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Hartmann, Vanessa; Wacker, Konstantin M.

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Poverty decompositions with counterfactual income and inequality dynamics

Vanessa Hartmann[1] | **Konstantin M. Wacker**[2]

[1]University of Mainz & KfW Development Bank, Frankfurt, Germany

[2]University of Groningen, Groningen, The Netherlands

Correspondence
Konstantin M. Wacker, University of Groningen, Groningen, The Netherlands.
Email: k.m.wacker@rug.nl

Abstract

Traditional poverty accounting decomposes changes in a country's poverty headcount ratio into changes in income and inequality. We argue that this approach is unsatisfactory from the perspective of policy analysis because it compares a country in two points of time without taking the country's initial situation, and hence its potential for poverty reduction, into account. We thus suggest comparing traditional poverty decompositions with a counterfactual situation. This counterfactual indicates what a country starting from its initial situation could be expected to achieve in terms of income, inequality, and, hence, poverty developments. We construct those counterfactuals by modeling income and inequality trends characterized by convergence and a "Kuznets" relationship between inequality and development. Parameters in those relationships are estimated using PovcalNet survey data from 144 countries and we construct our counterfactual poverty predictions for 71 developing countries. While there is overall a tight relationship between actual developments and counterfactuals, we identify several cases, where both deviate from each other and discuss the policy implications. We also check for commonalities in differently performing countries and find that those who fell particularly short of expectations often underwent political transition and state fragility.

KEYWORDS
income convergence, inequality convergence, Kuznets curve, poverty decomposition

JEL CLASSIFICATION
I32, O11

1 | INTRODUCTION

The importance of achieving the United Nation's Sustainable Development Goal 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., Crespo Cuaresma et al., 2018; Lakner et al., 2019; Ravallion, 2013). Another literature takes a backward-looking approach and investigates what one can learn from past contributions of growth and inequality to poverty trends, often referred to as "poverty accounting", or "poverty decomposition" (e.g., Assadzadeh & Paul, 2004; Bluhm et al., 2018; Datt & Ravallion, 1992; Fujii, 2017; Khan, 2003).

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 consider a-priori expectations about poverty trends. We thus propose to compare actual ex-post dynamics in poverty and their proximate sources to a hypothetical counterfactual, where the dynamics of income and inequality follow processes that have been suggested by the previous literature (e.g., Crespo Cuaresma et al., 2022; Kuznets, 1955; Ravallion, 2003, 2012).

To illustrate our point, consider the examples of Ethiopia and Brazil. Ethiopia has traditionally low levels of inequality. It may require serious policy effort to keep inequality at such low levels, whereas the Latin American experience has highlighted that mild reductions in inequality are comparably easy to achieve in more unequal societies. A traditional poverty decomposition will, however, not show any effect of inequality on poverty reduction in case Ethiopia maintains its inequality level. Conversely, if inequality in Brazil falls without much policy effort due to simple mean reversion (e.g., Ravallion, 2003), conventional poverty decompositions will attribute some positive role of poverty reduction to declining inequality in this case. From the perspective of policy evaluation, this is unsatisfactory because the redistributive policy effort may have been much higher in the Ethiopian case.

We address this shortcoming by suggesting a counterfactual approach to existing poverty decompositions. We start by asking the question what income and inequality trends countries can expect, given their initial situation, and how this would translate into poverty dynamics. We therefore assume that income levels across countries converge. For inequality, we assume convergence as well as an inverted-U-relationship with development (the "Kuznets' hypothesis"). To quantify those effects, we use estimates based on PovcalNet survey 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 Ethiopia to a completely different country like Brazil, but compare Ethiopia to a "counterfactual" Ethiopia, which starts out at the same initial income and inequality levels as the true Ethiopia. Likewise, Brazil is compared to a counterfactual with the same initial income and inequality as the true Brazil.[1]

Overall, we find a high correlation between the actual 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. In the above example of Ethiopia, even though the key contribution to poverty reduction between 1995 and 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. Laos (1992–2012) is another example where growth fell short of counterfactual expectations, leading to less favorable poverty developments than our counterfactual suggests, while Mexico (1984–2014) was expected to lower inequality, and associated poverty, much more than it actually did. But there are also successful cases such as Chad (2003–2011), where growth and associated poverty reduction outperformed expectations. We also highlight some alternatives for the construction of the counterfactual and investigate if there are certain common factors driving deviations between actual and counterfactual poverty trends, 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 prediction 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 illustrates how the estimated parameters can be applied to our proposed poverty decomposition using five countries as examples. Section 6 asks whether there is a broad pattern emerging from the deviations between projection and actual developments. Section 7 concludes.

2 | POVERTY DECOMPOSITIONS AND THE POVERTY–GROWTH–INEQUALITY TRIANGLE

To better understand the dynamics of poverty, researchers and analysts decompose poverty changes into its proximate sources: growth in mean incomes and changes to the income distribution.[2] Such "poverty decomposition" (or: "poverty accounting") became increasingly popular since the seminal contribution of Datt and Ravallion (1992) and the associated 1990 World Development Report. Poverty decompositions help to assess how much the poor benefitted from growth and which effect distributional changes had on poverty. It is hence widely used in policy analysis and relates to concepts of pro-poor growth (see Kakwani & Son, 2008).

