A novel approach to assess the policy contributions of growth and redistribution to poverty reduction

[conference pillar 3: Acceleration towards inclusive and sustainable development]

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Abstract

Inclusive and sustainable development requires the eradication of poverty. To better understand poverty developments, they can be decomposed into their proximate sources – changes in income and inequality.

In this paper, we propose a novel poverty decomposition approach that does not simply analyze observed income and inequality changes and their contribution to poverty reduction but compare those to a hypothetical counterfactual. We therefore predict expected income and inequality changes for each country, based on the economic rationales of convergence and a relationship between inequality and development ("Kuznets curve").

We use data from 144 countries to estimate those relationships and construct our counterfactual poverty predictions for 71 developing countries, based on those hypothetical income and inequality developments. Those predictions indicate the poverty reduction that countries could expect to achieve, given their initial income and inequality situation. We argue that comparing actual achievements against these predictions is a more appropriate measure for actual policy contributions to poverty reduction. For example, we can identify countries where growth fell short of expectations, with adverse poverty effects (e.g. Kenya, 1992-2005) while poverty reduction exceeded expectations in other countries, either due to an overperformance in growth (e.g. Chad, 2003-2011) or inequality reduction (e.g. Cabo Verde, 2001-2007). Countries that fell particularly short of expectations often underwent political transition and state fragility.

Keywords: poverty decomposition, inequality convergence, income convergence, Kuznets curve

1. Introduction

The importance of achieving the United Nation's Sustainable Development Goal (SDG) of eradicating extreme poverty by 2030 has given rise to several attempts to forecast poverty trends. Those studies usually rely on certain assumptions concerning income, inequality, and demographics (e.g. Ravallion, 2013; Crespo-Cuaresma et al., 2018; Lakner et al., 2019). Another literature takes a backward-looking approach to ask what one can learn from past contributions of growth and inequality to poverty trends, often referred to as "poverty accounting" (e.g. Datt and Ravallion, 1992; Khan, 2003; Fujii, 2017; Bluhm et al., 2018).

In this paper, we argue that a meaningful policy assessment of poverty dynamics needs to bring both approaches together: ex-post analysis of poverty dynamics needs to take into account a-priori expectations about poverty trends. We thus propose to compare actual ex-post dynamics in poverty and their proximate sources to a hypothetical 'control group', where dynamics of income and inequality are governed by economically reasonable laws of motion such as convergence patterns (see Crespo-Cuaresma et al., 2017).

To illustrate our point, consider the examples of Tanzania and South Africa. Tanzania has traditionally low levels of inequality, at least compared to other countries in Sub-Saharan Africa. It may require serious policy effort to keep inequality at such low levels, whereas mild reductions in inequality are comparably easy to achieve in more unequal societies, such as South Africa. A traditional poverty decomposition will, however, not show any effect of inequality on poverty reduction in case Tanzania maintains its inequality level. Conversely, it will attribute some positive role of poverty reduction in South Africa to declining inequality. From the perspective of policy evaluation, this is unsatisfactory because the redistributive policy effort to keep poverty in check may have been much higher in the Tanzanian case.

We address this shortcoming by proposing a novel poverty accounting approach. We start by asking the question what income and distribution trends countries could expect, given their initial situation, and how this would translate into poverty dynamics. We therefore assume that income levels across countries converge at a certain speed. For inequality, we assume convergence as well as an inverted-U-relationship with development (the "Kuznets' hypothesis"). To quantify both effects, we use data from 144 countries. We then use the fact that under certain distributional assumptions, mean income and a Gini index for inequality are satisfactory to explain poverty levels (see Bourguignon, 2003). We can hence calculate a 'counterfactual expectation' about income, inequality, and poverty trends for each individual country, given its initial income and inequality level. Comparing actual developments in those three variables to our created counterfactuals is of much more information for policy evaluation because it shows what a country has achieved compared to what it could expect to achieve, given its initial situation. In the above example, we no longer compare Tanzania to a completely different country like South Africa, but compare Tanzania to a 'counterfactual Tanzania, which starts out at the same initial income and inequality levels as the true Tanzania. Likewise, South Africa is compared to a counterfactual with the same initial income and inequality as the true South Africa. In some sense, we hence create an artificial 'control group' for each country. If countries simply follow average policies, actual poverty trends will not deviate from predicted counterfactuals and there is hence no particular 'treatment effect' of policies. We hence argue that one can learn most about policy effects from countries where actual trends in poverty and its proximate sources, income and inequality, deviate from predicted counterfactuals.

Overall, we find a high correlation between the actually observed and predicted developments in income, inequality and poverty which suggests that our counterfactual model adequately reflects average real developments. Our empirical analysis also highlights several cases, where both deviate from each other. For example, even though the key contribution to poverty reduction in Ethiopia (1995-2010) came from substantial income growth, its initially low income level suggested that an even higher growth rate would have been achievable in the period 1995-2010, with more beneficial poverty effects. Conversely, the modest contribution of declining inequality to poverty reduction was stronger than what one could have hoped for, given Ethiopia's already modest level of inequality in 1995. Shortfalls in growth relative to counterfactual expectations are even more drastic in countries like Belize (1993-1999), Cote d'Ivoire (1985-2015), or Kenya (1992-2005), leading to much more unfavorable poverty developments than our counterfactual suggests. Other countries exceeded predicted reductions in poverty, either because of growth beyond expectations (Chad, 2003-2011) or surprisingly favorable inequality developments (Cabo Verde, 2001-2007). We also investigate if there are certain factors driving such deviations across countries, using a cluster analysis. There seems to be little effect of political factors such as the political regime or orientation of the ruling party, but it stands out that the countries that performed particularly above or below expectations all experienced some kind of political transition that seems to have affected their poverty performance.

The remainder of the paper is structured as follows. Section 2 reviews the key previous literature on the poverty-growth-inequality triangle that is of relevance to our paper, with a focus on poverty decomposition techniques. Section 3 outlines the key idea of our alternative approach to create a counterfactual 'control group' using projected trajectories of income and inequality. Section 4 describes the data used to estimate the model and provides the respective results. Section 5 then applies the estimated parameters to our alternative poverty decomposition and presents the results across countries, highlighting some particularly interesting country cases. Section 6 asks whether there is a broad pattern emerging from the deviations between projection and actual developments. Section 7 concludes.

2. The poverty-growth-inequality triangle revisited

Our proposed approach relies on actual and predicted changes in countries' income and inequality levels and how they translate into poverty developments. For this purpose, we need to understand how changes in income and inequality translate into poverty developments, which we measure by the poverty headcount ratio H, capturing the fraction of the population that lives below a certain poverty line z. If one assumes a log-linear distribution of incomes, the percentage change in the headcount ratio, $\frac{\Delta H}{H_t}$, is given by[1]:

$$\frac{\Delta H}{H_t} = \lambda \left[\frac{\log(\frac{z}{\mu_t})}{\sigma} + \frac{1}{2}\sigma \right] * \left[- \frac{\Delta \log(\mu_t)}{\sigma} + \left(\frac{1}{2} - \frac{\log(\frac{z}{\mu_t})}{\sigma^2}\right) \Delta\sigma\right], \quad (1)$$

where μ is the mean income level of a country, σ is inequality (measured by the standard deviation of incomes), and λ is the ratio of the density to the cumulative function of the standard normal distribution.

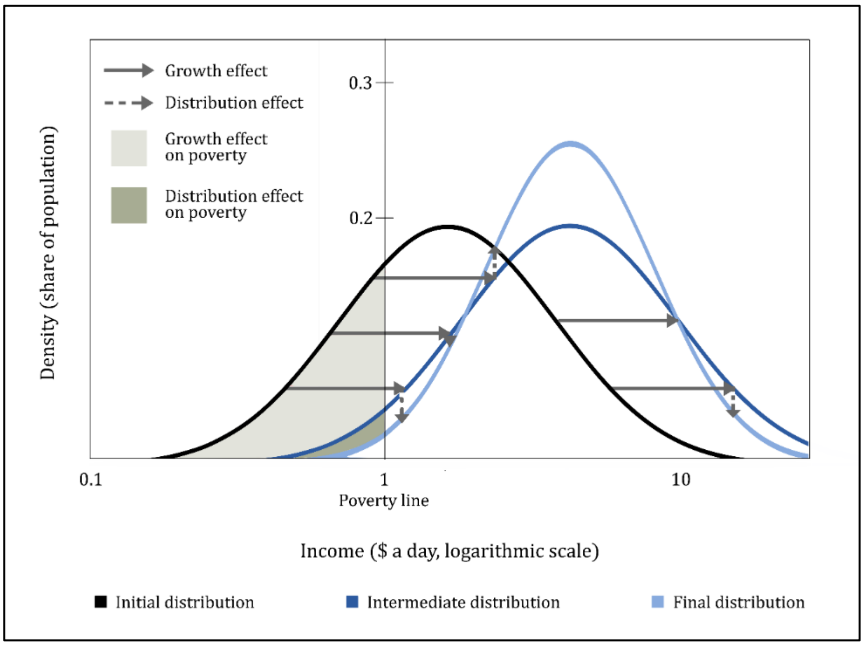
This illustrates that changes in poverty analytically can be separated into changes in income levels (holding the distribution of incomes constant) and changes in the distribution of incomes (holding the income level constant), which is visualized in Figure 1 for the case of log-normally distributed incomes.[2] The figure depicts the distribution of income and thus the amount of people at each (logarithmic) level of income. At a given poverty line (such as $z=1$ in the figure), every individual left of this line would be identified as poor and the size of the gray-shaded area relative to the overall density defines the headcount ratio for the initial distribution (black curve). A move from this initial income distribution to the final distribution (light blue curve) can analytically be separated into an intermediate step (dark

[1] For a detailed derivation see Bourguignon (2003) or Kalwij and Verschoor (2005).

[2] Other distribution families can be used and have been studied in the literature as well (see Bandourian, McDonald, and Turley, 2002; Bresson, 2009; Bluhm et al., 2018).

blue curve). This horizontal movement represents the growth effect with mean income increasing but keeping the distribution of income (shape of the curve) unaffected. The vertical transition from the intermediate to the final distribution then shows the redistribution effect with constant mean income but a shift in the income distribution.

Figure 1: Decomposition of a change in poverty into growth and redistribution



Source: Own presentation based on Bourguignon (2003, p. 9).

Different techniques of *"poverty accounting"* and *"poverty decomposition"* explore this relationship to decompose observed changes in poverty into its proximate sources: income and inequality changes. Examples following this rationale (but deviating from Bourguignon, 2003, in some assumptions) include Ravallion and Huppi (1991), Datt and Ravallion (1992) and Kakwani (1993), Ahuja, Bidani, Ferreira, and Walton (1997), Khan (2003), Contreras (2003), Assadzadeh and Paul (2004), Kalwij and Verschoor (2005), Fujii (2017), Bluhm et al. (2018). These studies for different countries broadly highlight that the proximate sources to explaining trends in poverty can vary considerably over countries and time, although the contribution of growth to poverty reduction dominated the contribution of redistribution in most countries. This finding is corroborated by Kraay (2006) who uses parametric approximations of Lorenz curves to study poverty trends in 80 developing countries during the 1980s and 1990s.

A key constraint in the literature on poverty accounting is that the analytical decomposition of observed poverty reduction into growth and redistribution by holding the other factor constant comes at the cost of simplifying the complex interactions that exist in the poverty-growth-inequality triangle (e.g. Ferreira, 2010; Inchauste et al., 2014). A particular problem we aim to tackle in our paper is the role of initial conditions and how they influence subsequent macroeconomic developments. Take the case of a low level of initial inequality. Analysis of equation (1) reveals that a country with low initial inequality will enjoy a high growth elasticity of poverty reduction so that its contribution to poverty reduction due to growth will be higher than in another country with the same growth rate but higher initial inequality. Additionally, lower initial inequality may foster economic growth additionally inflating the perceived contribution of growth to poverty reduction even if the ultimate source stems from equity considerations (cf. Deininger and Squire, 1998; Kalwij and Verschoor, 2005; Fosu, 2011). Finally, studies such as Deininger and Squire (1996) and Ravallion (2003) have suggested inequality convergence in the sense that countries starting out at low initial levels of inequality are expected to observe higher subsequent increases in inequality. Equation (1) highlights that this will negatively contribute to poverty reduction via the redistribution term $\Delta\sigma$. In other words, standard poverty accounting techniques are unlikely to ascribe a relevant contribution of poverty reduction to redistribution in case countries starting out at low initial inequality levels, even though those countries may put relevant effort into effective pro-poor redistribution. The converse holds for countries starting at high initial inequality levels and similar arguments can be made for different initial income levels.

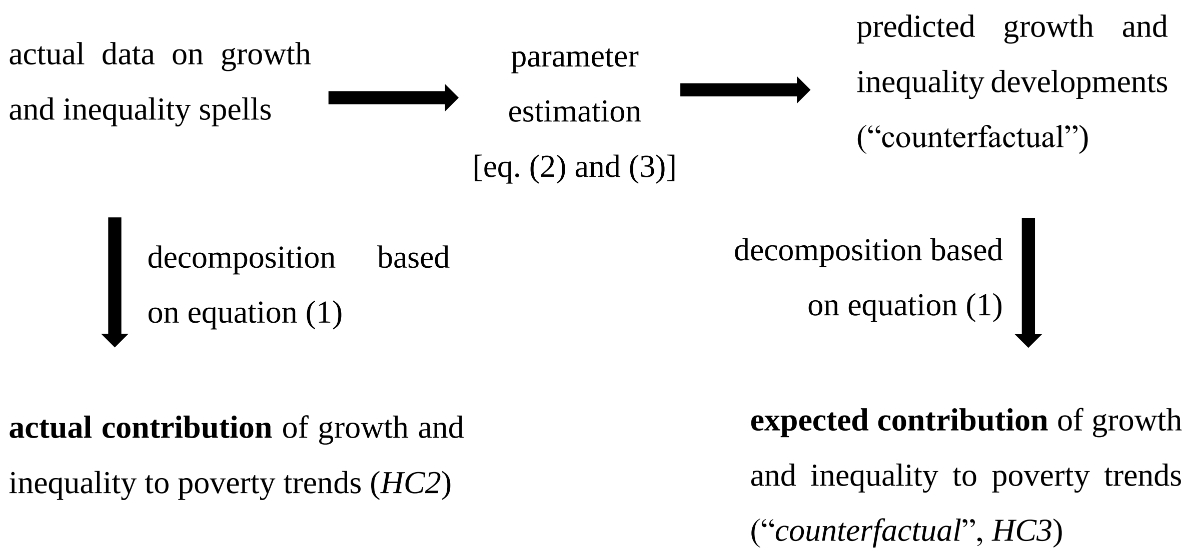
Standard poverty accounting techniques thus fail to provide a reasonable and policy-relevant ex-post decomposition of poverty trends into growth and redistribution for which they are essentially designed. Not surprisingly, Datt and Ravallion (1992) thus acknowledge that the approach cannot tell if an alternative growth process would have been more effective in reducing poverty nor whether a shift in distribution or mean income is politically or economically attainable.

With our paper, we contribute to this literature by suggesting to first use the initial levels of inequality and income (and a limited relation between the two) to predict a counterfactual that is indeed 'attainable' or expected and to benchmark actual developments against this counterfactual to evaluate the actual policy contributions via growth and redistribution to poverty reduction.

3. A counterfactual approach to poverty decompositions

To overcome the discussed drawbacks of conventional poverty accounting, we suggest an alternative approach to understand the dynamics of poverty reduction across countries. Our approach consists of the creation of suggested counterfactuals in two distinct stages that are illustrated in Figure 2. In a first step, we estimate regressions of growth and inequality developments to generate counterfactual levels of mean income and inequality for each country (top row of Figure 2). These counterfactuals can be interpreted as income and inequality developments that one would expect for each country given its initial values in both variables and based on general trends. In the second step, we then use Bourguignon's (2003) poverty decomposition method from equation (1) to calculate the contributions of income growth and changes in redistribution to poverty reduction for both, the real and estimated data (left and right columns of Figure 2, respectively). The former can be interpreted as the “treatment group” and the latter as a counterfactual “control group”. Taking differences of the former from the latter can thus be interpreted at the effect of policies of a country conditional on what one might expect, on average, for this country (given initial income and inequality levels).

