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# On track or not? Projecting the global Multidimensional Poverty Index

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ABSTRACT

This paper proposes a framework for modelling projections of multidimensional poverty. We use recently published repeated observations of multidimensional poverty, based on time-consistent indicators, for 75 countries. We consider and evaluate different approaches to model these countries' trajectories of poverty reduction. Our preferred model respects theoretical bounds, is supported by empirical evidence, and ensures consistency of our main measure with its subindices. In our empirical analysis we first use this approach to assess whether countries are on track to halve poverty incidence between 2015 and 2030 if recent trends continue – 51 are – before assessing the reasonableness of this target. Subsequently, we discuss implications of our modelling framework for computing projections under sustained efforts, setting poverty reduction targets, and the evaluation of trajectory changes. These implications mainly follow from the bounded nature of our outcome variables and are, therefore, applicable to a wide array of development indicators.

## 1. Introduction

In the report of the World Bank Commission on Monitoring Global Poverty, its chair Sir Tony Atkinson observed that the exercise of measuring global poverty is "highly controversial". While acknowledging that some might even regard the exercise as futile, he argued that "estimates of global poverty are flawed but not useless. By focusing on changes over time, we can learn [...] about the evolution of global poverty" (World Bank, 2017, p. xvi). In this report, and also in his last book (Atkinson, 2019), he stressed that poverty must be considered according to both national and international definitions and be measured in both monetary and multidimensional spaces.

An internationally comparable and widely recognised multidimensional poverty measure is the global Multidimensional Poverty Index (MPI) developed by Alkire and Santos (2014), which uses the method proposed by Alkire and Foster (2011). In their analysis of changes over time, Alkire et al. (2020c) report extensive progress in global poverty reduction. During the period of observation, 65 of the 75 countries made significant progress in reducing multidimensional poverty, while over 50 reduced the number of people in poverty. Yet the trends story is incomplete: the time periods covered range from three to twelve years and the period of analysis spans 2000–2019, with the initial observation for some countries well after the final observation for others. While informative, their analysis is limited to annualised absolute or relative rates of change during the period of observation. Deeper analyses are challenging, mainly due to data scarcity. For instance, little can be said about (i) the most recent levels of poverty at the national or global level, (ii) expected slow-downs or accelerations in poverty reduction, or (iii) whether countries are on track to meet their poverty reduction targets. A more detailed account of the evolution of poverty, therefore, directs attention towards the poverty trajectories that countries follow.

To overcome these limitations, in this paper we develop a framework based on a logistic dynamic model for computing projections of global multidimensional poverty at the country level. This framework respects theoretical bounds, is supported by empirical evidence, and ensures consistency of our main measure with its subindices.

Our work relates to similar exercises that have been conducted with other development indicators, in particular for extreme monetary poverty, health, and educational outcomes. While we build on these exercises, none of their approaches is immediately applicable to our context. The approach of the World Bank (2018), for instance, relies on covariates of monetary poverty that are more frequently observed (e.g., per capita GDP) and on assumptions about direct pass-through of economic growth to household income or consumption expenditure. Current practices to monitor and project health outcomes utilise several rounds of data. This permits implementation of non-parametric methods and regression-based approaches, applied to

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child mortality (UN IGME, 2019; Alkema and New, 2014) and child nutrition outcomes (WHO-UNICEF, 2017; JCME, 2020), respectively. Our current data, however, does not allow us to incorporate further covariates to project multidimensional poverty.[1] More importantly, evidence from cross-country analyses suggests that multidimensional poverty has a less direct relationship with, for example, economic growth than does monetary poverty (Santos et al., 2019). Finally, previously applied methods typically assume an exponential or constant relative change dynamic model, which only accounts for the theoretical lower bound of zero. As well as applications to health outcomes, this approach has been applied by Ram (2020) who, like us, explores multidimensional poverty as measured by the global MPI, but without considering its theoretical upper bound. A notable exception is research on schooling and other education indicators in which the underlying trajectories have been shown to be S-shaped (Meyer et al., 1992). This strand of the literature, to which our study most closely relates, routinely uses a logistic model to represent indicator dynamics (e.g., Permanyer and Boertien, 2019; Friedman et al., 2020).

For our empirical analysis we obtain projections from our modelling framework using recently observed trends. First, we analyse whether countries would be on track to meet the poverty reduction target of halving multidimensional poverty incidence by 2030 – a target closely related to Sustainable Development Goal (SDG) 1.2 – if recent progress continues.[2] We find that 51 of 75 countries analysed would, indeed, reduce poverty incidence at least by half by 2030. Taking sampling error into account, 36 countries would significantly exceed the target, reducing poverty incidence by significantly more than half. We also show that for many countries the target was hardly feasible from the outset, while at the same time, it was entirely unambitious for many others. These results resonate with research that criticises the Millennium Development Goals (MDGs) and SDGs for following a one-size-fits-all approach to set targets and further for being unfair and unfeasible in many instances (Clemens et al., 2007; Vandemoortele, 2009; Easterly, 2009; Allwine et al., 2015; Lange and Klasen, 2017). Moreover, our results also suggest that headcount ratios which measure *incidence* and are frequently used to assess progress towards development goals may conceal achieved progress, in particular for the poorer countries. We argue that refined measures such as the adjusted headcount ratio (Alkire and Foster, 2011), which also takes *intensity* of poverty into account, may help to overcome this limitation.

While some studies argue that such development goals should rather be country-specific and take historical progress and other peculiarities into account (e.g., Clemens et al., 2007; Ranganathan et al., 2017), the question of how to arrive at feasible *and* ambitious targets has received little attention so far. In this paper we argue that projections based on recent trends offer a useful reference point for a scenario of sustained efforts or 'business-as-usual', and that initial levels, country-specific historical progress, and an appropriate model are all essential to arrive at sensible projections. Our modelling framework also makes possible meaningful performance comparisons across geographical units and over time, thereby helping to identify feasible and ambitious targets. Finally, we also discuss how to test for changes of trajectory, which is important to establish, for instance, the efficacy of recent policy reforms or the impact of adverse shocks induced by conflict, political unrest and natural disasters. We conclude that for bounded outcome variables like multidimensional poverty, applying a logistic dynamic model is in general crucial for (i) establishing whether countries are on track to meet development goals, such as the SDGs, (ii) setting sensible development goals in the first place, and (iii) identifying changes in the indicators' trajectories.

Our results have consequences for applications beyond the global MPI. First, while our empirical analysis is of poverty as measured by the global MPI, the same modelling framework is directly applicable to many national multidimensional poverty measures, which are increasingly implemented as official poverty statistics in practice.[3] Second, our framework naturally extends to most development indicators, as those that are incidence measures must respect lower and upper bounds. The implications of our study therefore apply not only to the trajectories followed by most development indicators, but to their policy targets as well. And yet, most studies of the MDGs and SDGs have been implicitly or explicitly based on an exponential or constant relative change dynamic model (e.g., Fukuda-Parr et al., 2013; French, 2015; McArthur and Rasmussen, 2018; Ahimbisibwe and Ram, 2018). Similar assessments by practitioners, such as whether countries are on track to meet their development targets, are also frequently based on the implicit adoption of an exponential model (e.g., WHO-UNICEF, 2017). Our study demonstrates why choosing an exponential over a logistic dynamic model can lead to inaccurate description and misinterpretation of development indicator dynamics.

The paper proceeds as follows. In Section 2, we describe the data used in the study. In Section 3, we explore alternative models for country-level multidimensional poverty dynamics, identifying logistic trajectories as our preferred model on the basis of both theoretical adequacy and compelling cross-country evidence. We calibrate this model to obtain trajectory projections for each country. In Section 4 we analyse whether countries would meet a poverty reduction target, based on both obtained and plausible counterfactual trajectories. In Section 5 we discuss implications for setting poverty targets and for ways to test for changes of trajectory. In Section 6 we conclude.