Methodologically, most poverty decompositions rely on some assumption of the distribution of incomes around a mean income level μ. For example, Datt and Ravallion (1992) parameterize

Lorenz curves for Brazil and India. The growth component of poverty changes is then defined as the change in poverty due to a change in mean income while holding the Lorenz curve (hence, the income distribution) constant. Similarly, the redistribution component is defined as the change in poverty due to a change in the Lorenz curve while keeping mean income constant.[3] This approach requires a good approximation of the whole income distribution, which often limits applicability for broad cross-country assessments.

Without loss of generality, we rely on the decomposition approach of Bourguignon (2003) for the headcount poverty ratio in this paper, which assumes that incomes are log-normally distributed. This only requires knowledge of mean income and the Gini coefficient (which can be transformed into the standard deviation of the log-normal distribution) to approximate the whole income distribution for a given country and time. Given this modest data demand, this approach can be applied to a wide range of countries.

Figure 1 illustrates how Bourguignon's (2003) approach analytically separates changes in the poverty headcount ratio into changes in income levels (holding the distribution of incomes constant) and changes in the distribution of incomes (holding the income level constant). At a given poverty line z (such as $z = 1$ in the figure), every individual to the left of this poverty line in the income distribution is identified as poor and the size of the gray-shaded area relative to the overall density defines the poverty headcount ratio for the initial distribution (black curve). A move of this initial income distribution to the final distribution (light blue curve) can analytically be separated into an intermediate step (dark blue curve). This horizontal movement represents the growth effect with mean income increasing but keeping the distribution of income (i.e., the shape of the curve) unaffected. The vertical transition from the intermediate to the

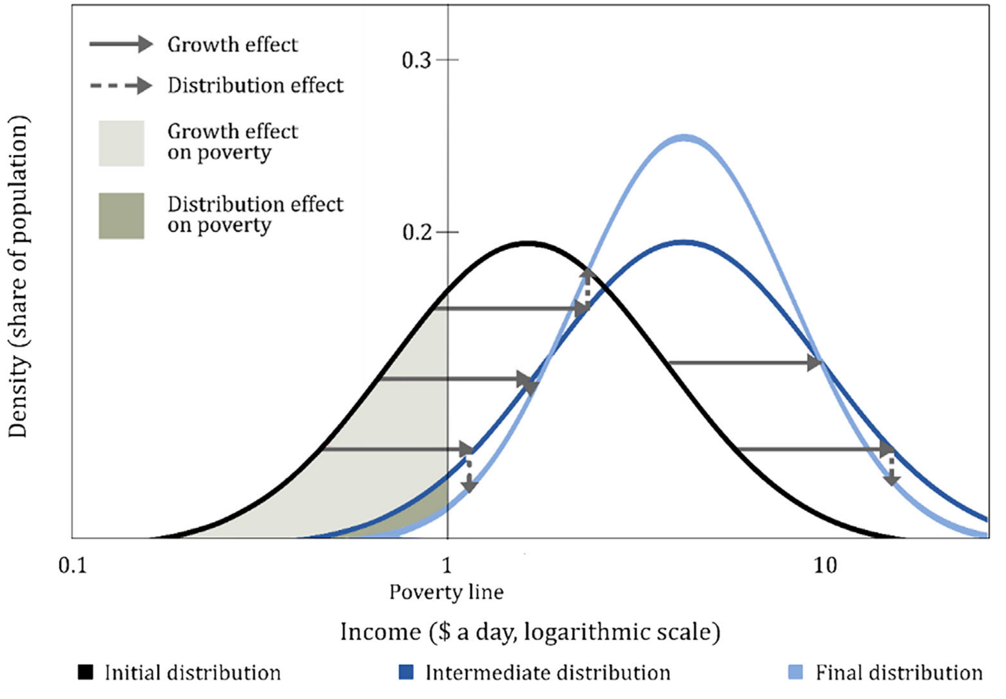

FIGURE 1 Decomposition of a change in poverty into growth and redistribution. *Source*: Own presentation based on Bourguignon (2003, p. 9). [Colour figure can be viewed at wileyonlinelibrary.com]

final distribution then shows the redistribution effect, which fixes mean income at its final level but shifts the distribution around this mean.

Since a (marginal) change in the poverty ratio, ΔH, is approximated by the density of the income distribution at income z, while the current headcount ratio, H_t, is equal to the cumulative distribution up to the poverty line z (gray area in Figure 1), the percentage change in the headcount ratio, $\Delta H/H_t$, under the assumption of log-normally distributed incomes is given by[4]:

$$\frac{\Delta H}{H_t} = -\lambda \left[\frac{\ln\left(\frac{z}{\mu_t}\right)}{\sigma} + \frac{1}{2}\sigma \right] \times \left[-\frac{\Delta \ln(\mu_t)}{\sigma} + \left(\frac{1}{2} - \frac{\ln\left(\frac{z}{\mu_t}\right)}{\sigma 2} \right) \Delta\sigma \right], \tag{1}$$

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, although the approach and our proposed counterfactual methodology can be applied to other distributional families as well.[5]

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 (in absolute terms) so that its contribution to poverty reduction due to growth will be higher than in another country with the same growth rate $\Delta\ln(\mu)$ but higher initial inequality σ. Additionally, lower initial inequality may foster economic growth, which in turn inflates the perceived contribution of growth to poverty reduction, even if the ultimate source stems from equity considerations (cf. Deininger & Squire, 1998; Fosu, 2011; Kalwij & Verschoor, 2005). Finally, studies such as those of 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 through 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, as the potential to grow may differ across 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.