Figure 2: Illustration of counterfactual vs. actual decomposition approach



In order to predict the change in mean income of a country, we first use a simple cross-country convergence regression to estimate a *growth process* of the form:

$$\Delta \ln \mu_{it+1} = \alpha + \Phi \ln \mu_{it} + u_{it+1} \ . \qquad (2)$$

μ_{it} is mean income of country i in year t (the initial observation year) and $\Delta \ln \mu_{it+1}$ is hence the growth rate, measured in annual percent changes in mean income between t and $t+1$. α is a constant and u_{it+1} is a zero-mean error term. Φ is a convergence parameter, expected to show a negative sign if incomes across countries tend to converge over time as the standard neoclassical growth model predicts. Evidence by Patel et al. (2018) and Ravallion (2012) suggests increasing tendencies of unconditional income convergence in national account data and robust convergence for mean household income across developing countries.

For the creation of our counterfactual we additionally assume an *inequality process* of the form

$$\Delta \ln G_{it+1} = \beta + \gamma \ln G_{it} + \delta \ln \mu_{it} + \theta (\ln \mu_{it})^2 + v_{it+1} , \qquad (3)$$

where G_{it} denotes inequality (measured by the Gini coefficient[3]) in country *i* in year *t*. β is a constant and v_{it+1} a zero-mean error term. The equation suggests that the annual change in (logarithmic) inequality of country *i* between two points in time, *t* and *t+1*, depends on its level of inequality in the initial year *t*, and an income component of quadratic form. The latter is motivated by Kuznets (1955), who proposed that the relationship between income and inequality follows an inverted U-shape, with inequality first increasing as an economy starts to develop and then decreasing again at later stages of development (see e.g. Frazer, 2006 or Higgins and Williamson, 2002 for related empirical evidence). Similar to Φ in the growth process (2), γ can be understood as an inequality convergence parameter, taking a negative sign if inequality levels tend to converge between countries over time. Such inequality convergence has been found i.e. in studies by Bénabou (1996), Deininger and Squire (1996), Ravallion (2003), and Crespo-Cuaresma et al. (2017).

After estimation of equations (2) and (3), we obtain the parameter estimates for α, Φ, β, γ, δ, θ, that can then be used to predict growth and inequality trends based on initial income and inequality levels (μ_{it} and G_{it}, respectively). Applying the decomposition formula of Bourguignon (2003) presented in equation (1) above, those predicted growth and inequality trends can then be used in the second step of our approach to calculate overall expected changes in poverty, $\frac{\Delta H}{H_t}$, as well as the expected individual contributions of growth and

[3] Note that the Gini coefficient can be analytically linked to the standard deviation of log-normally distributed incomes (see Bourguignon, 2003).

redistribution to poverty changes. In the end, this leaves us with the following three measures for poverty trends in the headcount rate *HC*:

1. *HC1* is the "true" development in the poverty headcount rate as reported by the World Bank.

2. *HC2* is the development in the poverty headcount rate implied by equation (2) when using *actual* data for growth and inequality spells.

3. *HC3* is the development in the poverty headcount rate implied by equation (2) when using *predicted* data for growth and inequality spells.

Note that it is not possible to decompose *HC1* into contributions from growth and redistribution but that such decompositions exist for *HC2* and *HC3*. Differences between *HC1* and *HC2* result from the fact that the latter requires a distributional assumption for incomes which only approximates reality, whereas differences between *HC2* and *HC3* (and their respective contributions of growth and redistribution) result from the fact that *HC2* uses actual while *HC3* uses predicted ('expected' or 'counterfactual') data for growth and redistribution. We construct our predictions for *HC3* (and the associated decompositions) such that the initial and end year match those in the actual data used to decompose *HC2*.

With the empirical framework being specified, we now move to the description of the database in the following section, including the estimation results for equations (3) and (4).

4. Data and estimation results

4.1 Data

We use household survey data on economic welfare and inequality for the 35 years between 1981 and 2016 from the World Bank's PovcalNet database (World Bank, 2018a).[4] The initial dataset includes 162 countries with 9 observations per country on average. "Income" is measured as the average monthly per capita income/consumption expenditure in 2011 PPP and ranges from $22.98 to $2217.97. When both mean income and consumption data are available for a country, the income data is dismissed as proposed by Ravallion (2012).[5] Inequality is measured by the Gini coefficient, which compares cumulative proportions of the population against cumulative proportions of the income they receive (OECD, 2018). For the sample of all 162 countries, the index moves between 16.2% and 65.8%.

The focus of our paper is to explore how much actual developments of income and inequality in a country contributed to poverty developments compared to a counterfactual situation where income and inequality are projected based on average trends (as explained in section 3). Our measure for poverty is the well-established official headcount ratio at the $1.90/day poverty line at 2011 PPP reported by the World Bank. This variable varies between 0% and 94%.

Since we are interested in the change in income and inequality, we discard countries with less than two observations or countries for which Gini or income/consumption data is unavailable.[6] We construct spells of maximum length for each country, restricting the sample

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[4] Available at http://iresearch.worldbank.org/PovcalNet/povOnDemand.aspx (accessed August 4, 2020).

[5] Ravallion (2012, p.509) suggests that consumption data should be preferred to income data due to the fact that it is generally a better measure of economic welfare and because its measurement is less prone to error. In the final sample, about two thirds of the data are consumption data.

[6] An exception here are China, India, and Indonesia for which no national Gini coefficients are provided but where rural and urban figures are reported separately by virtue of national reporting standards. While PovcalNet does provide a population-weighted estimate for mean incomes, no data is available for the national Gini index.

to spells of at least five years as in Dollar and Kraay (2002) and Kraay (2006). This results in non-uniform spell durations ranging from five to 34 years, with an average duration of 18.5 years. We exclude spells for which the annualized growth rate of mean income/consumption or Gini coefficient exceeds 15% in absolute value, as suggested by Kraay (2006), to avoid sufficiently unlikely extrema possibly caused by measurement error. These steps reduce the final dataset to 144 countries, which are used in the regression analysis to calculate estimates of changes in inequality and mean income. The list of countries can be found in online appendix A.1.

Within this set of countries, 25% are considered as high-income countries in their final year of the spell according to the World Bank's classification. Likewise, about the same amount are low-income states. The remaining part is made up by lower- and upper-middle income nations. These proportions are roughly representative of the global income class shares in 2015. Furthermore, the 144 countries may be distinguished according to the World Bank region they belong to. The regions that are most strongly represented are Europe & Central Asia (34%) and Sub-Saharan Africa (27%). Others include Latin America & Caribbean (14%), East-Asia Pacific (11%), Middle East & North Africa (8%), South Asia (5%) and North America (1%). As for the income classification, these shares are presentational for the worldwide proportions of countries in each region; it can thus be assumed that the sample as a whole is representative.

Looking at general income and inequality developments in the dataset, the histograms in Figure 3 suggest that a large fraction of countries experienced annual increases in mean income during their respective spells. The mean and the median are both around 2%, which

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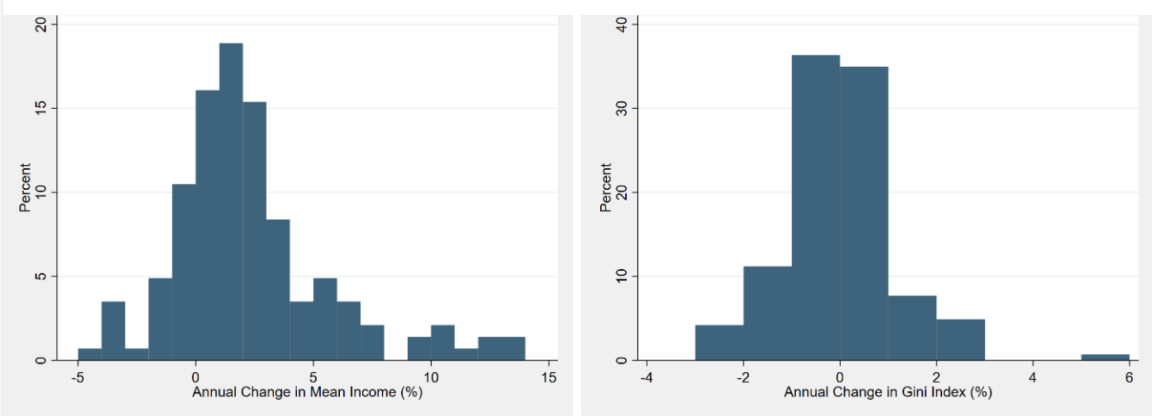
In light of the fact that the Gini coefficient is not subgroup-decomposable but that we consider China, India and Indonesia essential for our analysis, we follow the procedure of Bluhm et al. (2018) and use an approximation suggested by Young (2011) to obtain estimates for the Gini index of these countries. Details are available upon request. For robustness checks, we later exclude China, India and Indonesia and find that the estimated coefficients remain largely unaffected.

accords with general economic expectations of growth. For the case of the Gini index, the tendency seems more ambiguous. Whereas inequality increased slightly across all countries (mean change of 0.02% per year), there are about equally as many countries for which inequality increased as for which it decreased. The histograms confirm that the development of mean income and inequality varies widely across countries. Due to the prior data cleaning there are no major outliers for neither of the two variables.

Figure 3: Annual changes in mean income and Gini index across sample countries



Note: The graphic presents histograms of the percentage annual changes in mean income (left) and Gini index (right) for the full sample of 144 countries with their respective spell. The vertical axis shows the percentage share of countries represented by each bar as a fraction of the total sample. The width of each bar corresponds to a 1% annual change. Source: Own computations based on PovcalNet.

4.2 Estimation results for creating counterfactuals

To construct the counterfactual, we estimate the growth and inequality processes according to the empirical framework proposed in equations (2) and (3) in section 3. In our main specification, we use the spells of all 144 countries in our dataset with a minimum length of five years, weighted according to their respective spell duration. By use of the duration weights, we aim to account for the fact that longer spells are likely to provide more solid information. We also look at alternative specifications, i.e. discarding all high-income countries, neglecting the weights or including spells that are shorter than five years and obtain similar results (further robustness checks are presented in Appendix A.2). We report heteroscedasticity-robust standard errors in all regressions. Table 1 and Table 2 present the resulting regression outputs, which are used to calculate the income and inequality estimates for each country as well as subsequently the contribution of income and inequality to poverty reduction.

Table 1: Regression results for the income growth process (2)

Annual Mean Income Growth	
Initial Mean Income	-0.0145***
	(-7.43)
Consumption Dummy	-0.0159***
	(-3.87)
Constant	0.103***
	(8.50)
N	144
R^2	0.258

Note: The table reports the result from the OLS regression of income growth on initial income. Initial mean income and annual income growth are measured on a logarithmic scale. The consumption dummy takes the value 1 if consumption data was used and 0 if income data was used. Robust t-statistics are reported in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001. Source: Own computations based on PovcalNet.

Considering that the growth regression includes only two variables, (log-transformed) initial mean income as well as a dummy variable indicating if the data used was income (D=0) or consumption data (D=1)[7], we consider the explanatory power of 26% appropriate. As Table 1 shows, all variables are statistically significantly different from 0 and show the expected signs. The coefficient on initial mean income clearly indicates the anticipated income convergence: economic growth is higher in poorer countries; a marginal reduction of initial mean income yields a higher growth rate. The convergence parameter of -0.015 is in fact very similar to the results found by Ravallion (2012) for his full sample without controls,

[7] Due to the fact that PovcalNet provides either consumption or income data – depending on national reporting standards – this distinction was deemed necessary.

taking a value of -0.017. Depending on the specification, Ravallion (2012) finds the regression coefficient to vary between -0.007 and -0.047, always showing signs of income convergence. Dobson et al. (2003) compare 156 convergence coefficients across 25 studies from the 1980s and 1990s and observe that the coefficient's average value was around -0.0196 with a standard deviation of 0.022. In conclusion, the regression results of the growth process are congruous and are expected to yield decent estimates of mean income growth for the creation of the control group.

In view of the fact that the inequality regression includes not only the (log-transformed) initial Gini and consumption dummy variables but also the Kuznets component, it is not surprising that the model's explanatory power is considerably higher than that of the growth regression; it explains almost 50% of the variation in the data. As Table 2 shows, all variables are highly significant and show the expected signs.[8] The coefficient of -0.025 for the initial Gini index indicates that inequality levels across countries tend to converge and that thus inequality falls (rises) in countries with high (low) initial inequality. The coefficient is in the same range as the inequality convergence parameters of other studies: Bénabou (1996) finds a value of around -0.015 for the (non-logarithmic) initial Gini index using the Deininger and Squire (1996) dataset. Ravallion (2001) receives an estimate of -0.010 and claims that for both linear and logarithmic specifications inequality convergence was supported. He also estimates the steady state Gini index and finds it in the range of 40%. Using the same calculation, the steady state level in our model is around a value of 36% and thus on a very similar plane.[9] Lagged mean income and its square support the idea of a Kuznets relationship with inequality following an inverse U-shape, first increasing and then decreasing, as mean

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[8] Initial mean income and its square are jointly significant at the 0.1%-level.

[9] Following Ravallion (2001), the steady state level of the Gini index is calculated by dividing the negative of the convergence parameter $\hat{\gamma}$ by the constant (β): $-\frac{\hat{\gamma}}{\beta}$.

income grows further. It is however worth noting that the estimated turning point of inequality is tremendously high, at a monthly mean income of around $8,350 at 2011 PPP. This threshold is not surpassed by a single country in the world, which makes the interpretation of the relationship in the traditional Kuznets manner difficult. Kuznets (1955) suggested that the inequality turning point marks the transition from a traditional, agricultural to a modern, industrial economy; this is clearly not the case here since even the mean incomes of the most modern nations locate below the turning point threshold.

Table 2: Regression results for the inequality process (3)

Annual Gini Growth	
Initial Gini	-0.0245***
	(-10.53)
Initial Mean Income	0.0121*
	(2.39)
Initial Mean Income^2	-0.00134**
	(-2.90)
Consumption Dummy	-0.00618***
	(-4.60)
Constant	0.0678***
	(4.31)
N	144
R^2	0.494

Note: The table reports the result from the OLS regression of the change in inequality on initial inequality and a quadratic initial income component. Initial mean income, initial Gini index and annual growth in the Gini index are measured on a logarithmic scale. The dummy variable takes the value 1 if consumption data was used and 0 for the case of income data. Robust t-statistics are reported in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001. Source: Own computations based on PovcalNet.

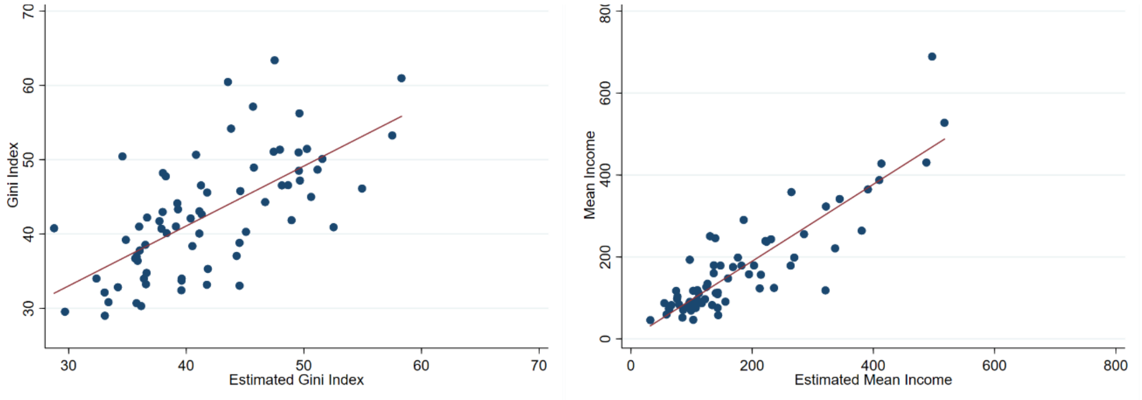
4.3 Aggregate comparison between actual and counterfactual data

We use the regression results to calculate the predictions for mean income and the Gini index for each country's final spell year.[10] Estimates and real figures for both variables are plotted

[10] Note that we apply those predictions only to 71 developing countries with a headcount ratio equal to or above 2%.

against each other in Figure 4. As one can infer, there is a clear relationship between the true and predicted ('counterfactual') inequality and growth data. Some variation between the two is expected and intended by our exercise, but on average the relationship is nearly 1 (see online appendix A.3) and the correlation coefficient between the true Gini coefficient and its estimate is almost 79% and even higher for mean income (88%).