## 2. Data

The primary data source for this study is the global MPI Changes over Time dataset, constructed by Alkire et al. (2020b), which contains intertemporally harmonised estimates of aggregate measures of multidimensional poverty for 80 countries in the developing world based on the global MPI. Of those, results reported in this paper focus on the 75 countries that are jointly analysed by OPHI and UNDP's Human Development Report Office (UNDP, OPHI, 2020).[4]

First published in the 2010 UNDP Human Development Report, the global MPI is a poverty index that aggregates 10 indicators, which are grouped under the dimensions of Health, Education and Living Standards (Alkire and Santos, 2014). As an adjusted headcount ratio (Alkire and Foster, 2011), the global MPI is based on the joint distribution of these indicators at household level, capturing intensity as well as incidence of multidimensional poverty. The definitions of the indicators were revised in 2018 to better align to the SDGs (Alkire et al., 2022; Alkire and Kanagaratnam, 2021). Table 1 shows the current structure of the global MPI. Each dimension is assigned an equal weight (1/3), and indicators are also assigned equal weights within dimensions. A person is identified as being multidimensionally poor if they live in a household that simultaneously experiences 1/3 or more of the weighted deprivations.

[1] With only two observations for each country, we have insufficient degrees of freedom to estimate a longitudinal model with country-specific trends.

[2] SDG target 1.2 is to, "by 2030, reduce at least by half the proportion of men, women and children of all ages living in poverty in all its dimensions according to *national* definitions" (UN, 2015, our emphasis). We use the global MPI rather than national MPIs for reasons of comparability and because not all countries have defined national MPIs.

[3] Currently, around 30 countries use a multidimensional poverty measure as an official statistic.

[4] To align with the OPHI-UNDP collaboration, results reported in this study omit five countries that (i) dropped a health or education indicator in the harmonisation process, or (ii) experienced large absolute or relative changes in the harmonised MPI value in comparison with the non-harmonised value (Alkire et al., 2020b, pp. 8–9). The omitted countries are Afghanistan, Montenegro, Trinidad & Tobago, Viet Nam, and Yemen.

**Table 1**
Global MPI.

| Dimension of poverty | Indicator | Deprived if ... | SDG area | Weight |
|---|---|---|---|---|
| Health | Nutrition | Any person under 70 years of age for whom there is nutritional information is *undernourished*. | SDG 2 | $\frac{1}{6}$ |
| | Child mortality | A child *under 18* has *died* in the household in the five-year period preceding the survey. | SDG 3 | $\frac{1}{6}$ |
| Education | Years of schooling | *No* eligible household member has completed *six years* of *schooling*. | SDG 4 | $\frac{1}{6}$ |
| | School attendance | Any school-aged child is *not attending* school *up to* the age at which he/she would complete *class 8*. | SDG 4 | $\frac{1}{6}$ |
| Living Standards | Cooking fuel | A household cooks using *solid fuel*, such as dung, agricultural crop, shrubs, wood, charcoal or coal. | SDG 7 | $\frac{1}{18}$ |
| | Sanitation | The household has *unimproved* or *no* sanitation *facility* or it is improved but *shared* with other households. | SDG 6 | $\frac{1}{18}$ |
| | Drinking water | The household's source of *drinking water* is *not safe* or safe drinking water is a *30-minute walk* or *longer walk* from home, roundtrip. | SDG 6 | $\frac{1}{18}$ |
| | Electricity | The household has *no electricity*. | SDG 7 | $\frac{1}{18}$ |
| | Housing | The household has *inadequate* housing materials in *any* of the three components: *floor*, *roof*, or *walls*. | SDG 11 | $\frac{1}{18}$ |
| | Assets | The household does *not own more than one* of these *assets*: radio, TV, telephone, computer, animal cart, bicycle, motorbike, or refrigerator, and does not own a car or truck. | SDG 1 | $\frac{1}{18}$ |

Notes: This is a simplified version, for more details on global MPI and Changes over Time data, see UNDP, OPHI (2020) and Alkire et al. (2020c), respectively.

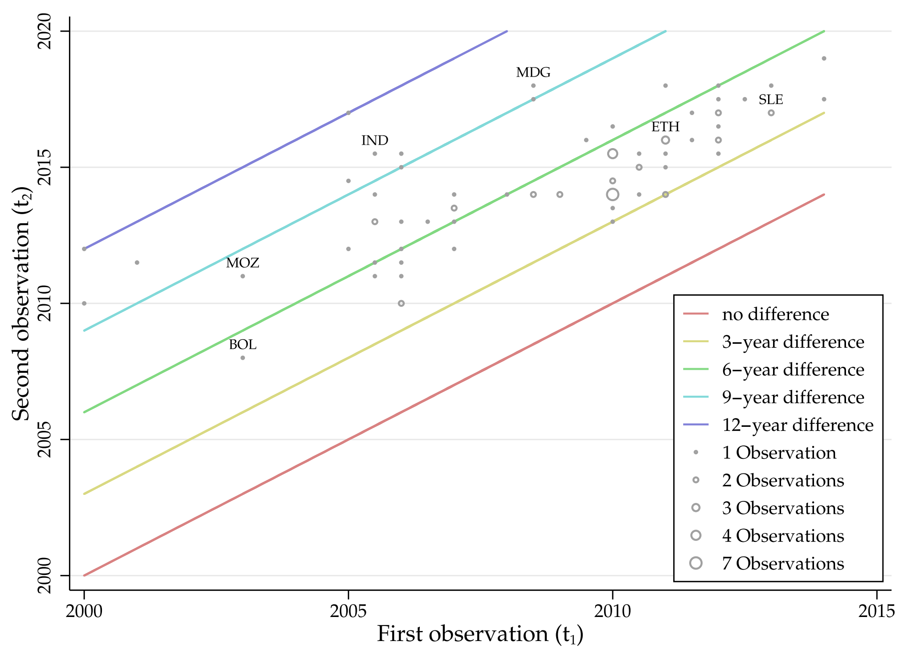


**Fig. 1.** Survey dates.
Notes: Only a few selected observations are labelled for reasons of readability. (For accurate rendering of coloured elements of this figure, the reader is referred to the web version of this article.)

Two observations are available for each country in the Changes over Time dataset. The timing of these observations depends on microdata survey availability; the earlier observation for each country is dated between 2000 and 2014 (median 2010) while the later observation is dated between 2008 and 2019 (median 2014). The elapsed time between observations is between 3 and 12 years (median 5 years). The distribution of survey dates is illustrated in Fig. 1, where one can see that for most countries, including Ethiopia and Sierra Leone, the period between the survey dates is between 3 to 6 years, and in many cases, both surveys are at least as recent as 2010. For some other countries, such as India and Madagascar, the first observation is slightly older (2008 and 2006, respectively) and the period between observations is 9 years or more. In fewer cases, such as Mozambique and Bolivia, we can only draw on data prior to 2005 for the first observation. For a complete list of countries, datasets, and survey years, see Table A.1 of the appendix.

Fig. 2 provides a first view of the data at hand. Each dot represents the observed MPI value for a specific country at a specific point in time, and they are connected by a line when they correspond to the same country. Several insights emerge at first glance. There is considerable heterogeneity of the first and second observed MPI values for each country, as well as of the elapsed period between observations. Most countries experienced poverty reductions over the period between observations, albeit to varying extents and with some visible exceptions, such as Benin or Serbia, where poverty has increased. Also, note that in some cases, changes in multidimensional poverty over time are minimal, such as in Benin and Serbia, and also Cameroon, Togo, Chad and Niger, among others. Finally, some countries achieved substantial poverty reduction in absolute terms, for example Sierra Leone and India. For a more detailed descriptive analysis of these data see Alkire et al. (2020c).