Our contribution also resolves another problem that conventional poverty accounting in a comparative setting suffers: that the complex interaction of income and inequality in the growth elasticity (1) can lead to very different proportionate poverty changes across countries, despite the same mean income growth rate and inequality trends (see Bluhm et al., 2018; Crespo Cuaresma et al., 2022; Fujii, 2017). For example, Bolivia in 1990 had a very similar income level as Brazil had in 1981—around \$220 (per month in 2011 PPPs). Suppose that subsequent growth in both countries, $\Delta \log(\mu_t)$, is identical. Since the Gini coefficient of Bolivia (42.0) was much lower than for Brazil (58.0), this equal growth rate translates into a much higher proportionate poverty reduction for Bolivia according to Equation (1), ceteris paribus. Conventional poverty decompositions will suggest that poverty reduction in Bolivia was hence more growth-driven than in Brazil but this conclusion is questionable, given that it results from differences in other parameters in Equation (1). This problem does not exist in our counterfactual approach, since actual developments are compared to counterfactual developments of the same country with the same initial levels of income and inequality in Equation (1).

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 actual and estimated data (left and right columns of Figure 2, respectively). Taking differences between actual contributions to poverty reduction and estimated counterfactual contributions can thus be interpreted at the effect of

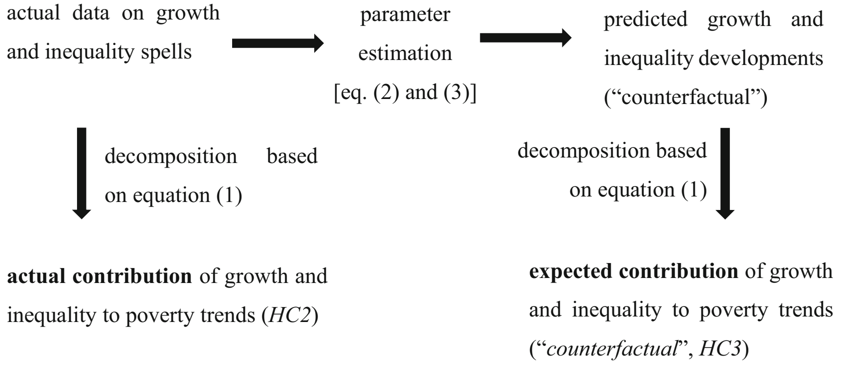

FIGURE 2 Illustration of counterfactual versus actual decomposition approach.

policies of a country conditional on what one might expect, on average, for this country (given initial income and inequality levels).

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:

$$\Delta \ln \mu_{it+n} = \alpha + \Phi \ln \mu_{it} + u_{it+n} \tag{2}$$

μ_{it} is mean income of country i in year t (the initial observation year) and $\Delta \ln \mu_{it+n}$ is the growth rate, measured in annual percent changes in mean income between t and $t+n$ (the latest available observation year). Note that t and n differ across countries. α is a constant and u_{it+n} 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. (2021) 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

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

where G_{it} denotes inequality (measured by the Gini coefficient[6]) in country i in year t. β is a constant and v_{it+n} 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 $t+n$, 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 & 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, that is, in studies by Bénabou (1996), Deininger and Squire (1996), Ravallion (2003), and Crespo Cuaresma et al. (2022).

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

1. *HC1* is the observed development in the poverty headcount ratio as reported by the World Bank.
2. *HC2* is the development in the poverty headcount ratio approximated by Equation (1) when using *actual* data for growth and inequality spells.

3. *HC3* is the development in the poverty headcount ratio approximated by Equation (1) when using *predicted* data for growth and inequality spells.

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. *HC2* and *HC3* both ignore residuals due to distributional approximation. 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 (2) and (3).

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).[7] 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 are dismissed as proposed by Ravallion (2012).[8] 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 are unavailable.[9] We construct spells of maximum length for each country, restricting the sample to spells of at least 5 years as in Dollar and Kraay (2002) and Kraay (2006). This results in non-uniform spell durations ranging from 5 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 Supporting Information 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.