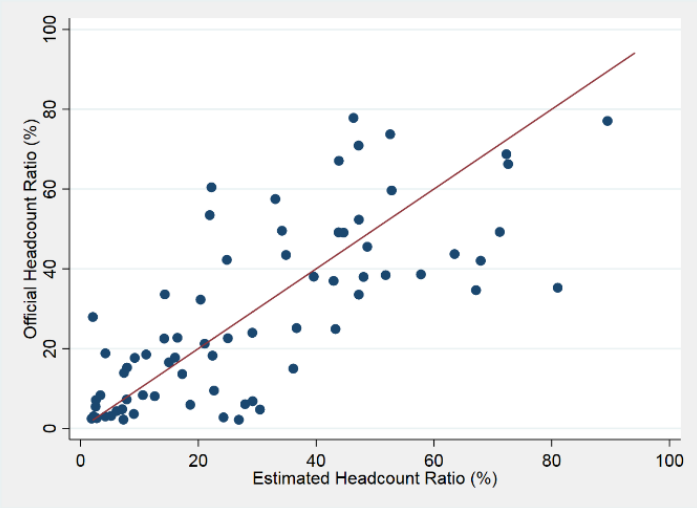
Figure 4: Scatterplots of estimated and true income and inequality data



Note: The graphics show the correlation between estimated (x-axis) and true (y-axis) inequality (left) and income (right) data in the form of a scatterplot. The Gini index is measured in %; monthly mean income is measured in 2011 PPP $. The graphics also include the respective regression lines. Source: Own computation based on PovcalNet.

Similarly, the poverty headcount ratios implied by our predicted counterfactual (*HC3*) on average exhibit a near-unity relationship with the observed poverty headcount ratios (*HC1*), as illustrated in Figure 5. Again, deviations from the 1:1 relationship are the purpose of our exercise and not worrisome if they cancel out on average and show no clear systematic pattern. The correlation coefficient between *HC1* and *HC3* is almost 75%.

Figure 5: Scatterplot of actual poverty headcount ratio (*HC1*) vs. headcount ratio implied by counterfactual (*HC3*)



Note: The figure shows the correlation between HC1 (vertical axis) and HC3 (horizontal axis). The red line is the 45°-line, indicating a 1:1 correlation. Source: own computation based on PovcalNet.

5. Cross country evidence and country examples

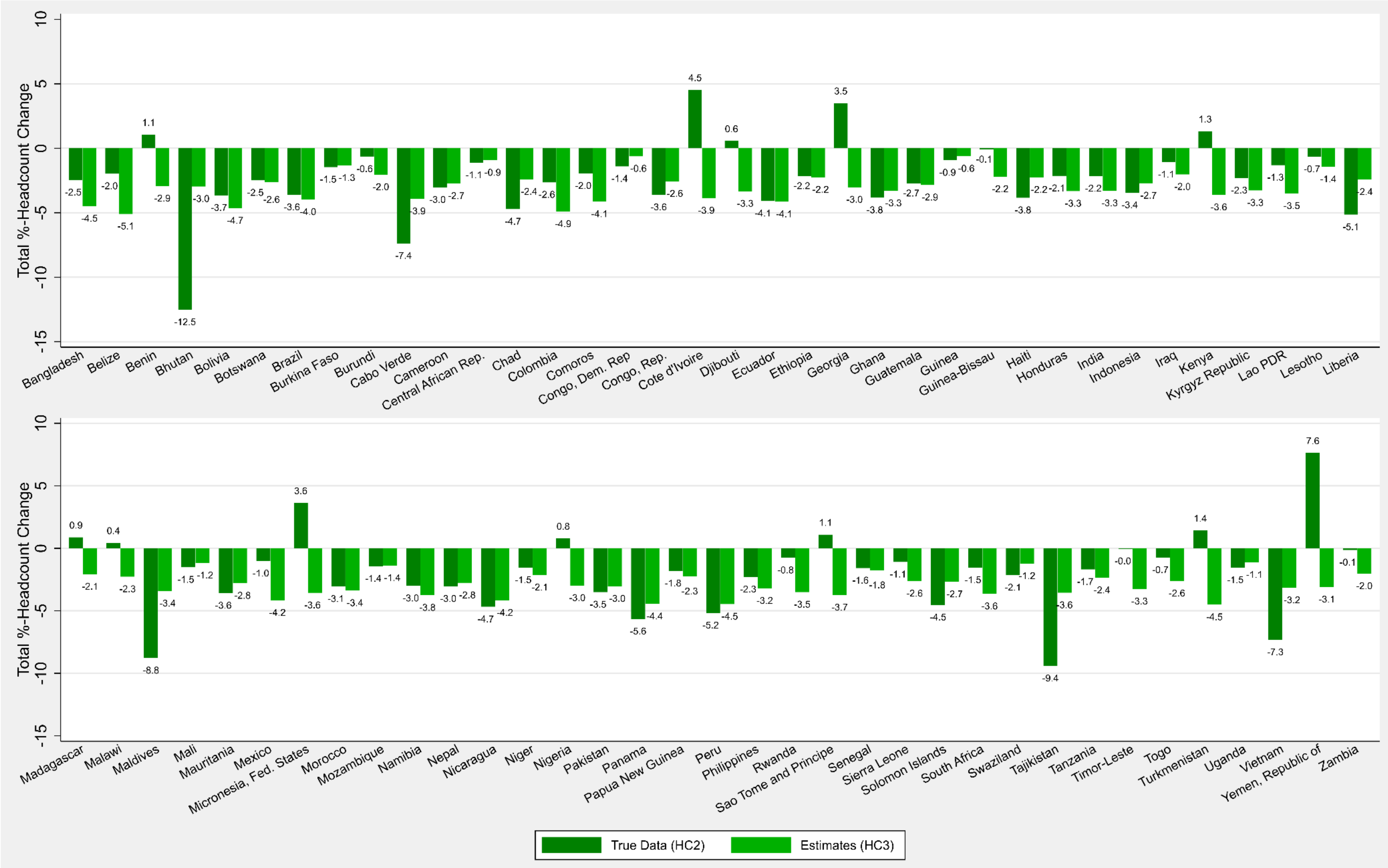
In this section, we present and discuss the results of our counterfactual poverty decompositions (*HC3*) explained in the previous sections and compare them to the conventional decomposition (*HC2*). Since we are primarily interested in the developments in poor countries, we discard countries for which poverty is negligible in either the initial or the final year of the spell for all further analyses.[11]

[11] To do so, we use the threshold of a headcount ratio of 2% as in Kraay (2006). This perimeter is slightly below the World Bank's definition of zero-poverty, being at a headcount ratio below 3%, however, it allows us to include ten more countries in the analysis, which are to a large extent only slightly below the 3%-mark. These countries include Peru with a headcount ratio of 2.99% in 2015, coming from 17% in the initial observation year, or Vietnam with 2.76% of the population living in poverty in 2014, coming from 49% in the initial year. Discarding the spells of non-poor countries entails several advantages. Firstly, it enables us to focus on those key countries that are more strongly in need of reducing their poverty levels. Secondly, and more importantly, we can avoid distortions from high-income countries when analyzing the relative headcount reductions in section 6. Without excluding these non-poor countries, a 23% poverty reduction in Sweden from 0.25% to 0.2% in headcount ratio would attract greater attention than a 16% reduction in Azerbaijan from 32% to 27% even though in absolute terms poverty in Azerbaijan declined much stronger (5 percentage points compared to 0.05 percentage points in Sweden).

Figure 6 compares changes in HC2, which uses actual growth and redistribution data in equation (2) to calculate changes in the poverty headcount rate, to HC3, which uses the predicted (counterfactual) growth and redistribution data in equation (2) to predict changes in the poverty headcount rate. Figure 7 shows the decompositions of the poverty headcount rates HC2 and HC3 into actual and counterfactual, respectively, growth and redistribution. In either case, a negative contribution indicates that poverty was reduced.

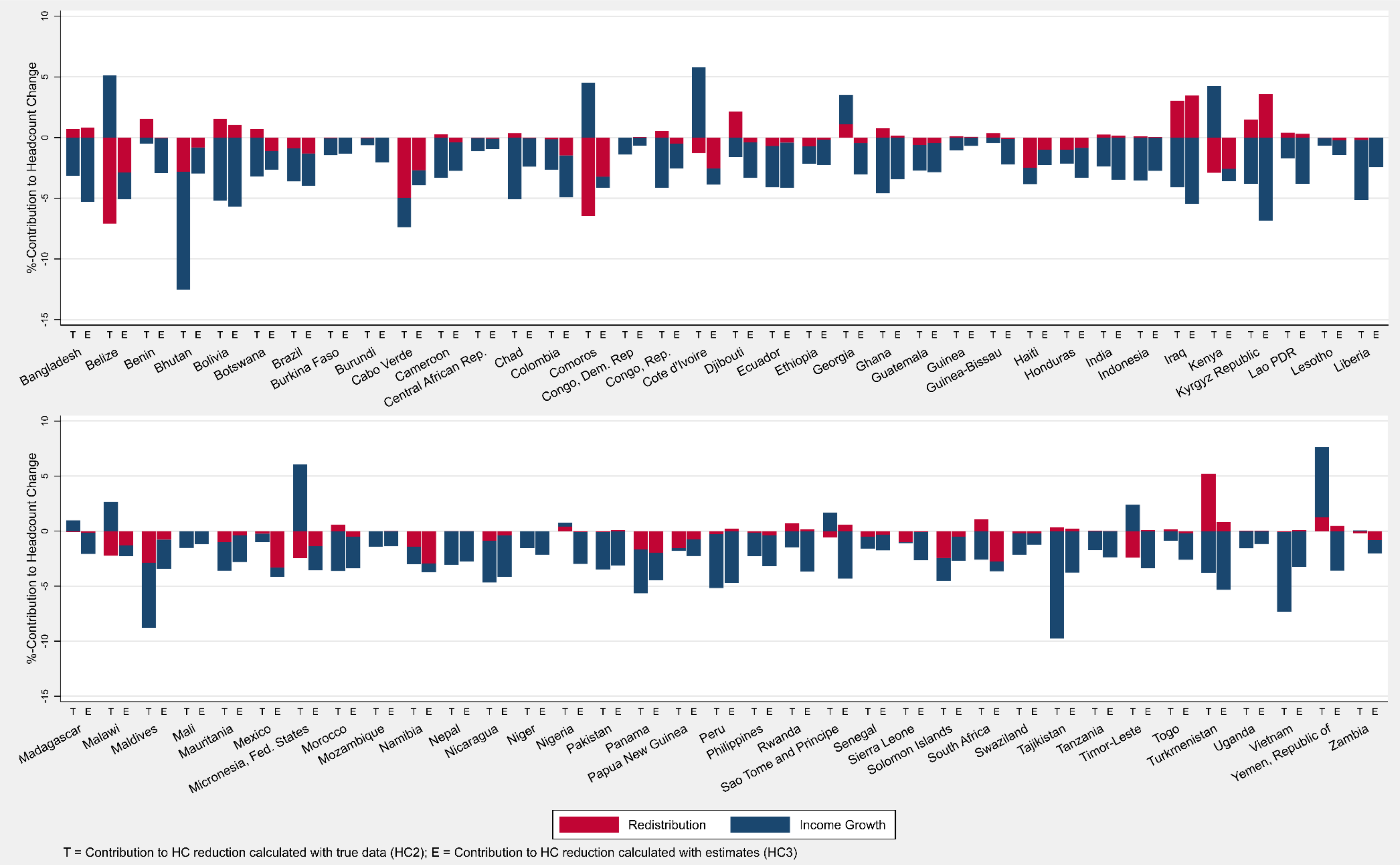
Figures 6 and 7 provide several revelatory insights and help to illustrate the core idea of our approach. Clearly, there are some countries for which the model very well predicts the total poverty headcount reductions as well as the contributions of inequality and growth to these poverty reductions. These countries include, for example, Burkina Faso, Ecuador, or Nepal. One could say that those countries achieved what was "generally expected of them", given their starting levels of income and inequality.

Figure 6: The total change in the poverty headcount ratio by country.



Note: The graphic depicts the total %-poverty reduction. It distinguished between true (dark green) and estimated (light green) data (HC2 and HC3). A negative contribution indicates that poverty declined.

Figure 7: The contribution of income growth and redistribution to the reduction of the poverty headcount ratio by country.



Note: The graphic depicts the %-contributions of income and distribution changes to poverty reduction. It distinguished between true (T) and estimated (E) data (HC2 and HC3). A negative contribution indicates that poverty declined.

To illustrate the relevance of our approach for policy analysis, let us consider the case of *Cote d'Ivoire* (1985-2015). When looking at the conventional poverty decomposition approach (HC2) in Figure 7, we would conclude that the decline in real income levels has contributed to the overall increase in poverty, but that declining inequality helped to somewhat reduce poverty. One could thus conclude that redistribution policies have been successful in poverty alleviation in the country. However, this neglects the fact that Cote d'Ivoire started out at initially very high levels of inequality, with a Gini index of 46% in 1985. Based on the experience of other countries, we would expect inequality to fall to 38% due to inequality convergence and the Kuznets relationship. In fact, however, actual inequality developments fell short of this expected development, with the Gini declining to only 42% in 2015.

Another interesting case is *Ethiopia*, which experienced a considerable acceleration in income growth after 2000 (see Moller and Wacker, 2017). Accordingly, a traditional poverty decomposition approach as in HC2 in Figure 7 would attribute the main share of poverty reduction in the country to growth and associated policies. Over the whole 1995-2010 spell analyzed in our sample, however, one can see from a comparison of actual developments in HC2 to the predicted counterfactual in HC3 that the process of income convergence in equation (2) would have suggested an even higher income growth rate, given Ethiopia's initially poor income level in 1995. Moreover, the contribution of reduced inequality is much higher than one would have expected, given that Ethiopia started out with an initially modest Gini of 45% that was reduced to 33% and thus far below the steady state that our equation (3) implies. Viewed from this perspective, one would possibly be more curious to understand the redistributive character of Ethiopia's policies for poverty reduction than a traditional decomposition approach suggests, possibly including the distributive effects of infrastructure (e.g. Bekele and Ferede, 2015) and a pattern of structural transformation that focused on labor-intensive lower-skilled activities, including agricultural development-led industrialization (e.g. Cornia and Martorano, 2017).

Further examples where inequality developments clearly outperformed expectations in the fight against poverty include several small and island states, such as *Timor-Leste*, *Solomon Islands*, *Micronesia*, *Papua New Guinea*, *Comoros*, *Cabo Verde*, but also *Belize*, *Haiti*, and *Malawi*. Interesting cases in this regard are *Iraq* (2006-2012) and *Kyrgyz Republic* (1988-2015). In both cases, a traditional poverty decomposition approach (HC2) suggests considerable adverse effects of increasing inequality for poverty reduction. However, this neglects the initially low inequality levels in both countries, with Ginis of 29% and 26%, respectively. Starting from such low inequality levels, one would have expected a much faster increase in inequality with even more detrimental effects on poverty, as HC3 in Figure 7 indicates. The likely conclusion from a traditional poverty decomposition that inequality policies in both countries were poorly designed and ineffective in poverty alleviation should thus be taken with a grain of salt.

Finally, *Bhutan* (2003-2012) is another interesting case to look at because of its remarkable progress in poverty reduction, which is largely attributed to pro-poor policies (e.g. World Bank, 2014). This rationale is reflected in our analysis: growth and inequality reduction have been fast and outpaced predicted expectations, as one can see from comparing HC2 to HC3 in Figure 7. World Bank (2014) highlights policies that supported food security, agricultural marketization, and infrastructure development, particularly in rural regions, as key contributors to these favorable developments.