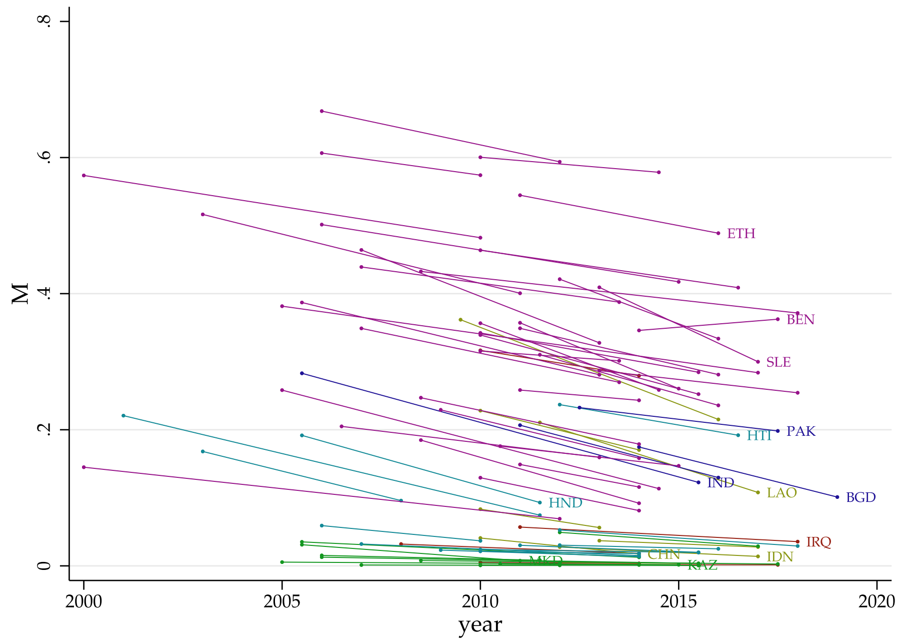


**Fig. 2.** Changes over time data: The adjusted headcount ratio (MPI).
Notes: Dots represent point estimates based on micro data; Countries are colour-coded by world region: ● Arab States; ● East Asia and the Pacific; ● Europe and Central Asia; ● Latin America and the Caribbean; ● South Asia; ● Sub-Saharan Africa. (For accurate rendering of coloured elements of this figure, the reader is referred to the web version of this article.)

## 3. Modelling multidimensional poverty dynamics

With multidimensional poverty estimates available at just two points in time for each country, we cannot precisely estimate nor forecast individual countries' multidimensional poverty trajectories.[5] Given our data constraints, in this section we explore alternative dynamic models that we may use to implement projections of countries' trajectories. We identify preferred models, which respect theoretical bounds on multidimensional poverty levels and are strongly supported by cross-country evidence on countries' trajectories. We conclude the section by implementing country-specific calibrations of these models.

### 3.1. Analytical framework and notation

#### 3.1.1. Multidimensional poverty

Multidimensional poverty is measured following the method established by Alkire and Foster (2011), in which the poor are identified through simultaneous deprivations in multiple indicators; the index thus depends on the joint distribution of the several deprivation indicators. Specifically, we focus on the global MPI described in Section 2, which is one particular implementation of this method. The standard exposition (see, for example, Alkire et al., 2015) develops sample estimators appropriate for a simple random sample; we establish the population analogue here.

Given achievements $x_{ij}$ in $d$ indicators $j = 1, 2, \ldots, d$, each of which is assigned a deprivation cutoff $z_j$ and weight $w_j$ such that $\sum_{j=1}^{d} w_j = 1$, an individual $i$'s deprivation score is

$$c_i = \sum_{j=1}^{d} w_j \mathbb{I}(x_{ij} < z_j). \tag{1}$$

[5] Note that we do not rely on any external additional information, thus our projections are not necessarily predictions of poverty levels in the statistical sense. Rather, we determine how poverty levels would change over time if observed trends continue.

Given also a poverty cutoff $k$ (which Alkire and Santos, 2014, set to $\frac{1}{3}$ for the global MPI), the individual is considered multidimensionally poor if $c_i \geq k$; their censored deprivation score $c_i(k) = c_i \mathbb{I}(c_i \geq k)$.

The level of multidimensional poverty (MPI level) in a population is then $M = \mathbb{E}\left(c_i(k)\right)$, the average censored deprivation score in that population.[6] Applying the law of iterated expectations,

$$\begin{aligned} M &= \mathbb{E}\left(c_i(k) | c_i \geq k\right) \mathbb{P}(c_i \geq k) + \mathbb{E}\left(c_i(k) | c_i < k\right) \mathbb{P}(c_i < k) \\ &= \mathbb{E}\left(c_i(k) | c_i \geq k\right) \mathbb{P}(c_i \geq k) + 0 \times \mathbb{P}(c_i < k) \\ &= \mathbb{E}\left(c_i | c_i \geq k\right) \mathbb{P}(c_i \geq k) \\ &= A \times H \end{aligned} \tag{2}$$

where $A$ is the *intensity* of multidimensional poverty $\mathbb{E}\left(c_i | c_i \geq k\right)$, the average deprivation score among the poor, and $H$ is its *incidence* or headcount ratio $\mathbb{P}(c_i \geq k) = \mathbb{E}(\mathbb{I}(c_i \geq k))$. As the product of $A$ and $H$, $M$ can thus be described as an *adjusted headcount ratio*, where the adjustment factor $A$ captures intensity of poverty. By construction, all three indices are bounded; $H \in [0, 1]$, $A \in [k, 1]$ and $M \in [0, 1]$.

#### 3.1.2. Trajectories

Countries are indexed $s = 1, 2, \ldots, S$. Our objects of interest are countries' time-paths (or trajectories) of multidimensional poverty, $M_s(t)$, its intensity $A_s(t)$ and incidence $H_s(t)$. We may write $y_s(t)$ to represent any of these outcomes of interest, or $y(t)$ when we do not refer to a specific country. Time-derivatives are notated with dots, so $\dot{y}(t) = \frac{\mathrm{d}y}{\mathrm{d}t}$.

An estimate obtained from microdata will be labelled with a hat, so $\hat{M}_s(t_{s\tau})$ is the estimated level of multidimensional poverty in country $s$ at time $t_{s\tau}$. (As discussed in Section 2, we have poverty estimates at two discrete points in time for each country, so $\tau = 1, 2$, but these points in time are different for different countries, thus $t$ must be labelled by $s$ as well as $\tau$.) An alternative, abbreviated notation for such estimates, which constitute the observations for our empirical

[6] Following Alkire and Foster (2011), the usual notation is $M_0$. To simplify notation, we drop the subscript 0 in this paper as we do not use any other members of Alkire and Foster's class of multidimensional indices.

models, is $\hat{M}_{s\tau}$ or even $M_{s\tau}$ (respectively, $H_{s\tau}$, $A_{s\tau}$ and in general $y_{s\tau}$). A projection obtained from a projection model is labelled with a wedge, so, for example, $\check{H}_s(t)$ is the projected incidence in country $s$ at time $t$ (continuous).

We observed above that multidimensional poverty may be decomposed as the product of intensity and incidence; at most two of $M_s(t)$, $A_s(t)$ and $H_s(t)$ can vary independently. Therefore, to ensure consistency, we shall model $M_s(t)$ indirectly as

$$M_s(t) = H_s(t)A_s(t) \tag{3}$$

throughout this paper.