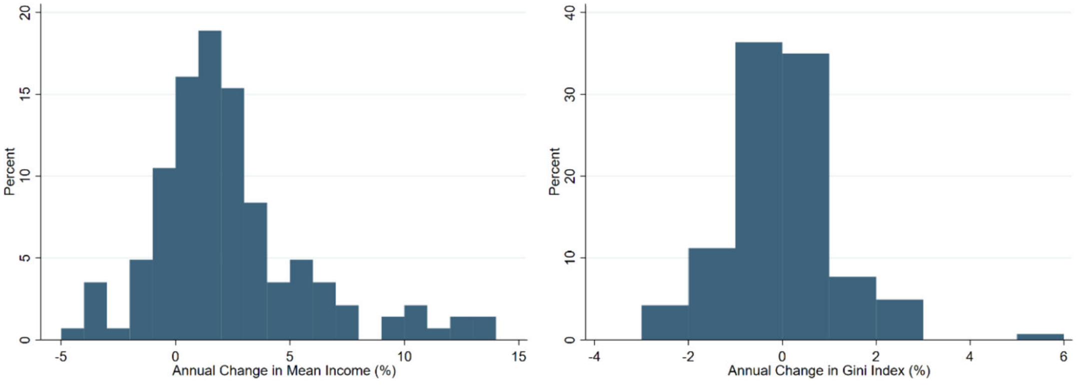

FIGURE 3 Annual changes in mean income and Gini index across sample countries. The graphic presents histograms of the percentage annual changes in mean income (left) and Gini index (right) for the full sample of 144 countries with their respective spell. The vertical axis shows the percentage share of 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. [Colour figure can be viewed at wileyonlinelibrary.com]

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 and 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 accords with general economic expectations of growth. For the case of the Gini index, the tendency seems more ambiguous. Although 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.

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 5 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, that is, discarding all high-income countries, neglecting the weights, allowing for the possibility of a "poverty trap" for growth, or including spells that are shorter than 5 years and obtain similar results (further robustness checks are presented in Supporting Information Appendix A.2). We report heteroscedasticity-robust standard errors in all regressions.

TABLE 1 Regression results for the income growth process (Equation (2)).

Variables	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 were used and 0 if income data were used. Robust t-statistics are reported in parentheses.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.*Source*: Own computations based on PovcalNet.

TABLE 2 Regression results for the inequality process (Equation (3)).

Variables	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 were 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.

Tables 1 and 2 present the resulting regression outputs in column 1, 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.

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 were income (D = 0) or consumption data (D = 1),[10] 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, 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 counterfactual prediction.

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.[11] 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.[12] 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 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 $8350 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.

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.[13] Estimates and actual figures for both variables are plotted against each other in Figure 4. As one can infer, there is a clear relationship between the actual 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 Supporting Information Appendix A.3) and the correlation coefficient between the actual Gini coefficient and its estimate is almost 79% and even higher for mean income (88%).

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%.

5 | COUNTRY EXAMPLES

To illustrate the relevance of our approach for policy analysis, this section presents and discusses the results of our counterfactual poverty decompositions for five example countries with non-negligible poverty headcount ratios and consistent household survey methodologies (see Section 5.2 for further details).[14] Figure 6 depicts the decompositions of the poverty headcount

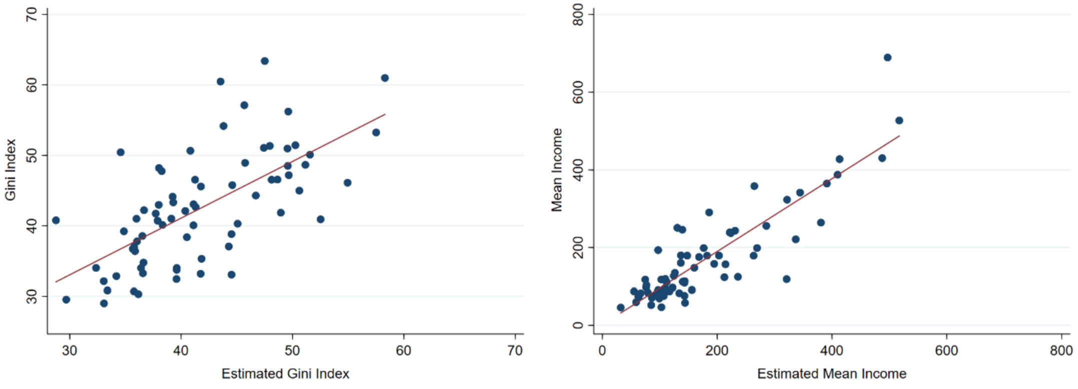

FIGURE 4 Scatterplots of estimated and actual income and inequality data. The graphics show the correlation between estimated (*x*-axis) and actual (*y*-axis) inequality (left) and income (right) data in the form of a scatterplot. The Gini index is measured in %; monthly mean income is measured in 2011 PPP $. The graphics also include the respective regression lines. *Source*: Own computation based on PovcalNet. [Colour figure can be viewed at wileyonlinelibrary.com]