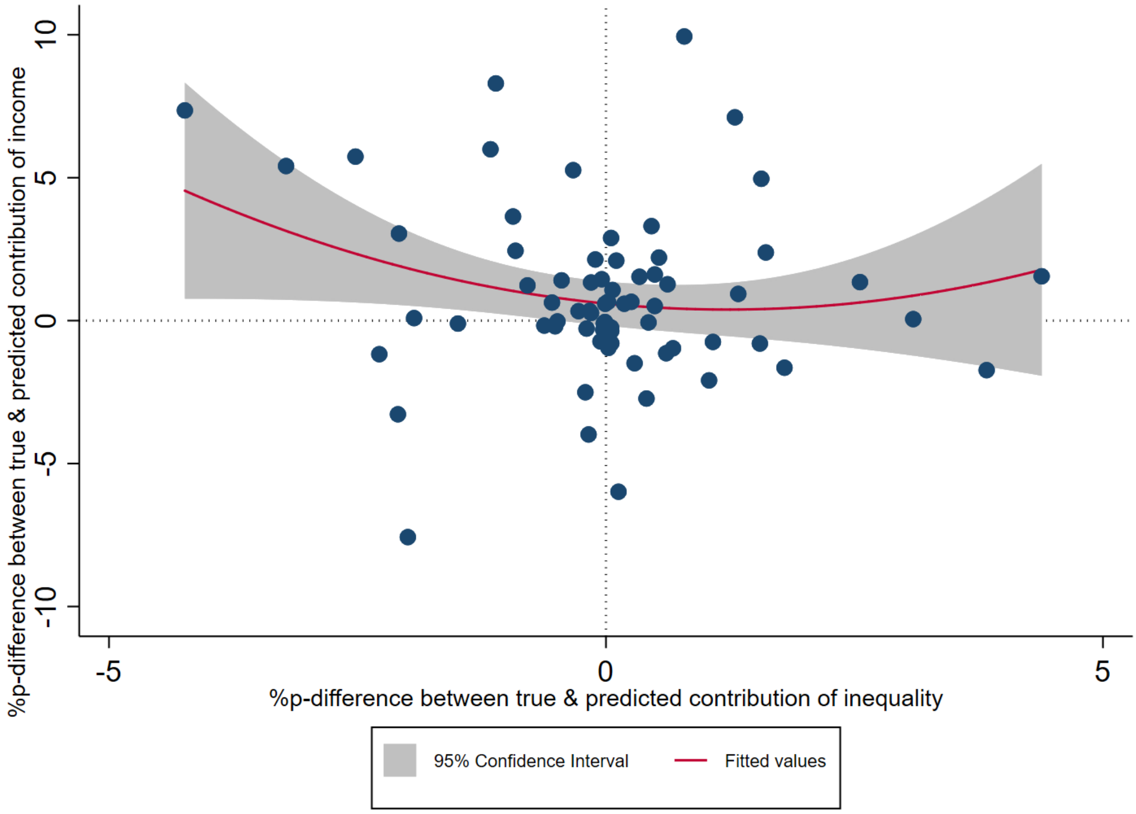
Those country examples illustrate that traditional poverty decomposition approaches may provide an incomplete picture about the contributions of growth and inequality to poverty reduction, because they do not take initial conditions in those variables, and thus the potential for action and progress into account. Comparing those traditional decompositions with our newly proposed counterfactual accounting approach will provide a more nuanced picture of countries' success in the macroeconomics of fighting poverty.

6. Is there an overall policy message?

In line with global poverty trends, most countries in our sample succeeded in decreasing poverty, independent of the length of the spell analyzed. Moreover, Figure 7 suggests that income contributed more strongly to poverty reduction than did redistribution. Using the decomposition with the true data (*HC2*), the average annual contribution of the Gini index to poverty reduction was -0.42% while the average annual contribution of mean income was almost four times higher (-1.64%). A qualitatively similar image can be obtained by looking at the estimated data (*HC3*) with an average annual contribution of the Gini index of -0.55% and -2.46% for mean income. The difference in the growth contribution to poverty reduction of about 0.8 percentage points suggests that growth in developing countries and its contribution to poverty reduction performed considerably below counterfactual expectations. At that stage, it is not clear whether this is due to a broad-based trend or because of individual countries with output shocks, such as Belize, Cote d'Ivoire, or Kenya.

To understand if there are certain patterns across countries in terms how much their actual contributions of growth and redistribution to poverty reduction deviated from counterfactual expectations, we plotted those deviations and performed a cluster analysis, which is extensively discussed in online appendix A.4. The key idea and pattern are illustrated in Figure 8: Moving to the left on the horizontal axis indicates that countries increasingly outperformed expectations in terms of redistributive contributions to poverty reduction. Countries on bottom of the vertical axis reduced poverty by growing faster than one could have expected. Each dot in Figure 8 represents a developing country in our sample and those in the lower-left quadrant managed to outperform counterfactual expectations in terms of growth and redistributive contributions to poverty reduction. In line with previous results, most countries concentrate in the center of Figure 8, indicating that there is no large deviation between true and expected growth and redistribution.

Figure 8: Relationship between true and predicted contributions of income and inequality to poverty developments



Note: The graphic depicts the quadratic regression line for percentage point-differences between true and predicted contribution of income and inequality. The shaded area represents a 95% confidence band.

Our k-means cluster analysis suggests the existence of five clusters in this two-dimensional space. One of them (#2, see appendix A.4) mainly contains the 'growth shortfalls' with mean incomes declining by almost 30% on average, which hindered poverty reduction in this group despite the fact that the poverty-alleviating distribution effect was two times higher than expected. Figure 8 further suggests that underperformance in growth was rather broad-based since a considerable part of developing countries is located in the upper half of the graph. Another cluster (#1, see appendix A.4) outperformed counterfactual expectations to the largest extent and essentially clusters in the lower third of Figure 8. The distribution effect for those countries was on average four times higher than expected, the growth effect was almost threefold. In absolute terms, however, overperformance in the growth effect contributed much more to poverty reduction than overperformance in redistribution for this group (see Table 7 in online appendix A.4).

To investigate whether countries within those two clusters share common characteristics, we performed an exploratory analysis focusing on the policy dimension. To be more specific, we investigated the types of political regime, political orientation, and the level of government expenditure of the countries within the clusters (see online appendix A.4 for details). We found large heterogeneity between countries within the two clusters in terms of those variables. The only pattern worth reporting in our view is the fact that all overperformers in cluster #1 experienced a modest improvement in the State Fragility Index, whereas all ‘growth shortfalls’ in cluster #2 suffered a modest deterioration in state fragility.

Finally, one could ask if there is a systematic relationship between the respective percentage point-differences between true and predicted contribution of income and inequality. In other words: is there a policy trade-off in the sense that overperformance in one dimension comes at the cost of underperformance in the other dimension? If so, we should see a negative relationship for countries’ performances in Figure 8. The depicted quadratic regression line suggests some trade-off in the left part of the figure: countries that increasingly overperform in poverty reduction through inequality reduction increasingly underperform in poverty reduction through growth. In this part of the sample, this relationship is nearly 1-to-1. However, the more one moves towards the right of Figure 8, the more this potential trade-off vanishes.

7. Conclusion

In this paper, we have presented the argument why traditional poverty decompositions are unsatisfactory from a policy analysis perspective: they do not take countries' initial income and inequality levels into account. We hence propose to model expected developments in those variables and associated poverty trends and benchmark actual developments against this counterfactual. Deviations from the expected counterfactual should then receive increased attention for further policy analysis (cf. Pfeiffer and Armytage, 2019).

We use data from 144 countries to model income and inequality developments, motivated by convergence dynamics and a Kuznets-type relationship between inequality and development. Applying the data to 71 developing countries show an overall reasonable fit between predicted and actual poverty developments. More interestingly, we can identify several countries where actual outcomes and proximate sources of poverty reduction significantly deviate from expectations based on initial conditions and provide a short policy discussion potentially explaining those deviations.

Our paper hence contributes to improved policy analysis but also opens space for further improvements in poverty decompositions from a policy perspective. Particularly, future work could make use of the increasing availability of panel-type household surveys and provide more dynamic models for income, inequality, and poverty. Another scope for advancement is to also use counterfactuals in the cross-elasticities in equation (1) linking income and inequality to poverty.

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Appendix A

Appendix A.1: Income & inequality – true data and estimates.

Country	Year	Mean income	Estimated mean income	Gini index	Estimated Gini index
Albania	1996	187.95		27.0	
Albania	2012	225.28	224.88	29.0	30.4
Algeria	1988	199.85		40.2	
Algeria	2011	247.73	253.40	27.6	37.9
Armenia	1996	162.45		44.4	
Armenia	2015	206.12	209.25	32.4	40.7
Australia	1981	1041.65		31.3	
Australia	2010	1661.82	1112.57	34.7	33.9
Austria	2004	1572.74		29.8	
Austria	2014	1689.53	1515.58	30.5	30.1
Azerbaijan	1995	171.36		34.7	
Azerbaijan	2008	312.41	201.73	31.8	35.3
Bangladesh	1983	72.95		25.9	
Bangladesh	2010	109.03	143.01	32.1	33.1
Belarus	1988	314.31		22.8	
Belarus	2015	611.60	347.87	26.7	30.0
Belgium	2004	1416.00		30.5	
Belgium	2014	1473.51	1385.47	28.1	30.9
Belize	1993	340.79		60.3	
Belize	1999	264.03	380.73	53.3	57.5
Benin	2003	78.63		38.6	
Benin	2015	82.56	104.68	47.8	38.3
Bhutan	2003	118.51		46.8	
Bhutan	2012	245.77	139.22	38.8	44.5
Bolivia	1990	220.52		42.0	
Bolivia	2015	387.52	409.72	45.8	44.6
Bosnia & Herzegovina	2001	367.48		30.0	
Bosnia & Herzegovina	2011	605.42	373.00	33.8	30.9
Botswana	1985	122.48		54.2	
Botswana	2009	290.39	186.05	60.5	43.5
Brazil	1981	224.87		58.0	
Brazil	2015	527.44	517.17	51.4	48.0
Bulgaria	1989	713.47		23.4	
Bulgaria	2014	569.50	866.16	37.4	31.7
Burkina Faso	1994	40.81		48.1	
Burkina Faso	2014	83.84	79.52	35.3	41.8
Burundi	1992	42.80		33.3	
Burundi	2013	52.08	84.98	39.2	34.9
Cabo Verde	2001	219.03		52.5	
Cabo Verde	2007	243.33	231.17	47.2	49.7

Country	Year	Mean income	Estimated mean income	Gini index	Estimated Gini index
Cameroon	1996	92.88		44.5	
Cameroon	2014	160.24	136.60	46.5	41.2
Canada	1981	1274.07		32.4	
Canada	2013	1745.13	1247.90	34.0	32.9
Central African Republic	1992	35.60		61.3	
Central African Republic	2008	73.72	62.66	56.2	49.6
Chad	2003	61.01		39.8	
Chad	2011	98.14	76.04	43.3	39.3
Chile	1987	348.39		56.2	
Chile	2015	657.85	579.11	47.7	47.3
China	1981	34.64		26.6	
China	2013	287.70	108.67	32.9	33.5
Colombia	1992	308.31		51.5	
Colombia	2015	430.37	487.50	51.1	47.4
Comoros	2004	246.86		55.9	
Comoros	2013	178.71	263.53	45.0	50.6
Congo, Democratic Rep.	2004	22.98		42.2	
Congo, Democratic Rep.	2012	45.83	32.07	42.1	40.4
Congo, Rep.	2005	90.07		47.3	
Congo, Rep.	2011	117.41	102.70	48.9	45.7
Costa Rica	1981	118.24		47.5	
Costa Rica	2015	680.23	373.31	48.2	48.0
Cote d'Ivoire	1985	267.16		45.5	
Cote d'Ivoire	2015	118.40	320.94	41.7	37.7
Croatia	1988	629.54		22.8	
Croatia	2014	546.68	807.42	32.2	32.3
Cyprus	2004	770.88		30.1	
Cyprus	2014	757.97	823.76	35.6	31.8
Czech Republic	1988	584.18		19.4	
Czech Republic	2014	824.33	770.67	25.9	30.8
Denmark	2004	1392.86		24.9	
Denmark	2014	1554.39	1366.09	28.5	26.5
Djibouti	2002	134.17		40.0	
Djibouti	2013	147.67	160.16	44.1	39.2
Dominican Republic	1986	109.56		47.8	
Dominican Republic	2015	427.28	301.61	44.9	48.1
Ecuador	1987	179.87		50.5	
Ecuador	2015	364.87	391.02	46.5	48.1
Egypt, Arab Rep.	1990	139.99		32.0	
Egypt, Arab Rep.	2015	183.13	206.16	31.8	35.1
El Salvador	1991	217.24		54.0	
El Salvador	2015	311.69	395.80	40.8	49.3
Estonia	1988	534.37		23.0	
Estonia	2014	828.70	729.04	34.6	33.1
Ethiopia	1995	66.64		44.6	
Ethiopia	2010	87.56	98.79	33.2	41.7

Country	Year	Mean income	Estimated mean income	Gini index	Estimated Gini index
Fiji	2002	208.27		38.1	
Fiji	2013	222.94	231.78	36.4	37.6
Finland	2004	1310.18		27.9	
Finland	2014	1487.87	1296.45	26.8	29.0
France	2004	1325.88		30.7	
France	2014	1600.34	1309.72	32.3	31.1
Georgia	1996	230.26		37.1	
Georgia	2015	198.48	269.43	38.5	36.5
Germany	2006	1611.42		31.8	
Germany	2013	1616.25	1566.33	31.4	31.6
Ghana	1987	83.02		35.4	
Ghana	2012	178.87	147.75	42.2	36.7
Greece	2004	1012.33		33.6	
Greece	2014	651.61	1039.88	35.8	34.0
Guatemala	1986	106.04		58.3	
Guatemala	2014	255.60	285.67	48.7	51.2
Guinea	1991	23.01		46.8	
Guinea	2012	87.30	55.19	33.7	39.6
Guinea-Bissau	1993	62.57		43.6	
Guinea-Bissau	2010	69.18	99.28	50.7	40.8
Haiti	2001	99.40		59.5	
Haiti	2012	126.75	124.47	40.9	52.5
Honduras	1989	154.76		59.5	
Honduras	2015	221.01	336.84	50.1	51.6
Hungary	1987	629.98		21.0	
Hungary	2014	620.18	815.54	30.9	31.8
Iceland	2004	1415.66		28.0	
Iceland	2014	1431.21	1385.18	25.6	28.9
India	1983	67.55		32.5	
India	2011	111.83	140.07	37.0	35.8
Indonesia	1984	53.24		32.7	
Indonesia	2016	179.69	136.83	41.0	36.0
Iran, Islamic Rep.	1986	283.51		47.4	
Iran, Islamic Rep.	2014	497.08	328.43	38.8	38.5
Iraq	2006	168.92		28.6	
Iraq	2012	178.81	182.36	29.5	29.7
Ireland	2004	1368.70		33.6	
Ireland	2014	1365.27	1345.80	31.9	33.3
Israel	1986	593.61		36.5	
Israel	2012	986.89	778.39	41.4	38.6
Italy	2004	1308.95		34.3	
Italy	2014	1197.69	1295.40	34.7	33.9
Jamaica	1988	234.57		43.2	
Jamaica	2004	368.03	266.60	45.5	40.1
Jordan	1986	342.29		36.1	
Jordan	2010	331.63	363.64	33.7	34.9

Country	Year	Mean income	Estimated mean income	Gini index	Estimated Gini index
Kazakhstan	1988	454.27		25.7	
Kazakhstan	2015	341.85	435.27	26.5	30.1
Kenya	1992	208.04		57.5	
Kenya	2005	124.39	236.12	48.5	49.6
Korea, Rep.	2006	1068.40		31.7	
Korea, Rep.	2012	1181.69	1080.67	31.6	32.1
Kosovo	2003	184.33		29.0	
Kosovo	2013	255.34	206.78	26.7	30.7
Kyrgyz Republic	1988	121.27		26.0	
Kyrgyz Republic	2015	157.81	194.85	29.0	33.1
Lao People's Democratic Rep.	1992	93.56		34.3	
Lao People's Democratic Rep.	2012	113.30	143.32	36.4	35.9
Latvia	1988	760.00		22.5	
Latvia	2014	936.19	907.95	35.1	31.3
Lesotho	1986	52.45		56.0	
Lesotho	2010	75.72	107.02	54.2	43.8
Liberia	2007	54.42		36.5	
Liberia	2014	82.38	66.75	33.2	36.6
Lithuania	1988	396.56		22.5	
Lithuania	2014	687.53	605.40	37.7	34.0
Luxembourg	2004	2142.84		30.2	
Luxembourg	2014	2171.78	1974.42	31.2	29.6
Macedonia	1998	239.01		28.1	
Macedonia	2014	317.00	348.73	35.6	34.1
Madagascar	1993	60.97		45.3	
Madagascar	2012	46.66	102.87	42.7	41.3
Malawi	1997	113.13		65.8	
Malawi	2010	57.94	144.02	46.1	54.9
Malaysia	1984	378.71		48.6	
Malaysia	2009	627.05	578.39	46.3	45.2
Maldives	2002	160.56		41.3	
Maldives	2009	198.52	176.47	38.4	40.5
Mali	1994	37.67		50.4	
Mali	2009	73.10	63.22	33.0	44.5
Mauritania	1987	95.37		43.9	
Mauritania	2014	175.37	168.35	32.4	39.6
Mauritius	2006	335.26		35.7	
Mauritius	2012	351.49	340.98	35.8	35.4
Mexico	1984	302.54		49.0	
Mexico	2014	341.49	344.30	48.2	38.0
Micronesia, Fed. States	2005	197.16		42.4	
Micronesia, Fed. States	2013	156.59	214.47	40.1	41.1
Moldova	1988	449.92		24.1	
Moldova	2015	293.76	432.73	27.0	29.5
Mongolia	1995	138.80		33.2	
Mongolia	2014	321.71	186.71	32.0	35.0