### 3.1.3. Canonical dynamic models

A very simple dynamic model for the trajectory of outcome $y(t)$ is the linear model

$$y(t) = \alpha^{\text{lin}} - \beta^{\text{lin}}t \tag{4}$$

in which the rate of change $\dot{y}(t) = -\beta^{\text{lin}}$ is constant. While simple, linear models are rarely used for projections of development indicators; an exception is Nicolai et al. (2015) who implemented simple linear projections for many SDG indicators. In the case of multidimensional poverty, a linear model does not respect the bounded nature of all outcomes of interest.

Another simple dynamic model for the trajectory of outcome $y(t)$, which respects a lower bound at 0, is the exponential or constant relative change dynamic model[7]

$$y(t) = e^{\alpha^{\text{crc}} - \beta^{\text{crc}}t} \tag{5}$$

in which the relative rate of change $\frac{\dot{y}(t)}{y(t)} = -\beta^{\text{crc}}$ is constant; equivalently, the rate of change $\dot{y}(t) = -\beta^{\text{crc}}y$ is proportional to $y$. Note that the log-transformation $\tilde{y}(t) = \ln(y(t)) = \alpha^{\text{crc}} - \beta^{\text{crc}}t$ is linear in the parameters. This is the dynamic model implemented to assess progress in child malnutrition (WHO-UNICEF, 2017) and by Ram (2020) to project the incidence of multidimensional poverty. It is a plausible candidate for trajectories of $H(t)$ and $M(t)$, which are bounded below at 0, and could be adapted for $A(t)$, which is bounded below at $k$.

A slightly more complex dynamic model for the trajectory of outcome $y(t)$, which respects both lower and upper bounds, is the logistic model

$$y(t) = \frac{1}{1 + e^{-\alpha^{\log} + \beta^{\log}t}} \tag{6}$$

in which the rate of change $\dot{y}(t) = -\beta^{\log}y(1-y)$ is quadratic in $y$, passing through $(0,0)$ and $(1,0)$. Note that the logit-transformation $\tilde{y}(t) = \ln(y(t)/(1-y(t))) = \alpha^{\log} - \beta^{\log}t$ is linear in the parameters; we will refer to the constant $\frac{\dot{y}(t)}{y(t)(1-y(t))} = -\beta^{\log}$ as the *logit rate of change*. Logistic models are routinely implemented to model education indicator dynamics (e.g., Permanyer and Boertien, 2019). The logistic dynamic model is a plausible candidate for trajectories of $H(t)$ and $M(t)$, which are bounded between 0 and 1, and could be adapted for $A(t)$, which is bounded between $k$ and 1.

Several observations are pertinent. First, for each of these models, there is a transformation $\tilde{y}(t) = \alpha - \beta t$ that is linear in the parameters; that shall prove useful in the subsequent empirical modelling. Moreover, in each case, the parameter $\beta$ represents the rate of change or speed of transition. Finally, each dynamic model is characterised by a first-order ordinary differential equation (ODE): $\dot{y}(t)$ is constant in the linear model, linear in $y(t)$ in the exponential (constant relative change) model and quadratic in $y(t)$ in the logistic model.

Fig. 3 illustrates linear (4), exponential (5) and logistic (6) trajectories calibrated to pass through a particular point with a particular rate of change. Note that in all three models, the respective $\beta$ determines the entire trajectory as illustrated in Fig. 3. It is evident that the linear model ignores the theoretical upper and lower bounds, the exponential model does not respect the upper bound, whereas the logistic model respects both. By implication, this also means that the logistic model features an initial period of accelerating poverty reduction, and a slowdown in poverty reduction when approaching the zero lower bound. In contrast, according to the exponential model, the entire trajectory is characterised by a slowdown of poverty reduction, whereas according to the linear model, neither acceleration nor slowdown occur.

**Table 2**
Dynamic models and their rates of change.

| Model | $y(t)$ | $\dot{y}(t)$ | $\dot{y}(t)/y(t)$ | $\frac{\dot{y}(t)}{y(t)(1-y(t))}$ |
|---|---|---|---|---|
| Linear | $\alpha^{\text{lin}} - \beta^{\text{lin}}t$ | $-\beta^{\text{lin}}$ | $-\beta^{\text{lin}}/y$ | $\frac{-\beta^{\text{lin}}}{y(1-y)}$ |
| Exponential | $e^{\alpha^{\text{crc}} - \beta^{\text{crc}}t}$ | $-\beta^{\text{crc}}y$ | $-\beta^{\text{crc}}$ | $-\beta^{\text{crc}}/(1-y)$ |
| Logistic | $\frac{1}{1+e^{-\alpha^{\log}+\beta^{\log}t}}$ | $-\beta^{\log}y(1-y)$ | $-\beta^{\log}(1-y)$ | $-\beta^{\log}$ |

It is important to note that each dynamic model implies specific profiles of absolute and relative rates of change in the underlying variable of interest, as summarised in Table 2. In the linear and the exponential models, the $\beta$s coincide with absolute and relative changes, respectively. According to the logistic model, however, absolute changes follow a u-shaped pattern (reflecting acceleration and slowdown), whereas relative changes decrease over the entire domain to converge towards $\beta^{\log}$ as $y \to 0$. It follows that at very low levels of poverty the exponential model is a good approximation for the logistic. Finally, it is instructive to note that in the logistic dynamic model, the (constant) logit rate of change $-\beta^{\log} = \frac{\dot{y}}{y(1-y)}$ captures adjusted changes in the outcome variable.

### 3.2. Cross-country evidence on poverty dynamics

As noted above, with observations at only two time-points for each country, we cannot estimate statistically or forecast trajectories at country level. We therefore utilise cross-country evidence to inform our choice of projection models.

For each outcome of interest, Fig. 4 illustrates the cross-country relationship between average annual change $\Delta y$, a proxy for $\dot{y}(t)$, and its level. In the case of $H$ and $M$, the relationship is clearly nonlinear; in the case of $A$ the pattern is less clear. While countries from different world regions tend to cluster at different levels of the headcount ratio, the emerging relationship between levels and changes is not driven by one particular world region, but rather supported by countries across the globe. There is, of course, substantial variation across different countries.

To explore the dynamics more systematically, we estimate cross-country models of average annual changes in the outcomes of interest $\Delta y$ as polynomial functions of levels of the outcomes. As the average annual change is a proxy for $\dot{y}(t)$ at both $t_1$ and $t_2$, we retain both observations for each country. We are relaxed about any artificial inflation of sample size, as this exercise is purely for model selection purposes and any effect will have a similar impact on all models.

Table 3 reports results for $H$, the incidence of poverty. Direct estimation of a constant rate of change (model 1), and linear functions for $\Delta H$ (models 2 and 3) are strongly rejected in favour of a quadratic (model 4). Adding a cubic term (model 5) slightly improves the fit, but the cubic coefficient is not significantly different from zero and the improvement in fit is too slight to justify the considerable extra complexity in the dynamic model.[8] Interestingly, a model with $H$, $A$ and their product (model 7) gives equally good fit, and adding $H^2$ (model 8) even better, but again, the slight gain does not outweigh the considerable extra modelling complexity. We conclude that the quadratic model $\dot{H}(t) = aH^2 + bH + c$ is most appropriate.

[7] Described as *proportional* in Alkire et al. (2020a).

[8] The corresponding ODE may not have a closed-form solution.