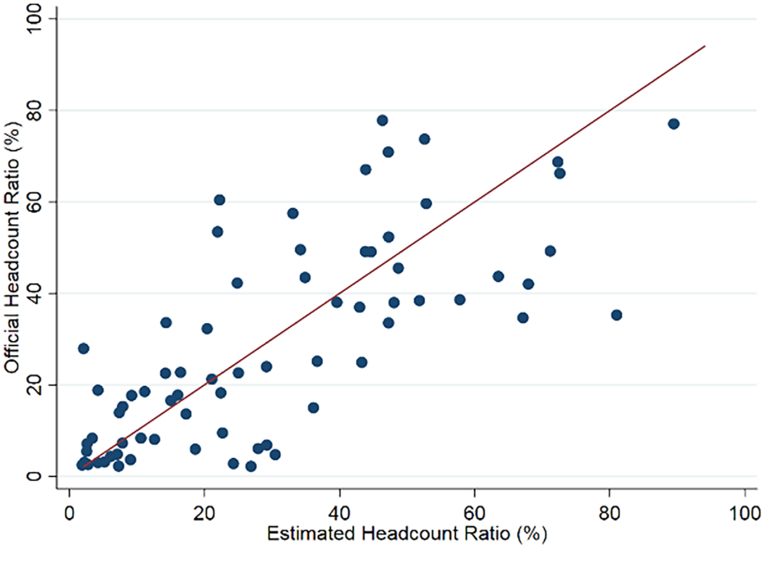

FIGURE 5 Scatterplot of observed poverty headcount ratio (*HC1*) versus headcount ratio implied by counterfactual (*HC3*). The figure shows the correlation between HC1 (vertical axis) and HC3 (horizontal axis). The red line is the 45°-line, indicating a 1:1 correlation. *Source*: own computation based on PovcalNet. [Colour figure can be viewed at wileyonlinelibrary.com]

ratio for those countries and includes a conventional decomposition (HC2, left bar) and a decomposition based on our predicted counterfactual (HC3, right bar).

Brazil reduced its poverty headcount ratio from 24.4 to 4.3% between 1981 and 2015. A conventional decomposition based on Bourguignon (2003; HC2) suggests that the reduction in inequality and the growth of mean incomes contributed 0.9 and 2.7 percentage points p.a., respectively, to poverty reduction.[15] Comparing those numbers to our counterfactual (HC3) reveals two additional insights. First, our counterfactual highlights that given Brazil's 1981

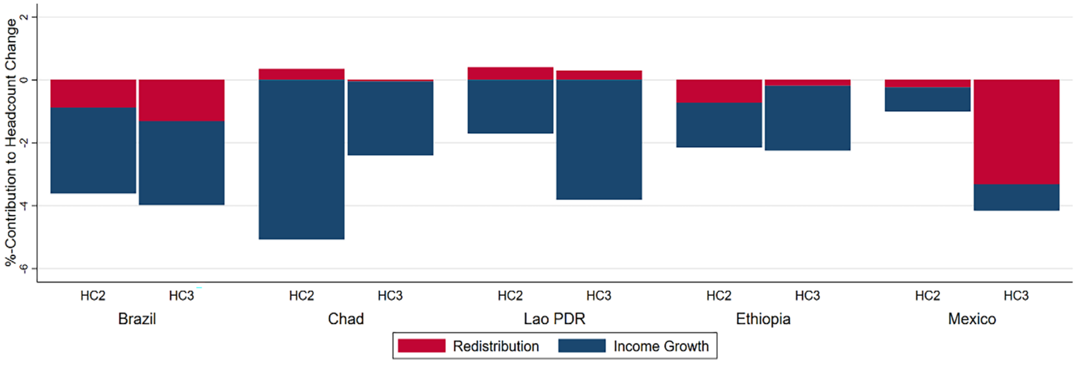

FIGURE 6 Actual and counterfactual poverty decompositions. The figure depicts the %-contributions of income and distribution changes to poverty reduction. Left bars (HC2) show conventional decompositions based on Bourguignon (2003), right bars (HC3) show our created counterfactual. A negative contribution indicates that poverty declined or is estimated to decline. [Colour figure can be viewed at wileyonlinelibrary.com]

levels of income and inequality, one could have expected even somewhat faster poverty reduction (4.0 instead of 3.6% p.a.). Second, our results highlight that this shortfall was mostly because reductions in inequality were smaller than expected. The Gini index has come down from 58 to 51.4, but Equation (3) suggests that a country with the initial inequality and development level as Brazil in 1981 should have reduced inequality to a Gini of 48 by 2015.

In the examples of Chad and Laos, actual and counterfactual poverty developments show even more considerable differences. Chad (2003–2011) reduced poverty much faster than one could have expected based on its 2003 income and inequality levels, mostly driven by a faster growth performance than the convergence Equation (2) would have predicted. Inequality was predicted to remain stable but increased by 3.5 Gini points, which had a detrimental effect on the poverty headcount ratio (and was unexpected). Laos (1992–2012), to the contrary, reduced poverty less than one could have expected based on our counterfactual exercise. A conventional decomposition based on HC2 would only see the overall progress in poverty reduction and that it was hampered by increasing inequality. What our counterfactual HC3 adds is a clear message that income growth and associated poverty reduction could have been much higher.

Another interesting case is Ethiopia, which experienced a considerable acceleration in income growth after 2000 (see Moller & Wacker, 2017). Accordingly, a traditional poverty decomposition approach (HC2 in Figure 6) would attribute the main share of poverty reduction in the country to growth and associated policies. Over the 1995–2010 spell analyzed in our sample, however, one can see from a comparison of 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 & Ferede, 2015) and a pattern of structural transformation that focused on labor-intensive lower-skilled activities, including agricultural development-led industrialization (e.g., Cornia & Martorano, 2017).