Country	Year	Mean income	Estimated mean income	Gini index	Estimated Gini index
Montenegro	2005	376.70		30.2	
Montenegro	2014	442.47	380.56	31.9	30.9
Morocco	1984	166.94		39.2	
Morocco	2006	238.74	221.87	40.7	37.9
Mozambique	1996	39.08		44.4	
Mozambique	2008	59.56	58.75	45.6	41.8
Namibia	2003	211.34		63.3	
Namibia	2009	237.07	223.75	61.0	58.3
Nepal	1984	49.56		30.1	
Nepal	2010	119.01	109.63	32.8	34.2
Netherlands	2004	1410.74		29.8	
Netherlands	2014	1496.58	1381.07	28.6	30.3
Nicaragua	1993	179.68		50.4	
Nicaragua	2014	323.13	321.79	46.6	48.6
Niger	1992	47.31		36.1	
Niger	2014	77.73	94.00	34.0	36.4
Nigeria	1985	81.83		38.7	
Nigeria	2009	75.86	143.03	43.0	38.0
Norway	2004	1650.27		31.6	
Norway	2014	2137.09	1579.24	26.8	31.3
Pakistan	1987	62.22		33.3	
Pakistan	2013	134.53	126.33	30.7	35.8
Panama	1989	288.78		58.9	
Panama	2015	688.93	496.84	51.0	49.5
Papua New Guinea	1996	92.52		55.4	
Papua New Guinea	2009	96.88	122.33	41.9	48.9
Paraguay	1990	423.59		40.8	
Paraguay	2015	531.96	621.20	48.0	41.8
Peru	1985	179.74		45.6	
Peru	2015	427.77	413.15	44.3	46.7
Philippines	1985	118.88		41.0	
Philippines	2015	179.12	203.10	40.1	38.3
Poland	1985	446.62		25.2	
Poland	2014	508.95	429.65	32.1	30.3
Portugal	2004	830.95		38.9	
Portugal	2014	775.65	878.35	35.6	38.4
Romania	1989	426.28		23.3	
Romania	2014	306.33	623.71	39.1	33.7
Russian Federation	1988	172.00		23.8	
Russian Federation	2015	681.72	241.03	37.7	31.7
Rwanda	1984	59.81		28.9	
Rwanda	2013	82.57	133.98	50.4	34.6
Sao Tome and Principe	2000	94.45		32.1	
Sao Tome and Principe	2010	86.95	116.74	30.8	33.4
Senegal	1991	63.78		54.1	
Senegal	2011	95.98	109.18	40.3	45.1

Country	Year	Mean income	Estimated mean income	Gini index	Estimated Gini index
Serbia	2002	395.00		32.0	
Serbia	2013	386.22	396.94	29.1	32.4
Seychelles	1999	584.29		42.8	
Seychelles	2013	699.05	678.26	46.8	41.8
Sierra Leone	2003	70.34		40.2	
Sierra Leone	2011	70.84	86.23	34.0	39.6
Slovak Republic	1988	600.04		19.5	
Slovak Republic	2014	664.99	783.64	26.1	30.8
Slovenia	1987	584.10		23.6	
Slovenia	2014	1022.55	778.86	25.7	33.5
Solomon Islands	2005	94.45		46.1	
Solomon Islands	2013	111.12	111.90	37.1	44.3
South Africa	1993	227.36		59.3	
South Africa	2011	358.22	264.72	63.4	47.5
Spain	2004	1020.28		33.3	
Spain	2014	1084.17	1046.86	36.1	33.8
Sri Lanka	1985	126.48		32.5	
Sri Lanka	2012	228.33	199.90	39.2	35.6
Swaziland	1994	46.60		60.5	
Swaziland	2009	117.23	74.67	51.5	50.3
Sweden	2004	1220.68		26.1	
Sweden	2014	1641.22	1220.34	27.2	27.8
Switzerland	2007	1926.68		34.3	
Switzerland	2013	2005.88	1851.38	32.5	33.4
Tajikistan	1999	62.97		29.5	
Tajikistan	2015	193.19	97.09	34.0	32.4
Tanzania	1991	50.85		35.3	
Tanzania	2011	78.60	92.96	37.8	36.0
Thailand	1981	166.07		45.2	
Thailand	2013	449.17	251.79	37.9	38.5
Timor-Leste	2001	83.56		35.9	
Timor-Leste	2007	75.75	95.90	30.3	36.2
Togo	2006	76.19		42.2	
Togo	2015	82.51	94.82	43.1	41.1
Tonga	2001	310.43		37.7	
Tonga	2009	295.64	320.36	37.5	37.1
Tunisia	1985	178.41		43.4	
Tunisia	2010	288.18	240.63	35.8	39.1
Turkey	1987	311.50		43.5	
Turkey	2014	540.24	345.97	41.2	37.4
Turkmenistan	1988	76.14		26.4	
Turkmenistan	1998	90.47	97.09	40.8	28.8
Uganda	1989	33.35		44.4	
Uganda	2012	103.07	76.82	41.0	39.1
Ukraine	1988	192.71		23.3	
Ukraine	2015	345.25	258.30	25.5	31.3

Country	Year	Mean income	Estimated mean income	Gini index	Estimated Gini index
United Kingdom	2004	1402.10		36.0	
United Kingdom	2014	1426.48	1373.83	34.1	35.0
United States	1986	1586.01		37.5	
United States	2013	1918.04	1430.44	41.0	33.0
Uruguay	1981	536.08		43.7	
Uruguay	2015	776.91	803.46	41.7	41.2
Uzbekistan	1988	196.85		25.0	
Uzbekistan	2003	57.50	230.57	35.3	28.7
Venezuela, RB	1981	628.31		55.6	
Venezuela, RB	2006	353.70	798.74	46.9	45.0
Vietnam	1992	76.64		35.7	
Vietnam	2014	250.62	130.57	34.8	36.6
West Bank and Gaza	2004	295.99		34.0	
West Bank and Gaza	2011	327.82	305.74	34.4	34.1
Yemen, Rep.	1998	174.64		35.0	
Yemen, Rep.	2014	123.29	212.54	36.7	35.7
Zambia	1991	93.40		60.5	
Zambia	2015	90.86	155.91	57.1	45.7

Note: The table presents the true data and estimates for mean income and inequality for the full sample. (Estimated) mean income is measured in 2011 PPP $; the (estimated) Gini index is measured in %. By nature of the model, estimates only exist for the final spell year.

Source: Own calculations based on data from PovcalNet (The World Bank, 2018a).

Table A.1: Alternative specifications of the growth process.

Annual Income Growth	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Initial Mean Income	-0.0145***	-0.0138***	-0.0175***	-0.0136***	-0.0095***	-0.0231***	-0.0146***	-0.0157***	-0.0145***
	(-7.43)	(-6.42)	(-7.42)	(-7.19)	(-6.37)	(-6.90)	(-7.49)	(-7.36)	(-7.18)
Consumption Dummy	-0.0159***	-0.0151**	-0.0132**	-0.0154***		-0.0256***	-0.0155***	-0.0212***	-0.0167***
	(-3.87)	(-3.04)	(-3.27)	(-3.73)		(-5.15)	(-3.75)	(-4.56)	(-3.92)
_cons	0.103***	0.0985***	0.115***	0.0977***	0.0669***	0.149***	0.104***	0.112***	0.103***
	(8.50)	(7.11)	(8.43)	(8.26)	(7.83)	(8.19)	(8.53)	(8.56)	(8.20)
N	144	144	118	141	144	98	146	121	127
R^2	0.258	0.208	0.296	0.230	0.191	0.328	0.251	0.282	0.294

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table reports the results from the OLS regressions of mean income growth on initial mean income. Initial mean income and annual income growth are measured on a logarithmic scale. The consumption dummy takes the value 1 if consumption data was used and 0 if income data was used. Robust standard errors are reported in parentheses. Explanation of the specifications: (1) Main specification. (2) Main specification without weighting spells. (3) Main specification excluding high-income countries (World Bank classification). (4) Main specification excluding China, India and Indonesia. (5) Main specification without dummy variable for consumption/income data. (6) Main specification restricted to countries with a headcount ratio of 2% or higher. (7) Main specification with all spells (not just spells with minimum duration of 5 years). (8) Main specification without Eastern European countries. (9) Main specification without transition economies.

Source: Own calculations.

Table A.2: Alternative specifications of the inequality process.

Annual Gini Growth	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Initial Gini	-0.0245***	-0.0273***	-0.0266***	-0.0244***	-0.0227***	-0.0265***	-0.0246***	-0.0261***	-0.0241***
	(-10.53)	(-9.14)	(-9.75)	(-10.02)	(-10.31)	(-6.36)	(-10.55)	(-6.60)	(-10.23)
Initial Mean Income	0.0121*	0.0132*	0.00143	0.0125*	0.0108*	0.0138	0.0120*	0.0148*	0.0136*
	(2.39)	(2.56)	(0.16)	(2.31)	(2.10)	(0.93)	(2.37)	(2.48)	(2.58)
Initial Mean Income^2	-0.00134**	-0.00150**	-0.000192	-0.00137**	-0.00102*	-0.00146	-0.00133**	-0.00157**	-0.00143**
	(-2.90)	(-3.23)	(-0.22)	(-2.83)	(-2.18)	(-0.91)	(-2.88)	(-2.84)	(-2.98)
Consumption Dummy	-0.00618***	-0.00718***	-0.00636***	-0.00616***		-0.00486**	-0.00612***	-0.00577**	-0.00519***
	(-4.60)	(-4.82)	(-4.54)	(-4.56)		(-2.70)	(-4.56)	(-3.31)	(-3.72)
_cons	0.0678***	0.0768***	0.0996***	0.0659***	0.0551***	0.0689	0.0682***	0.0663***	0.0601***
	(4.31)	(4.13)	(4.81)	(3.66)	(3.77)	(1.71)	(4.33)	(3.91)	(3.86)
N	144	144	118	141	144	98	146	121	127
R^2	0.494	0.435	0.546	0.491	0.449	0.367	0.493	0.353	0.500

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table reports the results from the OLS regressions of the change in inequality on initial inequality and a quadratic initial income component. Initial mean income, initial Gini index and annual growth in the Gini index are measured on a logarithmic scale. The dummy variable takes the value 1 if consumption data was used and 0 for the case of income data. Robust standard errors are reported in parentheses. Explanation of the specifications: (1) Main specification. (2) Main specification without weighting spells. (3) Main specification excluding high-income countries (World Bank classification). (4) Main specification excluding China, India and Indonesia (no national Gini coefficients). (5) Main specification without dummy variable for consumption/income data. (6) Main specification restricted to countries with a headcount ratio of 2% or higher. (7) Main specification with all spells (not just spells with minimum duration of 5 years). (8) Main specification without Eastern European countries. (9) Main specification without transition economies.

Source: Own calculations.

A.2 Alternative Specifications

We find robustness of our regression estimates looking at several alternative specifications, summarized in Table A.1 and A.2. Specification (1) is our main specification described in section 4.2, using the weighted spells of a minimum duration of five years of all 144 available countries. Specification (2) is identical to (1) only differing in the fact that it does not weigh the spells according to their respective duration. Interestingly, both the growth and inequality regression yield a predictive power that is about 5 percentage points lower than the one in the main specification whilst the estimated coefficients are of similar sizes. All variables remain highly significant at the 1%- or 0.1%-level.

In specification (3), we exclude countries that are classified as high-income countries by the World Bank in the initial year of their spell. Depending on the observation year, the threshold for being classified as a high-income country lay between a GNI per capita (calculated using the World Bank Atlas method) of $6,000 in 1987 and $12,235 in 2016. This adaptation reduces the number of spells to 118 and slightly decreases the coefficients for initial mean income and inequality, suggesting that initial mean income and inequality play a more crucial role for their growth rates in low- and middle-income countries. Whereas the coefficients remain highly significant in the growth regression and the predictive power increases in both cases by about 5 percentage points compared to specification (1), it ought to be noted that when discarding high-income countries, one can no longer find the Kuznets relationship as discovered in the main specification. Initial mean income and its square are no longer individually or jointly significant which is, however, consistent considering that one entire fraction of the data (those countries with high incomes) is discarded. A very similar trend can be uncovered when excluding non-poor countries with a headcount ratio below 2% as in specification (6). The reduction results in a sample size of 98 countries and the highest predictive power across all seven specifications. However, as in specification (3), initial mean income and its square are no longer jointly or individually significant; furthermore, the negative of the income convergence parameter is much bigger than in all other specification. We also exclude China, India and Indonesia from our observations (specification (4)) – countries for which we had to estimate the national Gini coefficients due to their differing inequality reporting standards – and find that this does not impact the size or significance of my coefficients as well as predictive power of the regressions. Furthermore, we discard the dummy variable for income/consumption data (specification (5)), include spells that are shorter than five years (specification (7)), and exclude Eastern

European (specification (8)) and transition countries (specification (9)) and do not find major deviations from the coefficients obtained in the main specification. In consequence, we consider my model to be a valid tool to obtain the required inequality and income estimates.

A.3: Actual vs. predicted data

To further the graphical analysis of the quality of the empirical model in the main part of our paper, we use regression analysis to investigate the correlation between estimated and true values of Gini Index and mean income. Table A.3 depicts the regression outputs for the linear regressions between estimated and true income and inequality data respectively, run without a constant. The tables indicate that the regressions have a very high explanatory power and that the data roughly represents a 1:1 relationship between true and estimated values. This notion is confirmed in both cases by testing the parameter, which is not significantly different from 1.

Table A.3: Regression outputs for linear regressions between estimated and true income and inequality data.

	Gini
Estimated Gini	1.013***
	(58.14)
N	71
R^2	0.980

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Mean Income
Estimated Mean Income	0.946***
	(29.04)
N	71
R^2	0.923

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The tables present the regression output for the linear regressions with no constant between estimated and true income (right) and inequality (left) data. Source: Own computation based on PovcalNet.

A.4 Cluster Analysis

To understand the deviations between expected and actual contributions of income and inequality to poverty reduction in further detail, we perform a *k-means cluster analysis*. The term cluster analysis generally describes a set of statistical procedures for partitioning data into different groups ("clusters"), with the purpose of creating homogenous groups that share common characteristics compared to the remaining data, based on selected variables (Gore, 2000). In k-means clustering, the data is automatically partitioned into k predefined groups through an iterative process of the following form (Wagstaff, Cardie, Rogers, & Schroedl, 2001):

1) Each observation x is assigned to its closest cluster center C_i.
2) Each cluster center C_i is updated to be the mean of its constituent observations.

Once there are no further changes in the assignment of observations to clusters, the algorithm converges, and the ultimate clusters are fixed. By use of the k-means cluster analysis, we aim to expose groups of countries, which either exceeded the expectations about the contributions of inequality and income to poverty reduction or developed more unfavorably than anticipated and elicit common characteristics.