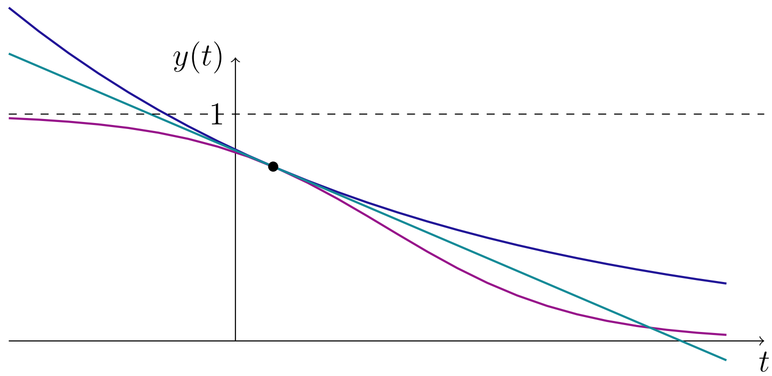


**Fig. 3.** Canonical dynamic models.
Notes: Linear model ——; exponential model ——; logistic model ——; all calibrated to pass through ● with a particular rate of change. (For accurate rendering of coloured elements of this figure, the reader is referred to the web version of this article.)

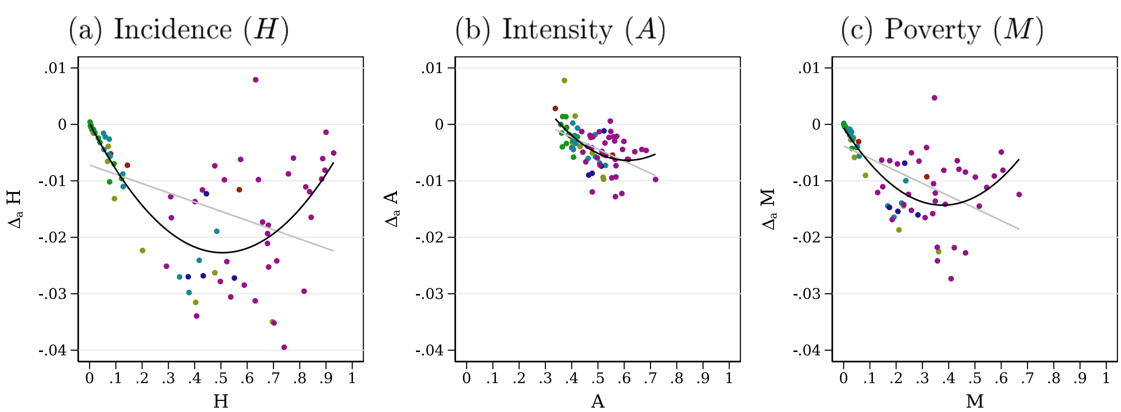


**Fig. 4.** Cross-country evidence.
Notes: Own calculations, changes on vertical axis are average annual changes, black lines show quadratic fit, grey lines linear fit. Countries are colour-coded by world region: ● Arab States; ● East Asia and the Pacific; ● Europe and Central Asia; ● Latin America and the Caribbean; ● South Asia; ● Sub-Saharan Africa. (For accurate rendering of coloured elements of this figure, the reader is referred to the web version of this article.)

**Table 3**
Dynamic model selection for $H(t)$.

| | (1)<br>$\Delta H$ | (2)<br>$\Delta H$ | (3)<br>$\Delta H$ | (4)<br>$\Delta H$ | (5)<br>$\Delta H$ | (6)<br>$\Delta H$ | (7)<br>$\Delta H$ | (8)<br>$\Delta H$ |
|---|---|---|---|---|---|---|---|---|
| $H$ | | $-0.0287^{***}$<br>[−11.62] | $-0.0148^{***}$<br>[−5.03] | $-0.0918^{***}$<br>[−13.57] | $-0.1271^{***}$<br>[−6.79] | $-0.0391^{***}$<br>[−5.77] | $-0.1611^{***}$<br>[−11.27] | $-0.1336^{***}$<br>[−8.40] |
| $H^2$ | | | | $0.0966^{***}$<br>[12.05] | $0.2034^{***}$<br>[3.53] | | | $0.0523^{**}$<br>[2.70] |
| $H^3$ | | | | | −0.0810<br>[−1.87] | | | |
| $A$ | | | | | | $0.0931^{***}$<br>[3.83] | $-0.0497^{*}$<br>[−2.11] | |
| $HA$ | | | | | | | $0.2688^{***}$<br>[9.88] | $0.1301^{**}$<br>[2.74] |
| Constant | $-0.0134^{***}$<br>[−15.20] | | $-0.0082^{***}$<br>[−8.00] | −0.0011<br>[−1.84] | 0.0005<br>[0.67] | $-0.0435^{***}$<br>[−4.66] | 0.0163<br>[1.83] | $-0.0016^{**}$<br>[−2.65] |
| N | 160 | 160 | 160 | 160 | 160 | 160 | 160 | 160 |
| $R^2$ | 0.000 | | 0.148 | 0.492 | 0.504 | 0.213 | 0.505 | 0.524 |
| adj. $R^2$ | 0.000 | | 0.143 | 0.486 | 0.494 | 0.203 | 0.496 | 0.515 |
| $AIC$ | −984.0 | −973.3 | −1007.6 | −1088.4 | −1090.2 | −1018.3 | −1090.6 | −1096.7 |
| $BIC$ | −980.9 | −970.2 | −1001.5 | −1079.1 | −1077.9 | −1009.1 | −1078.3 | −1084.4 |

Notes: Own calculations, $t$-statistics in brackets, indicated levels of significance are $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$. See A.1 for the list of datasets underlying these results.

**Table 4**
Dynamic model selection for $A(t)$.

| | (1) $\Delta A$ | (2) $\Delta A$ | (3) $\Delta A$ | (4) $\Delta A$ | (5) $\Delta A$ | (6) $\Delta A$ | (7) $\Delta A$ |
|---|---|---|---|---|---|---|---|
| $A$ | | −0.0088*** [−16.69] | −0.0184*** [−6.29] | −0.1045** [−3.23] | | | −0.0276** [−3.23] |
| $A^2$ | | | | 0.0871** [2.67] | | | |
| $H$ | | | | | −0.0052*** [−6.32] | −0.0131*** [−4.22] | −0.0175** [−3.23] |
| $H^2$ | | | | | | 0.0099** [2.76] | |
| $HA$ | | | | | | | 0.0330** [3.11] |
| Constant | −0.0040*** [−14.59] | | 0.0047** [3.33] | 0.0253** [3.23] | −0.0022*** [−5.75] | −0.0015** [−3.24] | 0.0090** [2.61] |
| $N$ | 160 | 160 | 160 | 160 | 160 | 160 | 160 |
| $R^2$ | 0.000 | | 0.184 | 0.223 | 0.182 | 0.219 | 0.235 |
| adj. $R^2$ | 0.000 | | 0.179 | 0.213 | 0.177 | 0.209 | 0.220 |
| $AIC$ | −1354.3 | −1377.1 | −1384.8 | −1390.7 | −1384.5 | −1389.9 | −1391.1 |
| $BIC$ | −1351.2 | −1374.0 | −1378.7 | −1381.5 | −1378.4 | −1380.7 | −1378.8 |

Notes: Own calculations, $t$-statistics in brackets, indicated levels of significance are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. See A.1 for the list of datasets underlying these results.

Recalling that the characteristic ODE for the logistic dynamic model is $\dot{y}(t) = -\beta y(1-y)$, this is equivalent to a quadratic with coefficients satisfying $a + b = 0$ and $c = 0$. The $p$-value for a Wald test of the joint hypothesis is 0.2078; we fail to reject it and so conclude that the logistic model (Eq. (6)) is most appropriate for $H(t)$.