Finally, Mexico (1984–2014) is another case where actual poverty reduction fell short of counterfactual expectations. A traditional poverty decomposition approach based on HC2 would probably notice a lower reduction than in other countries but could not plausibly quantify this shortfall because those other countries started out from different income and inequality levels. Our counterfactual approach, conversely, clearly suggests that a country with Mexico's 1984 levels of income and inequality should subsequently see a 4.2% p.a. reduction in the poverty headcount ratio—particularly through a reduction in inequality (which effectively remained largely unchanged).

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.

5.1 | What is the relevant reference group? Some alternatives

Our analysis so far has considered all developing countries as equally relevant for the prediction of our counterfactual. In practice, however, policymakers and analysts often benchmark their country to a subgroup of reference countries, for example, a certain region or income level, a group of small island developing states, or a country group that shares other structural features. Our provided methodology facilitates the construction of such specific reference groups, as we now illustrate for the cases of resource abundance and fragility.

We start by separately analyzing resource-abundant and resource-poor countries, as one may argue that income and inequality dynamics differ in those countries due to some resource-curse (e.g., Sachs & Warner, 2001). We follow Hayat and Tahir (2017) and split our sample at a threshold of total natural resource rents equal to 6.6% of GDP (according to WDI data, averaged between 1981 and 2016). Separate regression results by sub-group for the growth and inequality dynamics in Equations (2) and (3), respectively, are presented in Tables A.4 and A.5 in the Supporting Information Appendix. Despite some minor quantitative differences in the individual regressions, predicted poverty changes over most sample countries remain largely unaffected. Iraq is the most prominent of a small number of countries where the results look considerably different when analyzing resource abundant countries separately. Over the period 2006–2012, Iraq reduced the poverty headcount ratio by 1.1% p.a., which fell short of the counterfactual of a 2.0% p.a. reduction in the full sample baseline (see two leftmost bars in Figure 7). Yet, resource-abundant countries with similar income and inequality conditions as Iraq in 2006 typically grew less and saw incomes disperse more than Iraq in the subsequent 6 years. In such counterfactual countries, the poverty headcount ratio would hence usually have increased by 1.2% p.a. (see third bar in Figure 7), while it has actually decreased in Iraq. In other words, Iraq did underachieve in poverty reduction when compared to the overall developing world but overachieved relative to resource-abundant countries.

More drastic differences emerge when considering fragile states separately. According to a recent report of the World Bank (2020), extreme poverty is increasingly linked to fragility and conflict (see also Harttgen & Klasen, 2013). We hence separate our sample into fragile and non-fragile countries where we take a State Fragility Index (SFI) of 15 in the starting year as a threshold. The SFI is provided by the Center for Systemic Peace (2017) and has the advantage

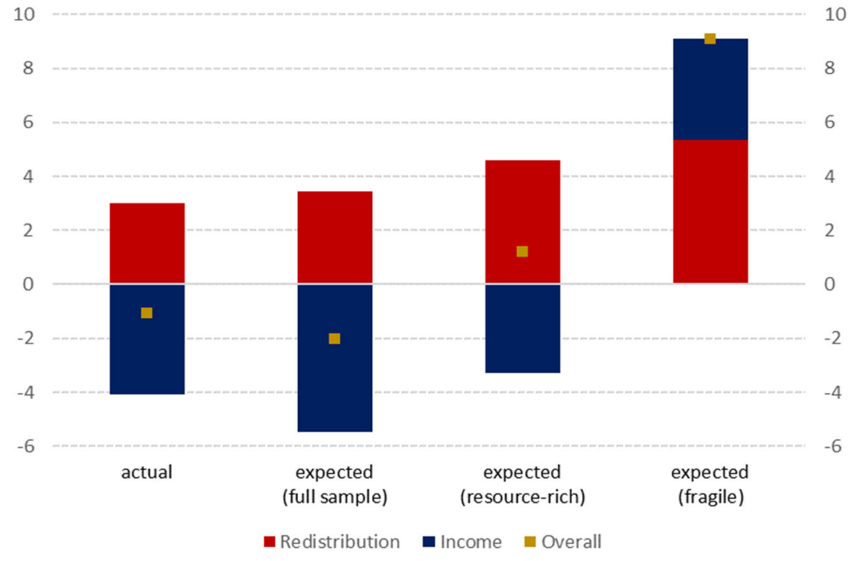

FIGURE 7 Alternative poverty counterfactuals for Iraq (2006–2012). The graphic depicts the %-contributions of income and distribution changes to poverty reduction. It distinguishes between actual (HC2) and expected (HC3) changes. A negative contribution indicates that poverty declined. [Colour figure can be viewed at wileyonlinelibrary.com]

of wide availability when compared to other indices (such as the CPIA, which we also considered). Tables A.4 and A.5 in the Supportinf Information Appendix suggest that (initially) fragile countries experienced different income and inequality dynamics.[16] In this case, the implications for our poverty counterfactuals are more relevant. Iraq again stands out: our framework suggests that a fragile country with Iraq's 2006 income and inequality level should have seen unfavorable growth and inequality trends that lead to an increase in the headcount poverty ratio of 9.1% p.a. (rightmost bar in Figure 7). With its small actual reduction in poverty over the 2006–2011 period, it hence appears as a considerable over-performer.