In a first step, we determine the optimal number of clusters, k*, by computing the clustering algorithm for a range of k = {1,...,20} values and comparing the results. As stressed by Gore (2000), determining the optimal number of clusters is critical for the cluster analysis and can be implemented by help of external criteria, using information outside of the cluster solution, or internal criteria, using information inherent in the cluster solution. To assess which number of clusters is optimal for our data, we investigate four different internal criteria for each of the 20 cluster solutions, following an approach by Makles (2012). According to the scholar, one approach to find k* consists of computing the within sum of squares (WSS) or its logarithm for all possible k's and finding the kink generated when plotting them. The within sum of squares is defined as the sum of the squared deviations from each observation and the respective cluster center and can be understood as a measure of the variability of the observations within each cluster. For a given set of clusters $S = (S_1, \ldots S_n)$ with centers $C = (C_1, \ldots, C_n)$ the WSS is expressed as:

$$\text{WSS}(k) = \sum_{i=1}^{k} \sum_{x \in S_i} \left|\left| x - C_i \right|\right|^2 \qquad (8.1)$$

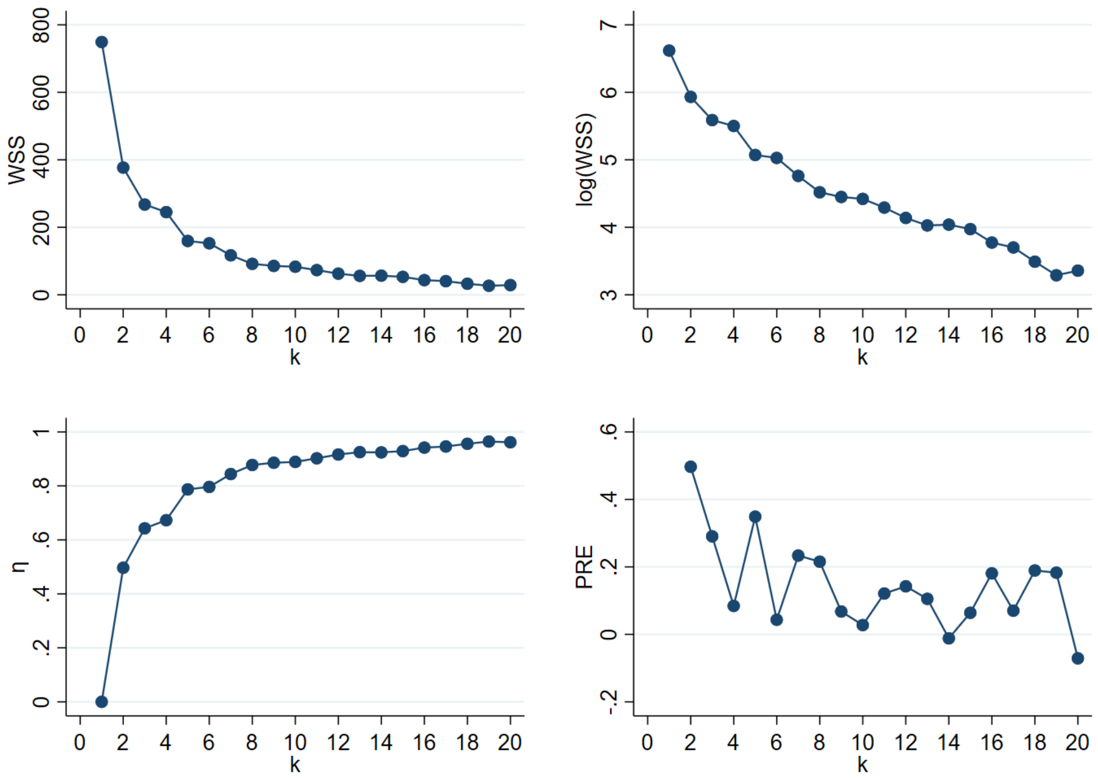
Alternatively, one might use the η^2-coefficient or the proportional reduction error (PRE) coefficient, being defined by the following expressions:

$$\eta_k^2 = 1 - \frac{WSS\ (k)}{WSS\ (1)} = 1 - \frac{WSS\ (k)}{TSS} \tag{8.2}$$

$$PRE_k = \frac{WSS\ (k-1) - WSS(k)}{WSS\ (k-1)} \qquad \forall\ k \geq 2 \tag{8.3}$$

The η^2-coefficient measures the proportional reduction of the within sum of squares compared to the total sum of squares (TSS) for each possible k and is thus similar to the R^2-measure. The PRE-coefficient shows the proportionate reduction of the WSS for k compared to the previous k-1 solution (cf. Makles 2012). By looking at all four criteria instead of a single criterion, we hope to get a clear indication which number of clusters k* to choose.

Figure A.1: Determining the optimal number of clusters k*.

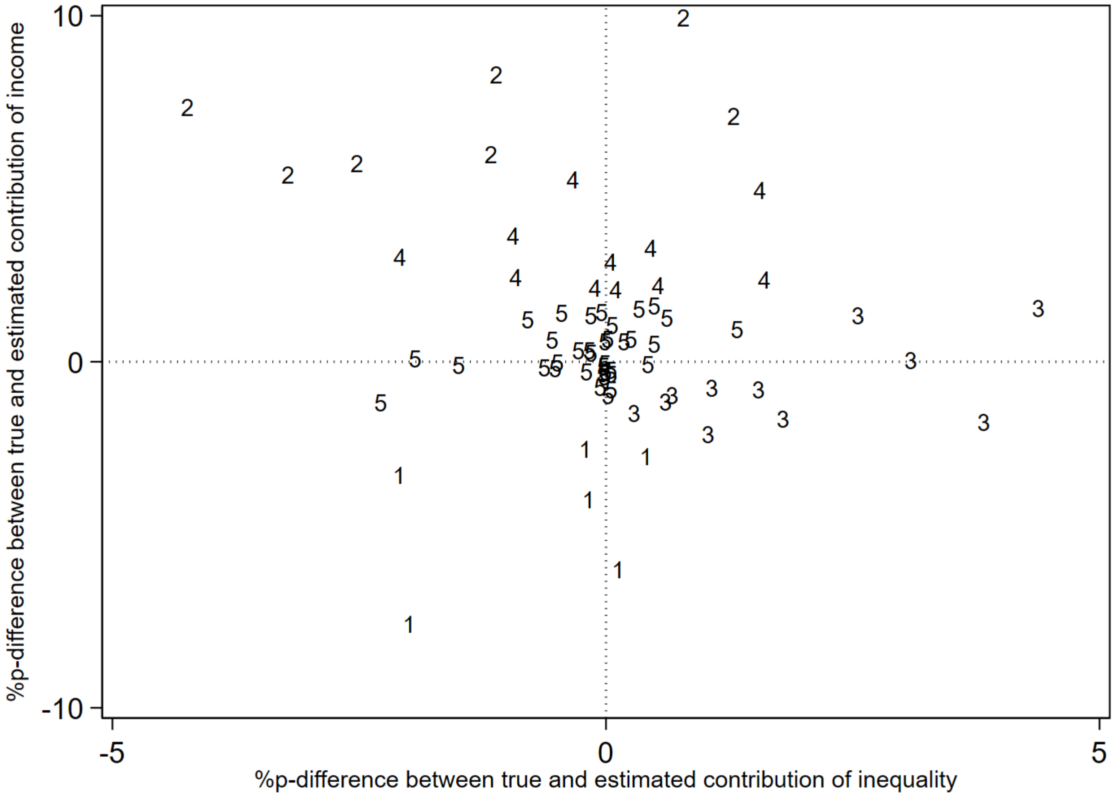


Note: The figure shows the WSS, logarithm of the WSS, η^2, and PRE for all k=1,...,20 cluster solutions.

Source: Own computations.

Figure A.1 presents the WSS, its logarithm, the η^2-, and the PRE-coefficient for each of the 20 cluster solutions using random starting points. The four graphs indicate rather clearly that k=5 is the optimal number of clusters to be selected for the current analysis. The WSS curve demonstrates a kink at this point and η^2 indicates a reduction of 79% of the WSS while the PRE-coefficient suggests a reduction of about 35% compared to the k=4 solution. The interpretation of the logarithm of the within sum of squares is not as clear-cut, however it neither contradicts the selection of k=5.

Figure A.2: Cluster solution from the k-means cluster analysis.



Note: The figure shows the scatterplot of the k-means cluster analysis between the percentage point difference between actual and expected contributions of inequality and income for k=5. A negative percentage point difference between the actual and estimated contribution indicates that the contribution was higher than expected – the country thus surpassed the anticipations.

Source: Own computations.

The cluster solution of the k-means clustering process for k=5 is visualized in the form of a scatterplot in Figure . The graphic displays the percentage point deviations between actual and expected contributions of inequality and income where negative values indicate that the contribution was larger than expected. Obviously, besides one cluster (#5) representing the broad average with only minor deviations between expectations and reality, the four other clusters exhibit discrepancies from this average into different directions. While in cluster #1 income and (in most cases also) inequality contribution exceeded the expectations and the additional contribution of income was stronger than that of inequality, the income effect in cluster #2 was always positive and hindered poverty reduction whereas inequality developed more favorably in the majority of the cases. In cluster #3, the effect of income, on average, tends to be in line with the expectations of the empirical model, but inequality deviates in part strongly and disadvantageously for poverty reduction. Finally, cluster #4 sees an unfavorable development for incomes but no clear trend in the deviations of the Gini coefficient. In addition to Figure A.2, these insights can be drawn from Table A.4 and Table A.5.

Table A.4: The mean effects of growth and redistribution by cluster.

	(1)	(2)	(3)	(4)	(5)	ALL
Distribution Effect (real)	-0.88	-2.72	0.72	0.01	-0.38	-0.42
Distribution Effect (exp.)	-0.22	-1.26	-1.18	0.02	-0.21	-0.43
Δ	-0.66	-1.45	1.90	-0.00	-0.16	0.01
Growth Effect (real)	-7.10	4.56	-3.01	-0.00	-2.02	-1.64
Growth Effect (exp.)	-2.76	-2.56	-2.32	-3.13	-2.30	-2.50
Δ	-4.34	7.12	-0.70	3.13	0.29	0.86
Observations	6	7	11	11	36	71

Note: The mean effects of growth and redistribution (in %) for real and estimated data including their absolute pp-deviation (Δ) for each of the five clusters. Negative figures indicate a poverty reducing effect.

Source: Own computations.

Table A.5: Further summary statistics by cluster.

		(1) Mean	SD	(2) Mean	SD	(3) Mean	SD
Initial period	Gini index	38.3	5.8	43.9	10.8	47.0	11.4
	Mean Income	89.0	42.0	200.7	93.0	163.2	82.7
	Headcount	46.7	21.4	17.2	13.7	31.3	14.3
Final period	Gini index	37.1	3.8	39.7	8.1	49.8	8.3
	Mean Income	178.1	72.2	143.4	64.2	259.0	167.5
	Headcount	15.7	17.8	24.2	10.9	18.6	13.2
Real %-contribution	Income	-7.1	2.2	4.6	1.8	-3.0	1.2
	Inequality	-0.9	1.5	-2.7	3.1	0.7	1.8
	Observations	6		7		11	

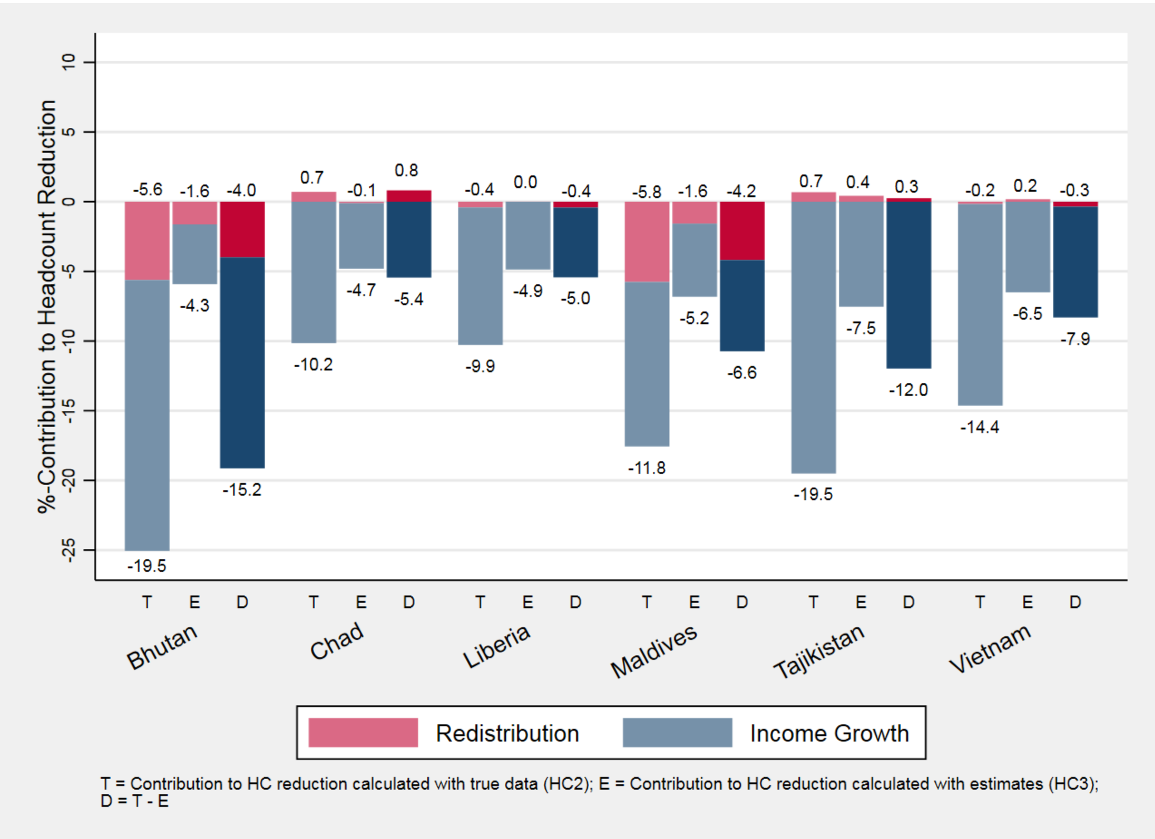
		(4) Mean	SD	(5) Mean	SD	ALL Mean	SD
Initial period	Gini index	39.8	12.5	46.5	9.6	44.6	10.5
	Mean Income	108.3	58.4	97.5	70.0	118.8	78.0
	Headcount	41.4	22.2	55.6	27.0	45.1	26.1
Final period	Gini index	40.8	7.2	42.3	7.6	42.5	8.0
	Mean Income	101.8	45.3	165.2	125.0	168.9	122.1
	Headcount	40.9	25.4	30.8	23.9	28.5	22.2
Real %-contribution	Income	-0.0	2.5	-2.0	1.3	-1.6	3.1
	Inequality	0.0	1.5	-0.4	1.2	-0.4	1.8
	Observations	11		36		71	

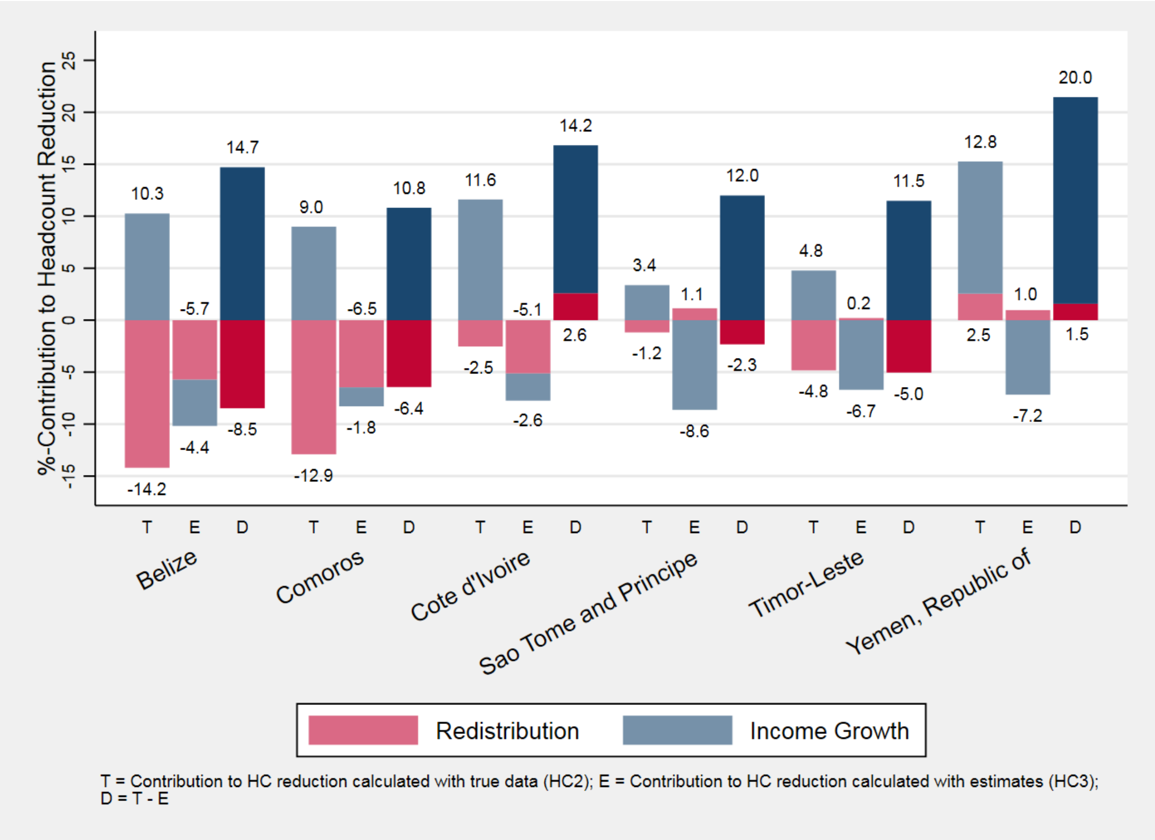
Note: The table shows the per-cluster mean and standard deviation (SD) for Gini index (in %), income (in $, 2011 PPP) and headcount ratio (%) for the initial and final spell year as well as the mean and standard deviation of the %-contributions of income and inequality to poverty reduction measured using the actual income and inequality figures.