We perform the same analysis also for our other outcome variables. Table 4 reports results for $A$, the intensity of poverty; we regress $\Delta A$ on polynomial functions of $A$ and $H$. A linear function of $A$ (model 3) explains only 18% of the variation in $\Delta A$ and adding the quadratic term (model 4) increases that to just 21%. Interestingly, $H$ has similar explanatory power (models 5 and 6), and a model with $A$, $H$ and their product (model 7) slightly more, but the gain is marginal over model 4. Despite the small difference in explanatory power between models 3 and 4, we prefer the quadratic function, which corresponds to a logistic trajectory, over the linear function, which corresponds to an exponential trajectory. Several countries actually experience increases in intensity of poverty, so it is important that our projection model respects the upper bound on $A$.

Given $\dot{A}(t) = aA^2 + bA + c$ (model 4), the $p$-value for the Wald test of the joint hypothesis $a + b = 0$ and $c = 0$ is indistinguishable from zero; we strongly reject the hypothesis and so cannot adopt the simple logistic model (Eq. (6)) for $A(t)$. This is natural, as $A$ is bounded below at $\frac{1}{3}$ rather than 0. The modified (three-parameter) logistic function that respects the bounds at $\frac{1}{3}$ and 1 is characterised by the ODE $\dot{A}(t) = \frac{1}{2}\beta(3A^2 - 4A + 1)$, which is equivalent to the quadratic coefficients satisfying $a = 3c$ and $b + 4c = 0$. The $p$-value for a Wald test of the joint hypothesis is 0.4990; we fail to reject it and conclude that the modified logistic dynamic model

$$y(t) = \frac{1 + 3e^{\alpha^{\mathrm{ml}} - \beta^{\mathrm{ml}} t}}{3(1 + e^{\alpha^{\mathrm{ml}} - \beta^{\mathrm{ml}} t})}, \tag{7}$$

is most appropriate for $A(t)$. In this case, the modified logit-transformation $\tilde{y}(t) = \ln((3y(t) - 1)/3(1 - y(t))) = \alpha^{\mathrm{ml}} - \beta^{\mathrm{ml}} t$ is linear in the parameters.

Finally, we turn to dynamic model selection for $M(t)$, the adjusted headcount ratio or level of multidimensional poverty, reported in Table 5. As noted above, $M(t) = H(t)A(t)$, so $\dot{M}(t) = \dot{H}(t)A(t) + H(t)\dot{A}(t)$. Given our preferred models for $H(t)$ and $A(t)$, we thus expect $\dot{M}(t)$ to be a polynomial function of $H$, $HA$, $H^2A$ and $HA^2$. Such a function (model 6) explains 54% of the variation in $\Delta M$. We may ask whether modelling $\dot{M}(t)$ as a function of $H$ and $A$ performs any better than as a function of $M$ itself; model 6 does indeed explain more of the variation in $\Delta M$ than polynomial functions of $M$ (models 3–5). This reassures us that our approach to modelling $M(t)$ is appropriate.

We therefore conclude (i) that a logistic dynamic model is the most appropriate for trajectories of incidence of poverty $H(t)$, (ii) that for the intensity of poverty $A(t)$ a modified logistic model (which accounts for the lower bound of $A$ being $\frac{1}{3}$) is the most appropriate and (iii) that $M(t)$ is best modelled as the product of $A(t)$ and $H(t)$.

### 3.3. Calibration of projection model parameters

The dynamic models developed above account for a remarkable proportion of the changes in multidimensional poverty across the countries in our dataset. Of course, there remains significant unexplained variation across countries, so in order to implement projections for individual countries we calibrate the model parameters separately for each country. As each of our models is a two-parameter model that may be linearised in the parameters, this is straightforward.

Given incidence and intensity estimates $H_{s1}$, $A_{s1}$ and $H_{s2}$, $A_{s2}$ for country $s$ at $t_{s1}$ and $t_{s2}$, its calibrated parameters $\check{\alpha}^{\log}_{hs}$, $\check{\beta}^{\log}_{hs}$, $\check{\alpha}^{\mathrm{ml}}_{as}$ and $\check{\beta}^{\mathrm{ml}}_{as}$ solve

$$H^{\log}(t_{s\tau}; \check{\alpha}^{\log}_{hs}, \check{\beta}^{\log}_{hs}) = \frac{1}{1 + e^{-\check{\alpha}^{\log}_{hs} + \check{\beta}^{\log}_{hs} t_{s\tau}}} = H_{s\tau}, \qquad \tau = 1, 2,$$

and

$$A^{\mathrm{ml}}(t_{s\tau}; \check{\alpha}^{\mathrm{ml}}_{as}, \check{\beta}^{\mathrm{ml}}_{as}) = \frac{1 + 3e^{\check{\alpha}^{\mathrm{ml}}_{as} - \check{\beta}^{\mathrm{ml}}_{as} t_{s\tau}}}{3(1 + e^{\check{\alpha}^{\mathrm{ml}}_{as} - \check{\beta}^{\mathrm{ml}}_{as} t_{s\tau}})} = A_{s\tau}, \qquad \tau = 1, 2.$$

The calibrated projection models for incidence, intensity and level of multidimensional poverty are then

$$\begin{aligned} \check{H}^{\log}_s(t) &= H^{\log}(t; \check{\alpha}^{\log}_{hs}, \check{\beta}^{\log}_{hs}), \\ \check{A}^{\mathrm{ml}}_s(t) &= A^{\mathrm{ml}}(t; \check{\alpha}^{\mathrm{ml}}_{as}, \check{\beta}^{\mathrm{ml}}_{as}), \quad \text{and} \\ \check{M}^{\log}_s(t) &= \check{H}^{\log}_s(t)\check{A}^{\mathrm{ml}}_s(t). \end{aligned}$$

Parameter calibration and trajectory projection for all three outcomes of interest are illustrated for a hypothetical country in Fig. 5. The coloured dots represent the observations of $H$, $A$ and $M$, while the coloured lines represent the calibrated projection models.

Fig. 6 shows the distribution of the calibrated parameters $\check{\beta}^{\log}_{hs}$ and $\check{\beta}^{\mathrm{ml}}_{as}$, which represent the speed of reduction in poverty incidence and intensity, respectively. Short dashed lines indicate the global median

**Table 5**
Dynamic model selection for $M(t)$.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $\Delta M$ | $\Delta M$ | $\Delta M$ | $\Delta M$ | $\Delta M$ | $\Delta M$ |
| $M$ | | −0.0339*** | −0.0213*** | −0.0750*** | −0.1242*** | |
| | | [−12.38] | [−7.11] | [−10.23] | [−8.84] | |
| $M^2$ | | | | 0.1076*** | 0.3427*** | |
| | | | | [7.71] | [4.88] | |
| $M^3$ | | | | | −0.2711** | |
| | | | | | [−3.32] | |
| $H$ | | | | | | −0.2098*** |
| | | | | | | [−3.54] |
| $HA$ | | | | | | 0.5814** |
| | | | | | | [2.87] |
| $H^2A$ | | | | | | 0.0309 |
| | | | | | | [1.38] |
| $HA^2$ | | | | | | −0.4643** |
| | | | | | | [−2.86] |
| Constant | −0.0084*** | | −0.0044*** | −0.0013*** | −0.0001 | 0.0000 |
| | [−15.06] | | [−8.05] | [−3.52] | [−0.19] | [0.13] |
| $N$ | 160 | 160 | 160 | 160 | 160 | 160 |
| $R^2$ | 0.000 | | 0.274 | 0.489 | 0.523 | 0.550 |
| adj. $R^2$ | 0.000 | | 0.269 | 0.482 | 0.514 | 0.539 |
| $AIC$ | −1129.8 | −1145.6 | −1179.0 | −1233.2 | −1242.4 | −1249.7 |
| $BIC$ | −1126.7 | −1142.6 | −1172.8 | −1224.0 | −1230.1 | −1234.3 |

Notes: Own calculations, $t$-statistics in brackets, indicated levels of significance are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. See A.1 for the list of datasets underlying these results.