Perhaps not surprisingly, those results suggest that the counterfactual reference group can make a substantial difference in the assessment of progress in poverty reduction for individual countries. To limit cherry-picking of reference groups, we hence suggest to always show benchmarks against the full sample of (developing) countries for such a counterfactual exercise. Obviously, additional approaches to account for country-specifics can be developed, such as continuous interaction terms (e.g., initial income × percentage of resource rents) or higher-order interaction terms (e.g., initial income × resource abundance × fragility). However, such increasingly specific counterfactuals are beyond the scope of the paper and can be tailored to individual country needs based on our suggested approach.

5.2 | Looking at spells with consistent survey methodology

Over time, countries occasionally change their household survey designs such that measures for poverty, income, or inequality may not be consistent over the period of an investigated spell. Atamanov et al. (2019) provided a PovcalNet comparability indicator that identifies PovcalNet surveys that are consistent with each other. We used this indicator to redo our analysis for

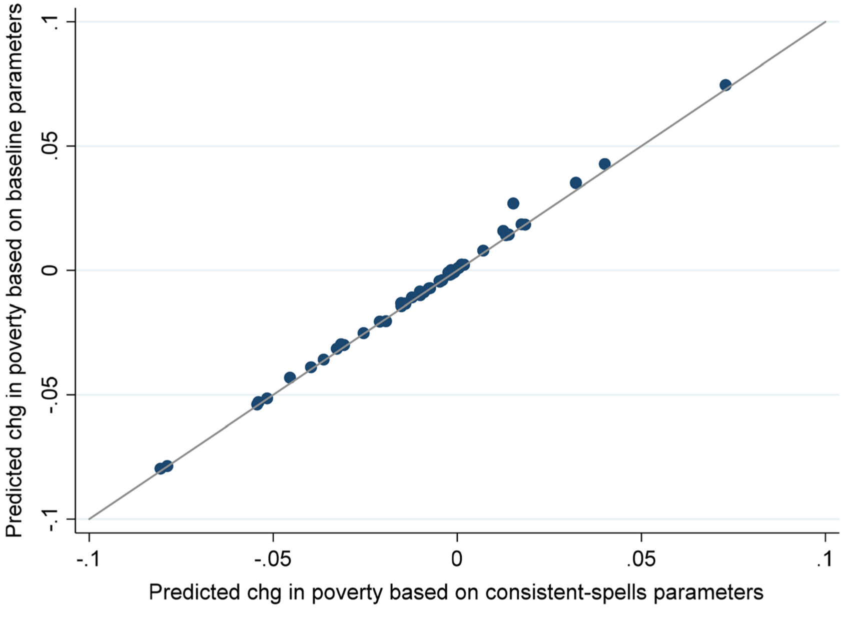

FIGURE 8 Comparison of baseline and "consistent-spells" results. [Colour figure can be viewed at wileyonlinelibrary.com]

comparable spells only and analyzed the longest spells for a country given the same poverty measurement. Where spells of different poverty measurements had the same spell length, we used the most recent spell. As previously, spells had to have a minimum duration of 5 years.

Parameter estimates for the income growth and inequality Processes 2 and 3 of this "consistent-spell" sample are provided in Column 11 of Supporting Information Appendix Tables A.1 and A.2, respectively. While results for the growth process are nearly identical, there appear to be some differences for the inequality process. Given the non-linearity in the relationship and the collinearity between income levels and initial inequality, the consequences of those parameter differences are not straightforward to assess. We hence proceed as follows: we take initial income and inequality from the sample with consistent spells and predict income growth and inequality dynamics (Equations (2) and (3), respectively) with the parameters from the benchmark sample and the "consistent-spells" sample. The respective values for $\Delta \log(\mu_t)$ and $\Delta\sigma$ are then plugged into Equation (1) to predict changes in poverty for those two sets of parameters. The results are depicted in Figure 8, which compares predicted changes of poverty ratios across both parameter sets. As one can see, the differences are negligible, the correlation between the predicted proportionate poverty changes is 99.9%.[17] This finding clearly supports the robustness of our benchmark results and possibly reflects that measurement errors may cancel each other out across countries. That, however, does not mean that one does not have to ensure a certain degree of survey consistency if one aims to analyze poverty developments in a particular country.

6 | IS THERE AN OVERALL POLICY MESSAGE?

To understand if there are certain patterns why countries' actual contributions of growth and redistribution to poverty reduction deviated from counterfactual expectations, we plotted