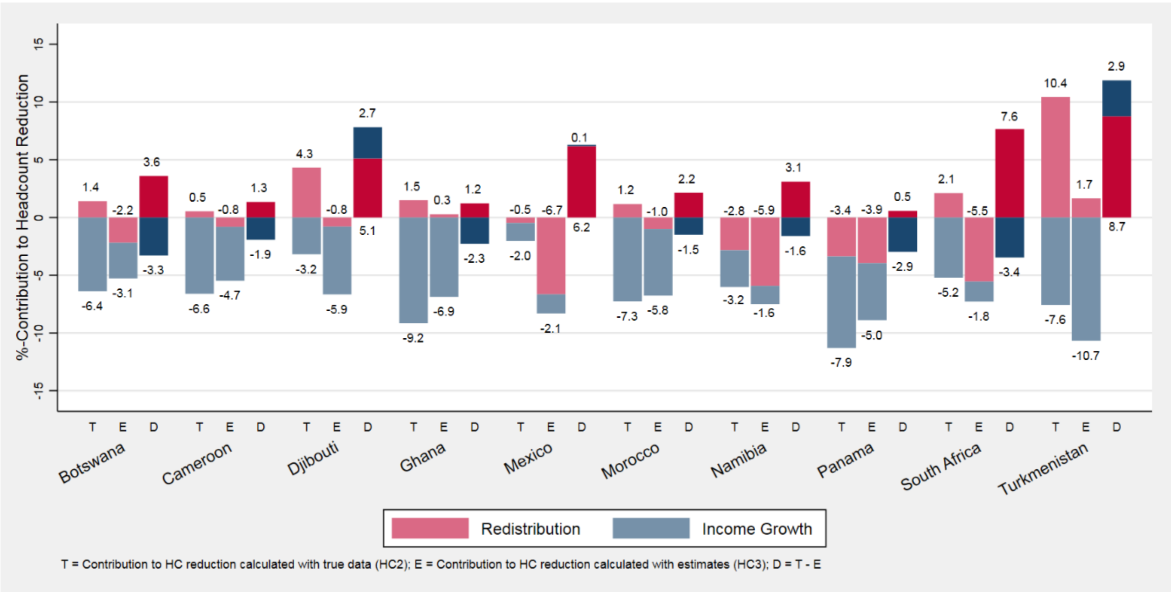
Source: Own computations.

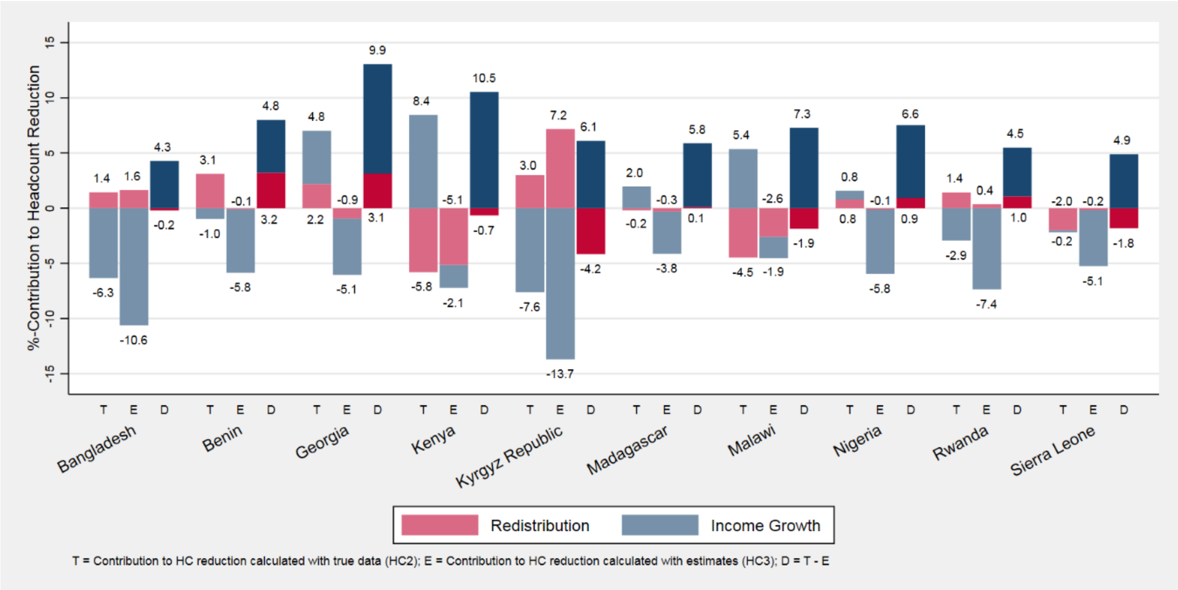
One should bear in mind that the clustering is solely based on the percentage point deviations between the expected and real contributions of income and inequality rather than their %-contributions (estimated or real data) because we are primarily interested in the characteristics of over-/under-performers and not in the actual amount of poverty reduction. As can be inferred from Figure , the %-contributions of income and inequality can vary widely between countries despite similar percentage point deviations. Comparing South Africa and Turkmenistan from cluster #3, the difference between actual and expected contribution of inequality is on a similar level (around 8pp), however, whereas in South Africa inequality contributed only to a slight increase in poverty of 2.1% it was the fivefold in Turkmenistan (10.4%). This discrepancy stems from the varying expectations of changes in inequality between Turkmenistan and South Africa. In addition to that, the cluster analysis neither includes the levels of income, inequality and poverty. Keeping to the example of South Africa and Turkmenistan, these figures vary heavily: In the final spell year, the poverty headcount ratio amounted to 17% in South Africa whereas it was as high as 42% in Turkmenistan. Thus, caution needs to be exercised when interpreting the results of the cluster analysis.

Figure A.3: The deviations between true and expected contributions to changes in the poverty headcount ratio (by cluster).




%-Contribution to Headcount Reduction
Belize
Comoros
Cote d'Ivoire
Sao Tome and Principe
Timor-Leste
Yemen, Republic of
Redistribution
Income Growth
T = Contribution to HC reduction calculated with true data (HC2); E = Contribution to HC reduction calculated with estimates (HC3); D = T - E


%-Contribution to Headcount Reduction
Botswana
Cameroon
Djibouti
Ghana
Mexico
Morocco
Namibia
Panama
South Africa
Turkmenistan
Redistribution
Income Growth
T = Contribution to HC reduction calculated with true data (HC2); E = Contribution to HC reduction calculated with estimates (HC3); D = T - E

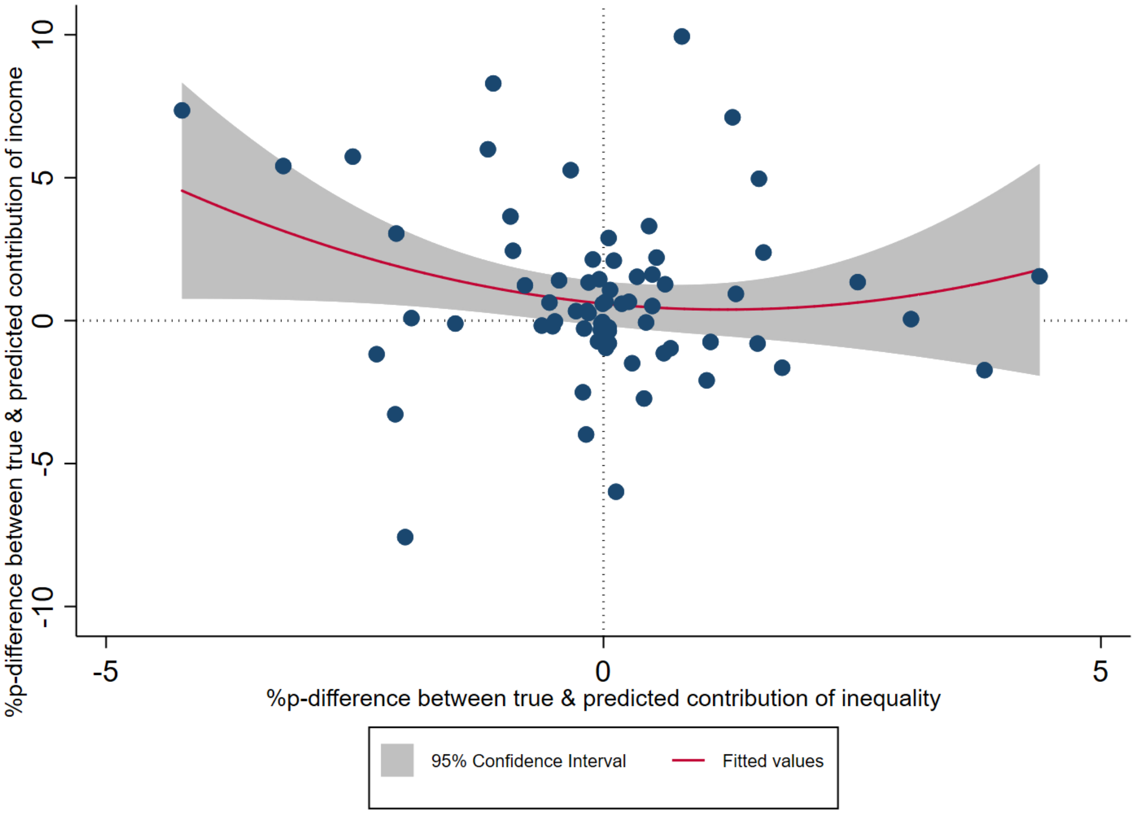


Note: %-contributions of redistribution and income growth to headcount reduction of true and estimated data and their pp-deviations for clusters 1-4 (starting with #1). The pp-deviations are highlighted in intense colors.

Source: Own compilation.

A final point that needs to be made is regarding the relationship between the two variables defining the clusters, the respective percentage point-difference between true and predicted contribution of income and inequality. A regression analysis can inform about this relationship. As can be inferred from Figure A.4, assuming a quadratic relationship the regression line is U-shaped with a turning point at a percentage point-difference between true and predicted contribution of inequality of 1.2. This indicates that while there is a policy-tradeoff between inequality and income when the contribution of inequality is stronger or only slightly worse than expected (meaning that a stronger than expected contribution of inequality results in underperformance on the income dimension) a stronger underperformance of the contribution of inequality for poverty reduction (1.2pp or more below expectations) likewise results in an underperformance on the income dimension. This finding supports the idea that efforts to decrease inequality in a country shall by no means left out in the design of poverty-reducing policy. It also needs to be noted, however, that both, the linear and quadratic relationships between the two variables of interest are insignificant.

Figure A.48: Graphical representation of the quadratic regression analysis between the respective percentage point-difference between true and predicted contribution of income and inequality.



Note: The graphic depicts the quadratic regression line for percentage point-differences between true and predicted contribution of income and inequality. The shaded area represents the 95% confidence band.

To shed light on the question whether countries in the different clusters share communalities other than a similar poverty performance, we perform an exploratory case study, investigating common characteristics within countries of clusters #1 and #2 on a political dimension. To be more specific, we investigate the types of political regime, political orientation and the level of government expenditure in the clusters with the aim to distinguish them based on these political variables.

We expect that the higher the *level of democracy* in a country, the bigger its ability to reduce poverty. This understanding is based on the notion that in a democracy, leaders can be held accountable for their actions through electoral outcomes and are thus more responsive to the needs of the population (Pribble et al., 2009; Przeworski et al., 1995; Przeworski, 2009). Przeworski et al. (1995) highlight that if the market-generated distribution of income is rightskewed (as it is usually the case) and the median voter is decisive[12], a country will likely end up with a more equal income distribution in the future. Furthermore, democracies encourage investment through the protection of property rights, which fosters economic growth (Przeworski, 2009). Thus, we expect that countries of cluster #1 generally have a stronger tendency towards democracy than countries in cluster #2.

Little work has been done concerning the relationship between poverty reduction and the *political orientation* of a country's ruling party. Generally speaking, whereas a leftist government favors redistributive economic and social policies, the right wing promotes capitalism and the protection of private property. Which orientation might be more favorable for poverty reduction is not a priori clear. By all means, one could conceive that the political spectrum might concatenate the countries within a specific cluster bearing in mind the differences in poverty performance between leftist and rightist governments in Latin America for instance. Consequently, this variable is included in the analysis of the policy dimension.

In terms of the *level of federal spending*, we presume that higher government expenditure results in greater poverty reduction, in line with the findings of i.e. Ravallion and Datt (2002), Lustig, Pessino, and Scott (2013) or Ferreira (2010). It can be argued that besides the direct income-increasing effect of higher government expenditure in the social sphere through monetary or in-kind transfers, public spending raises aggregate demand and hence output which stimulates economic growth and employment. This is even more so the case if public spending reaches the poorest parts of a population, owing to the fact that these income groups have a higher propensity to consume additional (transient) income (Ravallion, 2009). Hence, an increase in or a high level of government expenditure could be another characteristic linking the countries of interest.

Due to a strong lack of data availability, the deduction of insights with regards to federal social expenditure and poverty reduction is somewhat difficult. We use the World Bank's ASPIRE ("The Atlas of Social Protection: Indicators of Resilience and Equity") database, being the most up-to-date compilation of global social protection and labor (SPL) indicators based on household survey and administrative data from over 150 countries (The World Bank, 2018b). From this databank, we investigate different variables such as the average transfer amount of social protection and labor programs among program beneficiaries, and

[12] The median voter theorem states that "a majority rule voting system will select the outcome most preferred by the median voter" (Holcombe, 2006).

the absolute and relative amounts of social government expenditure. As can be seen from Table A.6, in most of the cases the database does not offer figures for the specific years or countries of interest. Using the available data, there seems to be a general trend of increases in average per capita transfers in cluster #1 and decreasing transfers in cluster #2. Similarly, annual social expenditure tends to be higher in cluster#1-countries, excluding the exceptionally high figures for Timor-Leste. It ought to be noted, however, that these insights are based on very little data and should be treated with caution.

To strengthen the perception about the positive correlation between high government expenditure and poverty reduction, we further examine total government consumption expenditure as percentage of the countries' GDP as provided in the World Bank's World Development Indicators (WDI) (Table A.7). In spite of the fact that social government expenditure might be more closely related to its poverty achievements, total consumption expenditure could be a substantive alternative variable since high government expenditure in general raises aggregate demand and thus fosters economic growth. The table reveals that total government consumption expenditure was on average higher in c#2 than it was in cluster #1. This relationship continues to hold after excluding the extreme case of Timor-Leste with an average government consumption expenditure of 107.87% of its GDP during the time period under investigation. Across all low- and middle-income nations, an average government consumption expenditure of 13.9% is recorded. This figure is surpassed by almost all countries from the second cluster but by only one third of the countries from cluster #1. Hence, the data does not confirm the notion that higher government expenditure characterizes poverty reduction in the country groups of interest. All in all, the findings are ambiguous and do not allow to draw solid conclusions about the relationship between poverty alleviation and (social) public spending.

Table A.6: Selected social expenditure indicators.