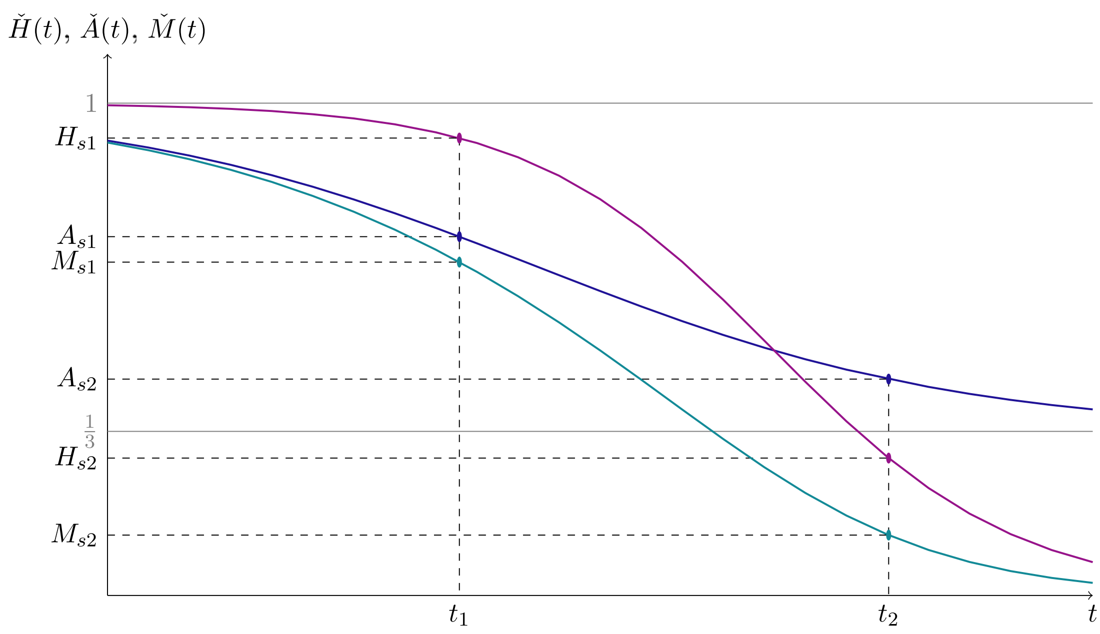


**Fig. 5.** Parameter calibration and trajectory projection.
Notes: Illustration of parameter calibration and trajectory projections given hypothetical observations $H_{s1}$, $H_{s2}$, $A_{s1}$ and $A_{s2}$. (For accurate rendering of coloured elements of this figure, the reader is referred to the web version of this article.)

for each set of parameters, and long dashed lines represent the 25% and 75% quantiles, respectively. Countries are colour-coded by world region. In terms of poverty incidence reduction, regional top performers include Sierra Leone in Sub-Saharan Africa, Honduras in Latin America and the Caribbean, and China in East Asia and the Pacific. At the global level, we observe a median $\check{\beta}^{\log}_{hs}$ of approximately 0.1 and an interquartile range of approximately 0.07–0.13, which provides a sense of magnitude and variation of poverty incidence reduction globally. In terms of poverty intensity, we find a median of about 0.04 and an interquartile range of 0.02–0.06 at the global level. Moreover, we find both parameters to be positively correlated in general. In some instances, however, we also observe that poverty intensity can increase while incidence decreases (which may occur when largely the least poor leave poverty).

Fig. 7(a) illustrates the Changes over Time data for $H$ by translating the time variable for each country $s$ by its calibrated logistic dynamic model parameters, $\check{t}^{\log}_{s\tau} = t_{s\tau} - \check{\alpha}^{\log}_{hs}/\check{\beta}^{\log}_{hs}$. This lines up each country's calibrated trajectory such that the point of inflection occurs at $\check{t}^{\log}_{s\tau} = 0$, allowing easier comparison across countries. Each country's two observations are illustrated (connected by a straight line) but its calibrated

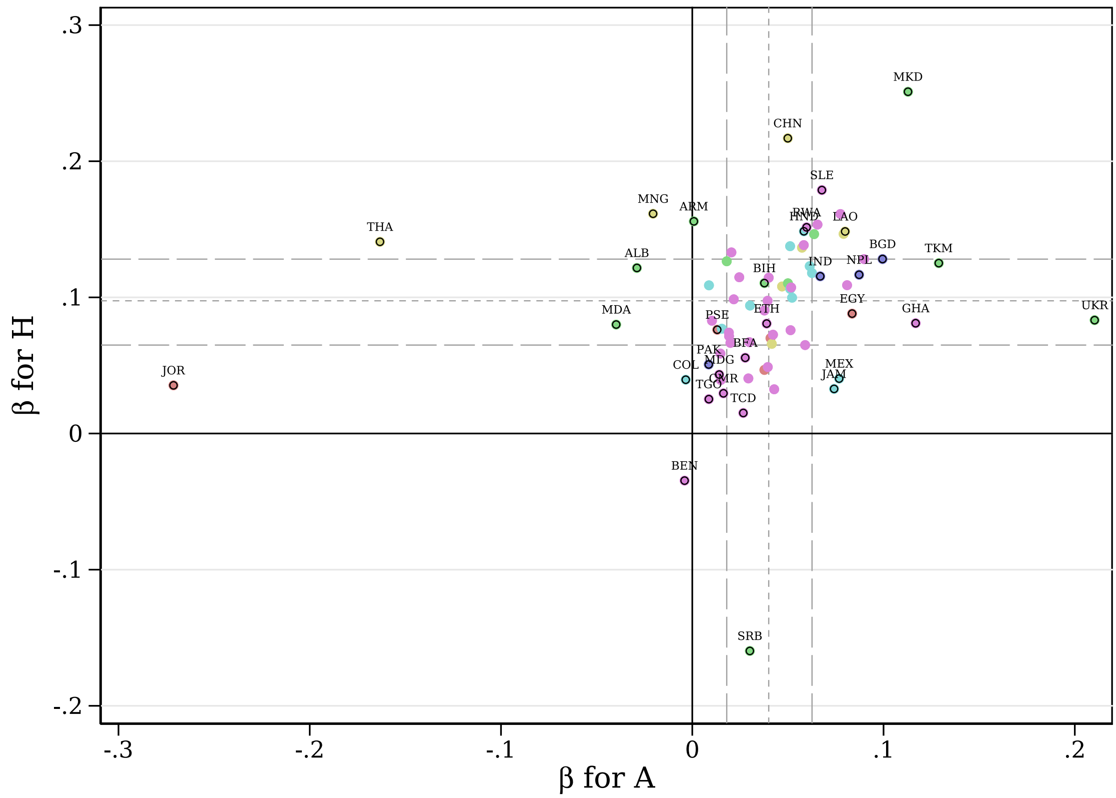


**Fig. 6.** Distribution of $\breve{\beta}^{\log}_{hs}$ and $\breve{\beta}^{\mathrm{ml}}_{as}$ for logistic dynamic model.

