972)	(0.00437)	(0.00440)	(0.00753)
Growth rate	-2.587***		-1.082***	-2.523***	-2.601***	-2.602***	-2.425***
	(0.366)		(0.296)	(0.329)	(0.339)	(0.340)	(0.186)
Growth rate interacted with log initial headcount index	2.812***			2.714***	2.816***	2.639***	2.549***
	(0.479)			(0.422)	(0.434)	(0.517)	(0.277)
Volatility		-2.329**	-2.034**	-1.694**	-0.587**	-0.624**	-0.643
		(1.117)	(0.870)	(0.742)	(0.239)	(0.274)	(0.543)
Volatility interacted with log initial headcount index		0.554**	0.472**	0.360*			0.131
		(0.276)	(0.211)	(0.183)			(0.167)
Volatility interacted with log initial headcount index and growth rate						3.974	
						(5.044)	
Constant	0.00869	0.112*	0.0988**	0.120***	0.0542**	0.0573**	0.0545**
	(0.0204)	(0.0632)	(0.0468)	(0.0400)	(0.0208)	(0.0225)	(0.0268)
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	WLS
Weight	-	-	-	-	-	-	Survey sample size divided by population
Observations	89	88	88	88	88	88	82
R-squared	0.680	0.157	0.494	0.766	0.733	0.735	0.903

The dependent variable is the annualized change in log poverty rate for $2 a day. Heteroscedasticity robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Theoretically, potential interaction effects present in equation (6) derive from interaction terms in the mean convergence equation (1), as shown in Appendix B. We turn thus to explore the effect of macroeconomic volatility on the dynamics of mean country income. The first column of Table 4 reproduces the results of Ravallion (2012) concerning cross-country convergence in mean income. The second column shows that unconditional mean convergence also holds when observations are weighted by the survey size relative to population (and sampling size decreases accordingly). An essential point for Ravallion's (2012: 513ff) argument is that the initial poverty level exercises a robust negative effect on growth in means in his study (see Ravallion, 2012: table 3). This negative effect appears empirically if we control for poverty in this specification, as is shown in column 3 of Table 4.[12] In column 4, we include our measure for volatility and interact it with initial income and initial poverty. The finding that initial poverty exercises a drag on mean convergence appears to depend on the degree of macroeconomic volatility experienced by the economy. After volatility is taken into account, the initial poverty incidence no longer exercises a significant impact on mean convergence on its own but only due to its interaction with volatility; and as volatility increases, the negative interaction term becomes important as a barrier to mean convergence. Column 5 in Table 4 confirms that a similar result also holds when using WLS, although the estimates are then a borderline case of statistical significance.

Table 4: Mean Convergence Equations with Interaction Terms

	Model in Ravallion (2012) (1)	Model in Ravallion (2012), WLS (2)	Model in Ravallion (2012) (3)	Model with volatility interactions (4)	Model with volatility interactions, WLS (5)
Initial log mean	-0.0174*** (0.00544)	-0.0210*** (0.00584)	-0.0348*** (0.0069)	-0.0173 (0.0146)	0.00894 (0.0317)
Initial log mean interacted with volatility				-0.358* (0.209)	-0.628 (0.415)
Volatility				2.210* (1.238)	4.411 (2.841)
Log initial headcount index			-0.0100** (0.00416)	0.00225 (0.00954)	0.0349 (0.0264)
Volatility interacted with log initial headcount index				-0.213* (0.120)	-0.553* (0.317)
Intercept	0.0934*** (0.0249)	0.105*** (0.0284)	0.197*** (0.0415)	0.0835 (0.0905)	-0.136 (0.226)
Estimation	OLS	WLS	OLS	OLS	WLS
Weight	-	Survey sample size divided by population	-	-	Survey sample size divided by population
Observations	97	90	84	83	78
R-squared	0.135	0.135	0.242	0.317	0.327

The dependent variable is the annualized change in log mean. Heteroscedasticity robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

[12] Ravallion (2012) shows this effect conditional on other control variables such as education or school enrollment. Depending on the specification, the estimated parameter varies between -0.017 and -0.027 and is hence somewhat larger than in our specification.

Finally, our findings imply that economic volatility prevents mean convergence if initial poverty is high. This highlights our considerations above concerning the fact that volatility especially affects poor households in their investment choice. With high initial poverty rates, many agents are thus constrained in their investment choice, which in turn exercises a drag on mean convergence.

6. Conclusions

Our findings add an important piece to the puzzle put forward by Ravallion (2012), i.e."why countries starting out with a higher incidence of poverty tend to face worse growth prospects and enjoy less poverty reduction from a given rate of growth" (Ravallion, 2012, p. 521). Our results indicate that macroeconomic volatility interacts with the initial level of poverty and thus affects the convergence process of poverty rates negatively. In fact, poverty convergence appears to be present and be robust among countries with a relatively low level of volatility.