Country	Spell	Cluster	Year	Average transfer amount ($/day p.c.)	Ann. social spending (% of GDP)	Ann. social spending p.c.
Bhutan	2003-2012	1	2007	0.05	..	..
Bhutan	2003-2012	1	2009	..	0.33	20
Bhutan	2003-2012	1	2012	0.81	..	..
Chad	2003-2011	1	2011	1.03	..	..
Chad	2003-2011	1	2014	..	0.69	10
Liberia	2007-2014	1	2007	0.98	..	..
Liberia	2007-2014	1	2010	..	2.64	23
Liberia	2007-2014	1	2014	17.90	..	..
Maldives	2002-2009	1	2004	0.79	..	..
Maldives	2002-2009	1	2009	2.07	..	..
Maldives	2002-2009	1	2010	..	1.21	135
Tajikistan	1999-2015	1	2011	0.44	..	..
Tajikistan	1999-2015	1	2014	..	0.56	18
Vietnam	1992-2014	1	2006	0.78	..	..
Vietnam	1992-2014	1	2010	0.84	..	..
Vietnam	1992-2014	1	2012	0.69	..	..
Vietnam	1992-2014	1	2014	1.39	1.02	57
Belize	1993-1999	2	2009	0.79	..	..
Comoros	2004-2013	2	2004	1.53	..	..
Comoros	2004-2013	2	2016	..	0.67	11
Cote d'Ivoire	1985-2015	2	2002	0.49	..	..
Cote d'Ivoire	1985-2015	2	2008	0.33	..	..
Cote d'Ivoire	1985-2015	2	2015	0.45	0.01	0
Micronesia	2005-2013	2	2000	1.56	..	..
Sao Tome & Principe	2000-2010	2	2014	..	0	0
Timor-Leste	2001-2007	2	2007	0.26	..	..
Timor-Leste	2001-2007	2	2011	0.08	..	..
Timor-Leste	2001-2007	2	2015	..	6.48	116
Yemen, Rep.	1998-2014	2	2005	0.63	..	..

Note: The table provides selected social protection and social expenditure indicators for the two clusters of interest. Due to limited data availability, data for all available years for the respective countries is included. Average transfer amount refers to the average transfer amount of Social Protection and Labor programs among program beneficiaries (per capita, daily $PPP). Annual social spending per capita is measured in 2011 $PPP. Dots indicate that no data was available.

Source: Own compilation based on the ASPIRE database (The World Bank, 2018b).

Table A.7: General government final consumption expenditure.

Country	Cluster	Initial year	Final year	Spell average	Average 1985-2015	Cluster mean 1985-2015
Bhutan	1	20.43	19.18	20.31	18.81	11.91
Chad	1	7.59	6.48	6.03	8.17	
Liberia	1	13.61	16.67	16.05	13.77	
Maldives	1	..	..	..	..	
Tajikistan	1	9.93	14.79	10.94	11.93	
Vietnam	1	5.76	6.27	6.54	6.85	
Belize	2	14.84	13.5	14.42	15.08	32.13
Comoros	2	13.21	15.7	15.34	18.97	
Cote d'Ivoire	2	14.09	11.94	14.03	14.03	
Micronesia, Fed. Sts.	2	..	..	..	..	
Sao Tome & Principe	2	..	..	..	..	
Timor-Leste	2	151.08	107.92	107.87	98.10	
Yemen, Rep.	2	16.32	12.19	13.78	14.47	
Low & middle income		12.87	14.60		13.86	
EAP		13.68	13.57		13.20	
ECA		..	16.03		16.26	
LAC		10.49	17.19		14.53	
MENA		18.61	15.84		14.54	
SA		10.80	10.07		10.79	
SSA		17.67	14.60		15.69	

Note: General government final consumption expenditure in % of GDP for clusters #1 and #2 for the initial and final spell year. The table also displays the spell average final consumption expenditure and the average over the 30 years between 1985-2015. The regional averages exclude high income countries. Dots indicate that no data was available.

Source: Own compilation based on data from The World Bank (2018d).

To determine the prevailing level of democracy, we use two different datasets: The Polity IV Regime Authority Characteristics and Transitions dataset, published by the Center for Systemic Peace (CSP), and the Bormann and Golder (2013) Democratic Electoral Systems (DES) dataset, which can be found in joint tabulated form in Table A.8. The Polity 2 measure, taken from the Polity IV dataset, combines ratings of institutionalized democracy and autocracy in a single indicator and ranges from -10 (autocracy) to +10 (full democracy).[13] The DES dataset provides a simple classification scheme of political regimes where countries are assigned to one of six regime categories.[14] Using both datasets allows

[13] For details about the underlying variables and determination of ranking points, see Marshall (2017).

[14] The categories include parliamentary democracy, semi-presidential democracy, presidential democracy, civilian dictatorship, military dictatorship, and royal dictatorship. For details about the classification, refer to Bormann and Golder (2013).

us to fill data lacks, such that we have at least one indicator for each country in the two clusters, and enables us to counter-check the reliability of the data. We find that both datasets are largely congruent with regards to the political regime. However, contrary to expectations, it is not possible to distinguish a clear trend regarding the level and development of democracy across the two groups. While a promising trend towards democracy may be detected for some countries in cluster #1, such as Bhutan, the same is true for the second cluster. Vietnam (cluster #1) even remains in autocracy whereas more countries from cluster #2 are denominated as democracies or open anocracies (Polity 2 score >0). Hence, with the available data it is not possible to distinguish clusters #1 and #2 based on their political regimes.

A similar conception arises when investigating the political orientation in the different countries. The political orientation of the ruling party is determined using the Inter-American Development Bank's (IDB) "Database of Political Institutions" (DPI), first compiled by researchers of the World Bank Development Research Group in 2000 (Scartascini, Cruz, & Keefer, 2018). It can take on the values 1 (right orientation), 2 (center orientation), 3 (left orientation) or 0 (no information or case does not fit into any of the other categories) and provides data for 180 countries for over 40 years (1975-2017).[15] As can be seen from Table A.9, apart from the fact that two of the 13 countries (Sao Tome & Principe and Micronesia) were not included in the dataset, the majority of countries is assigned a "0" in the classification of the political orientation in at least one year, indicating either special cases (i.e. the party's platform does not focus on economic issues, or there are competing wings) or that no information was available about the political spectrum. Along with the findings for the political regime, this creates the impression that the countries in the two clusters of interest could represent exceptional cases, which could be why political data is often unavailable. Indeed, in the case of Bhutan, for instance, the first ever elections were held during the spell period (2007), resulting in major political changes (The World Bank, 2014). Terrorism, war and political upheaval pervaded Yemen's 2000s (The World Bank, 2015) and Chad and Timor-Leste witnessed civil wars between 2005-2010 and 2006-2007 respectively (The World Bank, 2011, 2013). The latter gained independence as a sovereign state as late as in 2002. Tajikistan, formerly belonging to the Soviet Union and likewise experiencing a civil war subsequent to its independence until 1997, also suffered the cross-border effects of the Afghan civil war in the early 2000s (Azevedo, Atamanov, & Rajabov,

[15] For more information regarding the classification and dataset, refer to Scartascini et al. (2018).

2014). Indubitably, all of the countries in the two clusters witnessed some kind of political conflict and economic transition that make it difficult to analyze aspects of the political dimension without delving into country-specific details.

Table A.8: The type of regime and level of democracy.

Country	Cluster	Year	Polity IV		DES
			Polity 2 value	Category	Type of regime
Bhutan	1	2003	-10	Autocracy	Parliamentary democracy
Bhutan	1	2012	3	Open Anocracy	Parliamentary democracy
Chad	1	2003	-2	Closed Anocracy	..
Chad	1	2011	-2	Closed Anocracy	..
Liberia	1	2007	6	Democracy	Civilian dictatorship
Liberia	1	2014	6	Democracy	Presidential democracy
Maldives	1	2002	..	..	..
Maldives	1	2009	..	..	Presidential democracy
Tajikistan	1	1999	-1	Closed Anocracy	..
Tajikistan	1	2015	-3	Closed Anocracy	..
Vietnam	1	1992	-7	Autocracy	..
Vietnam	1	2014	-7	Autocracy	..
Belize	2	1993	..	..	Parliamentary democracy
Belize	2	1999	..	..	Parliamentary democracy
Comoros	2	2004	6	Democracy	Presidential democracy
Comoros	2	2013	9	Democracy	Presidential democracy
Cote d'Ivoire	2	1985	-9	Autocracy	..
Cote d'Ivoire	2	2015	4	Open Anocracy	..
Micronesia, Fed. Sts	2	2005	..	..	..
Micronesia, Fed. Sts	2	2013	..	..	Presidential democracy
Sao Tome & Principe	2	2000	..	..	Semi-presidential democracy
Sao Tome & Principe	2	2010	..	..	Semi-presidential democracy
Timor-Leste	2	2001	6	Democracy	..
Timor-Leste	2	2007	7	Democracy	Semi-presidential democracy
Yemen, Republic of	2	1998	-2	Closed Anocracy	..
Yemen, Republic of	2	2014	0	Closed Anocracy	..

Note: The type of regime and level of democracy are determined using two different datasets: The Polity IV Regime Authority Characteristics and Transitions dataset and the Democratic Electoral Systems (DES) dataset. The Polity 2 Measure ranges from -10 (autocracy) to +10 (full democracy). If a country was colonized in a given year, it is encoded as -20. In the DES dataset, every country is assigned one of the following six regime types: parliamentary democracy, semi-presidential democracy, presidential democracy, civilian dictatorship, military dictatorship, and royal dictatorship. Dots indicate that no data was available.

Source: Own compilation based on data from Bormann and Golder (2013) and Center for Systemic Peace (2017).

Table A.9: Political orientation of the ruling party.

Country	Cluster	Year	Political Orientation
Bhutan	1	2003	0
Bhutan	1	2012	0
Chad	1	2003	0
Chad	1	2011	0
Liberia	1	2007	0
Liberia	1	2014	0
Maldives	1	2002	1
Maldives	1	2009	0
Tajikistan	1	1999	3
Tajikistan	1	2015	3
Vietnam	1	1992	3
Vietnam	1	2014	3
Belize	2	1993	1
Belize	2	1999	1
Comoros	2	2004	0
Comoros	2	2013	3
Cote d'Ivoire	2	1985	0
Cote d'Ivoire	2	2015	0
Micronesia, Fed. Sts	2	2005	..
Micronesia, Fed. Sts	2	2013	..
Sao Tome & Principe	2	2000	..
Sao Tome & Principe	2	2010	..
Timor-Leste	2	2001	0
Timor-Leste	2	2007	0
Yemen, Republic of	2	1998	0
Yemen, Republic of	2	2014	0

Note: The table displays the political orientation of the ruling party for each country in its initial and final spell year. The party orientation with respect to economic policy is coded using the following criteria: Right (1): for parties that are defined as conservative, Christian democratic, or right-wing. Left (3): for parties that are defined as communist, socialist, social democratic, or left-wing. Center (2): for parties that are defined as centrist or when party position can best be described as centrist (e.g., party advocates strengthening private enterprise in a social-liberal context). Not described as centrist if competing factions “average out” to a centrist position. 0: for all those cases which do not fit into the above-mentioned category (i.e., party’s platform does not focus on economic issues, or there are competing wings), or no information. Dots indicate that no data was available. For more information regarding the classification and dataset, refer to Scartascini et al. (2018).

Source: Own compilation based on data from the IDB’s Database of Political Institutions 2017 (DPI2017).

Table A.10: The State Fragility Index.

	(1)		(2)		(3)		(4)		(5)		ALL	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Initial SFI	15.8	4.8	15.5	1.3	12.3	4.0	17.4	4.2	15.4	4.0	15.2	4.2
Final SFI	12.6	5.7	16.3	3.8	8.3	4.4	13.9	3.1	12.8	4.7	12.4	4.8
Observations	5		4		11		10		36		66	

Note: The table presents summary statistics (mean and standard deviation) on the State Fragility Index (SFI) per cluster and in total. The SFI ranges from 0 "no fragility" to 25 "extreme fragility (Marshall & Elzinga-Marshall, 2016). If the initial year of a country's spell was not covered in the dataset, the earliest available score (1995) is used. The dataset does not cover the following countries: Belize, Georgia, Maldives, Micronesia, and Sao Tome & Principe.

Source: Own computations based on data from the Center for Systemic Peace (Marshall & Elzinga-Marshall, 2016).

To investigate this notion in further detail, we consult the State Fragility Index (SFI), published by the Centre for Systemic Peace for the period 1995-2016 (Marshall & Elzinga-Marshall, 2016). The SFI scores countries in four performance dimensions (security, political, economic, social) based on both their effectiveness and legitimacy and combines these ratings into one aggregate score which ranges from 0 ("no fragility") to 25 ("extreme fragility).[16] Across all 167 countries covered by the database, the average SFI was 11.0 in 1995 and decreased to 8.0 in 2016, both indicating medium fragility. Looking at only the (developing and transition) countries covered in our dataset, these figures are considerably higher, as presented in

[16] According to Marshall and Elzinga-Marshall (2016), a SFI between 20 and 25 indicates extreme fragility; fragility is very high in countries with scores between 16-19. An SFI from 12-15 denounces countries in which fragility is high whereas scores of 8-11 show medium fragility. State fragility is low between 4-7 and there is "no fragility" if the SFI is below a value of 4.

Table A.10: fragility was on average "high" in both the initial and final year of observation but decreased by almost 3 points. Paying special attention to clusters #1 and #2, it stands out that they started at very similar SFI levels which also coincided with the overall average (15.8, 15.5 and 15.2 respectively), but that whereas the fragility index decreased in cluster #1 (12.6) and for the total average (12.4), cluster #2 witnessed an increase in fragility (16.3). Notably, this cluster is the only one where the SFI increased between the initial and final observation year. This confirms the perception that political and economic changes in the second cluster negatively affected its poverty performance. It ought to be noticed that out of the five countries that are not included in the SFI database (and that are analyzed within the thesis), four (Belize, Maldives, Micronesia, Sao Tome & Principe) belong to either the first or the second cluster which complicates the interpretation. However, from the cluster #2-countries covered, all experienced (larger or smaller) increases in the SFI whereas for all countries from cluster #1 fragility declined.

Table A.11: Worldwide Governance Indicators.

INITIAL YEAR

	(1) Mean	SD	(2) Mean	SD
Voice & Accountability	-0.79	0.7	0.10	0.7
Political Stability & Absence of Violence	-0.49	0.8	-0.01	0.9
Government Effectiveness	-0.57	0.7	-0.60	0.6
Regulatory Quality	-0.88	0.3	-0.58	0.7
Rule of Law	-0.62	0.6	-0.50	0.8
Control of Corruption	-0.51	0.8	-0.41	0.4
Observations	6		7	

FINAL YEAR

	(1) Mean	SD	Δ	(2) Mean	SD	Δ
Voice & Accountability	-1.00	0.4	-0.21	-0.05	0.9	-0.15
Political Stability & Absence of Violence	-0.06	1.0	0.43	-0.51	1.2	-0.50
Government Effectiveness	-0.49	0.8	0.08	-0.86	0.7	-0.26
Regulatory Quality	-0.43	0.7	0.45	-0.76	0.7	-0.18
Rule of Law	-0.60	0.6	0.02	-0.60	0.8	-0.10
Control of Corruption	-0.48	0.9	0.03	-0.59	0.5	-0.18
Observations	6			7		

Note: The tables display summary statistics per cluster on the six Worldwide Government Indicators (WGI) for the initial and final year of the respective spell. Each indicator ranges from -2.5 to 2.5 where higher values indicate better governance. The methodology and indicators of the WGI project are explained in due detail in Kaufmann et al. (2010).

Source: Own computations based on WGI data (The World Bank, 2018c)

A similar picture emerges when analyzing the quality of governance in the clusters of interest. This exercise can be performed by use of the Worldwide Governance Indicators (WGI), published by The World Bank (2018c) on an annual basis since 1996. The WGI comprises of six dimensions of governance, covering over 200 countries.[17] Notably, all 71 countries from the current analysis are included in the dataset. As stated by Kaufmann, Kraay, and Mastruzzi (2010), the WGI draws together data on perceptions of governance from a variety of 31 sources, such as perceptions as reported by survey respondents, NGOs, or public sector organizations worldwide. Summary statistics of the WGI for the two clusters of interest are reported in Table A.11. It stands out that while cluster #1 witnessed improvements across most governance dimensions (except from the Voice and Accountability indicator), governance on average deteriorated in all dimensions for cluster #2. Whilst in the final spell year the mean levels of some dimensions are very similar across the two clusters (VA, RQ, RL, CC) it is apparent that the levels and changes of the Political Stability and Government Effectiveness indicators deviate strongly. Hence, the WGI likewise confirms the perception that (un)favorable political developments impacted on the poverty alleviation performance in the clusters under investigation.

[17] These dimensions are Voice and Accountability (VA), Political Stability and Absence of Violence/ Terrorism (PS), Government Effectiveness (GE), Regulatory Quality (RQ), Rule of Law (RL), and Control of Corruption (CC).