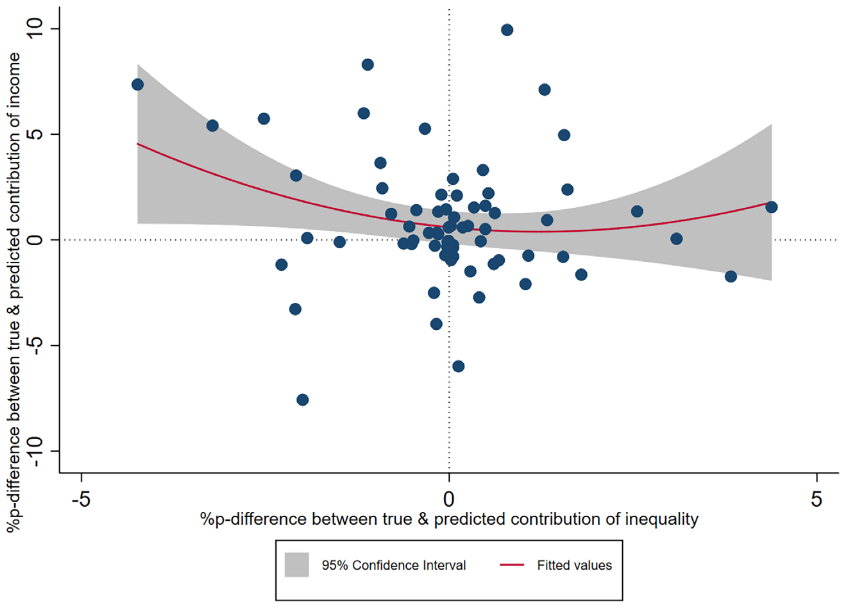

FIGURE 9 Relationship between true and predicted contributions of income and inequality to poverty developments. The graphic depicts the quadratic regression line for percentage point-differences between actual (true) and predicted contribution of income and inequality. A negative number indicates "overperformance" in poverty reduction (compared to the counterfactual). The shaded area represents a 95% confidence band. [Colour figure can be viewed at wileyonlinelibrary.com]

deviations between the two and performed a cluster analysis, which is extensively discussed in Supporting Information Appendix A.5. The key idea and pattern are illustrated in Figure 9: 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 9 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 9, indicating that there is no large deviation between actual and expected growth and redistribution.

Our k-means cluster analysis suggests the existence of five clusters in this two-dimensional space. One of them (#2, see Supporting Information Appendix A.5) 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 9 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 Supporting Information Appendix A.5) outperformed counterfactual expectations to the largest extent and essentially clusters in the lower third of Figure 9. 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 Supporting Information Appendix A.5).

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 Supporting Information Appendix A.5 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 SFI, 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 actual 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 9. 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 one-to-one. However, the more one moves toward the right of Figure 9, 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 & 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. Furthermore, our proposed counterfactual approach can be applied to other distributional assumptions and counterfactual reference groups than those presented in the paper.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available via World Bank's "Poverty and Inequality Platform": https://pip.worldbank.org/home. Replication files are available through Figshare: https://doi.org/10.6084/m9.figshare.22509829.

ORCID

Konstantin M. Wacker https://orcid.org/0000-0003-1923-0386

ENDNOTES

[1] To facilitate policy analysis based on our approach, this article is accompanied by a simple Excel tool to calculate expected developments in poverty, inequality, and income for 161 countries, based on the parameters of our model, and by STATA replication files to construct alternative estimates and counterfactuals. Those files are available through Figshare: https://doi.org/10.6084/m9.figshare.22509829.

[2] Some decompositions extend this by incorporating, for example, population changes and shifts (e.g., Mishra, 2015; Ravallion & Huppi, 1991), labor incomes (e.g., Inchauste et al., 2012), and broader sectors of the economy (Fujii, 2017). This generally creates higher demands for data, limiting the analysis to individual or a handful of countries.

[3] Other contributions relying on distributional assumption include Ravallion and Huppi (1991); Kakwani (1993); Ahuja et al. (1997); Bourguignon (2003); Son (2003); Khan (2003); Contreras (2003); Assadzadeh and Paul (2004); Kalwij and Verschoor (2005); Mishra (2015); and Fujii (2017). An alternative to this approach is poverty accounting based on regressions of poverty changes on growth and inequality changes. See particularly Bluhm et al. (2018) and references therein.

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

[5] See, for example, Bandourian et al. (2002); Bresson (2009); and Bluhm et al. (2018). The previous literature suggests that the log-normal approximation works well in a cross-country context (e.g., Bergstrom, 2020; Crespo Cuaresma et al., 2022; Lopez & Serven, 2006). For our sample of 71 countries, the approximation in Equation (1) explains about 74% of the actual variation in percentage changes in headcount ratios. Bergstrom (2020: section II) provides a more general treatment beyond log-normality.

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

[7] PovCalNet in the meantime has been updated and presented as the new "Poverty and Inequality Platform", available at https://pip.worldbank.org/home. The data for this paper were originally retrieved from http://iresearch.worldbank.org/PovcalNet/povOnDemand.aspx (accessed August 4, 2020).

[8] 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.

[9] 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 were available for the national Gini index at the time when our analysis was performed. 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.

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

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

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

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

[14] A figure including all countries of our sample is available upon request.

[15] Note that the actual p.a. decline in the poverty headcount ratio in this case is $5.1\% = [\ln(24.4) - \ln(4.3)]/34$. The difference to 3.6% (HC2) is a residual due to the log-normal approximation.

[16] Note that changes in the prefix for parameters in the inequality process in Equation (3) are not particularly worrisome since the inequality convergence and Kuznets effect are not independent of each other. For example, it is not clear to what extent an inequality reduction in a high-income country is due to inequality convergence and due to non-linear income effects via the Kuznets terms.

[17] Overall, predicted poverty reduction is somewhat faster with the "consistent-spells" parameters (−1.01% p.a.) than in the benchmark case (−0.86% p.a.). This mainly results from a higher predicted growth rate due to the smaller income convergence coefficient in the sample of consistent spells.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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