Our findings highlight the importance of macroeconomic stabilization for effective poverty reduction and emphasizes the importance of future work to identify other barriers to poverty convergence. Unveiling the nature of the mechanisms linking macroeconomic volatility to poverty alleviation requires further research on the microeconomic scale to identify how volatility prevents the poor from benefiting from the 'advantages of backwardness' and the 'advantages of growth' which would then lead to lacking (average unconditional) poverty convergence on the macro level.

Appendix

Appendix A. Derivation of equation (3) from equations (1) and (2)

From equation (2) we know that $\ln H_{it} = \delta_i + \eta_i \ln \mu_{it} + \nu_{it}$, so that we can express

$$\Delta\ln H_{it} = \delta_i + \eta_i \ln \mu_{it} + \nu_{it} - (\delta_i + \eta_i \ln \mu_{i,t-1} + \nu_{i,t-1}), \qquad \text{(A.1)}$$

which simplifies to

$$\Delta\ln H_{it} = \eta_i \Delta \ln \mu_{it} + \nu_{it} - \nu_{i,t-1}. \qquad \text{(A.2)}$$

Substituting $\Delta \ln \mu_{it}$ from equation (1), we obtain

$$\Delta\ln H_{it} = \eta_i(\alpha_i + \beta_i \ln \mu_{i,t-1} + \varepsilon_{it}) + \nu_{it} - \nu_{i,t-1}. \qquad \text{(A.3)}$$

Note that isolating $\ln \mu_{it}$ in equation (2) gives

$$\ln \mu_{it} = 1/\eta_i (\ln H_{it} - \delta_i - \nu_{i,t-1}). \qquad \text{(A.4)}$$

Plugging (A.4) into (A.3) results in

$$\begin{aligned} \Delta\ln H_{it} &= \eta_i\alpha_i + \beta_i\left(\ln H_{i,t-1} - \delta_i - \nu_{i,t-1}\right) + \eta_i\varepsilon_{it} + \nu_{it} - \nu_{i,t-1} = \\ &= \eta_i\alpha_i - \beta_i\, \delta_i + \beta_i \ln H_{i,t-1} + \eta_i\varepsilon_{it} + \nu_{it} - (1+\beta_i)\nu_{i,t-1}, \end{aligned} \qquad \text{(A.5)}$$

which can be expressed as

$$\Delta\ln H_{it} = \alpha_i^* + \beta_i^* \ln H_{i,t-1} + \varepsilon_{it}^* \qquad \text{(A.6)}$$

with $\alpha_i^* = \eta_i\alpha_i - \beta_i\, \delta_i$, $\beta_i^* = \beta_i$, $\varepsilon_{it}^* = \eta_i\varepsilon_{it} + \nu_{it} - (1+\beta_i)\nu_{i,t-1}$, which constitutes equation (3) in the text.

Appendix B. Effects of redefinitions (5a)-(5d) in (1) and (2) on equation (3)

Substituting (5a)-(5d) into (A.1) changes (A.5) to:

$$\Delta\ln H_{it} = (h_i + \theta_{3i}B_i)(z_i + \theta_{1i}B_i) - (p_i + \theta_{4i}B_i)(d_i + \theta_{2i}B_i) + (p_i + \theta_{4i}B_i)\ln H_{i,t-1} + (h_i + \theta_{3i}B_i)\varepsilon_{it} + \nu_{it} - (1 + (p_i + \theta_{4i}B_i))\nu_{i,t-1}, \quad \text{(B.1)}$$

which simplifies to

$$\Delta\ln H_{it} = a_i + b_{1i}B_i + b_{2i}B_i^2 + p_i \ln H_{i,t-1} + \theta_{4i}B_i \ln H_{i,t-1} + u_{i,t}, \quad \text{(B.2)}$$

with

$$a_i \coloneqq h_i z_i + p_i d_i \quad \text{(B.3a)}$$
$$b_{1i} \coloneqq h_i\theta_{1i} + z_i\theta_{3i} + p_i\theta_{2i} + d_i\theta_{4i} \quad \text{(B.3b)}$$
$$b_{2i} \coloneqq \theta_{1i}\theta_{3i} + \theta_{2i}\theta_{4i} \quad \text{(B.3c)}$$
$$e_{it} \coloneqq (h_i + \theta_{3i}B_i)\varepsilon_{it} + \nu_{it} - \big(1 + (p_i + \theta_{4i}B_i)\big)\nu_{i,t-1}, \quad \text{(B.3d)}$$

with $\mathbf{E}(e_{it}) = 0$ and where $\sigma(e_{it})$ is a function of h, p, θ_3, θ_4, B, $\sigma(\varepsilon)$ and $\sigma(\upsilon)$.

Under the assumption that we can linearly approximate the term $B_i(b_{1i} + b_{2i}B_i)$ as $\omega_i B_i$, (B.2) boils down to equation (6). Note that θ_{4i}, which stems from (5d), is the parameter associated to the interaction in (B.2), i.e. any interaction with a barrier in the reduced form equation (6) should also be interacted with the initial mean in the mean-convergence equation.

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