Notes: Short dashed lines indicate the global median for the logit rates of change $\breve{\beta}^{\log}_{hs}$ and $\breve{\beta}^{\mathrm{ml}}_{as}$. Long dashed lines represent the respective 25% and 75% quantiles. Countries are colour-coded by world region: ● Arab States; ● East Asia and the Pacific; ● Europe and Central Asia; ● Latin America and the Caribbean; ● South Asia; ● Sub-Saharan Africa; only selected countries are labelled for reasons of readability. (For accurate rendering of coloured elements of this figure, the reader is referred to the web version of this article.)

trajectory is not. From the figure, it is clear that many countries are following similar trajectories, but are at different points along those trajectories. There is some variation, with some countries making faster progress (following a steeper curve) while others make slower progress (following a shallower curve).

Moreover, Fig. 7(a) also depicts trajectories for selected quantiles of the empirical distribution of our calibrated logit rates of change $\breve{\beta}^{\log}_{hs}$, which provides a sense of the implications of the value of $\beta$ for the shape of the trajectory. Specifically, the trajectory of the median $\beta$ ($\beta_{Q50} = 0.098$) is depicted as a turquoise line, the trajectory of the upper quartile $\beta$ ($\beta_{Q75} = 0.128$) is depicted in blue, and the one of the lower quartile $\beta$ ($\beta_{Q25} = 0.065$) is depicted in olive-green.

The lower charts in Fig. 7 show the implied time profiles of absolute changes (b) and relative changes (c) over the same timeline and for the same quantiles of the observed distribution of betas. Several observations are salient: First, both graphs neatly expose phases of acceleration and slow-down in poverty reduction as captured by the logistic dynamic model. Moreover, the quantile trajectories in graph (c) also illustrate the convergence of the logistic dynamic model to an exponential (constant relative change) model as $t \to \infty$. Finally, one can also observe how challenging and potentially deceptive cross country comparisons using simple absolute or relative changes can be. For example, the same absolute change may reflect a point either on the accelerating or decelerating side of the trajectory. Furthermore, the same absolute change may be associated with entirely different trajectories and, likewise, the same relative change may be associated with entirely different trajectories.

While the logistic dynamic model for $H(y)$, the modified logistic model for $A(y)$ and their product for $M(y)$ are our strongly preferred models, for comparison purposes we also implement projections using the linear and exponential models for $H$. For further details on these models see Appendix B.

## 4. Projection results

### 4.1. On track analysis

In this section we perform an on track analysis in which we explore whether countries would meet a particular poverty reduction target in a given year of reference under the assumption that recent trends continue. Our poverty reduction target is closely related to SDG 1.2 and calls for reducing the proportion of people living in multidimensional poverty at least by half by 2030 compared with the reference value in 2015.[9] As the target refers to the proportion of people living in poverty, that is, its incidence, we focus this section on the headcount ratio $H$. We discuss related findings for the adjusted headcount ratio or level of multidimensional poverty, $M$, as well.

Fig. 8 presents the results for all 75 countries and contains the projected poverty reduction from 2015 to 2030 according the logistic dynamic model (red arrows), the confidence intervals for the 2030 projection of the logistic dynamic model (grey bars), the projected headcount ratio in 2030 according to the exponential or constant relative change model (purple dot), and the poverty target value in 2030 (black line). If the red arrow reaches below the black line for any country, then we can state that it is on track to halve poverty – as measured by the headcount ratio of the global MPI – between 2015 and 2030. According to this analysis 51 countries would be on track (shown on the right of the figure), whereas 24 countries are off track (shown on the left of the figure). Visual inspection reveals that in many, but not all cases, the exponential model suggests similar

[9] The actual SDG target 1.2 refers to *national* definitions. Besides our lack of appropriate data and measures for most countries, using national definitions would further complicate the cross-country analyses that we offer.

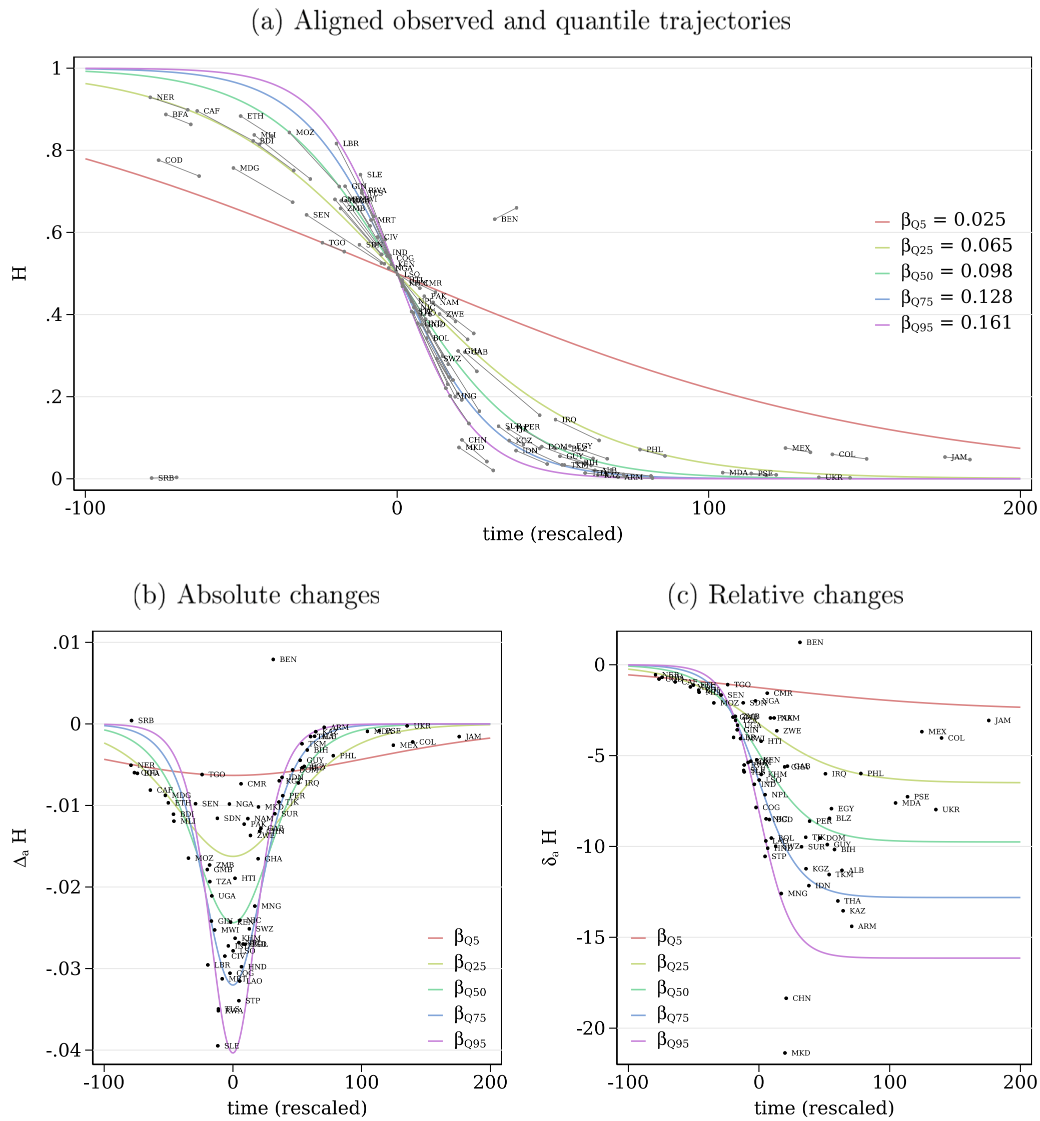


**Fig. 7.** Trajectory and change profiles of calibrated logistic models for $H$.
Notes: Years are translated as follows: $\tilde{t}^{\log}_{s\tau} = t_{s\tau} - \breve{\alpha}^{\log}_{hs}/\breve{\beta}^{\log}_{hs}$. (For accurate rendering of coloured elements of this figure, the reader is referred to the web version of this article.)

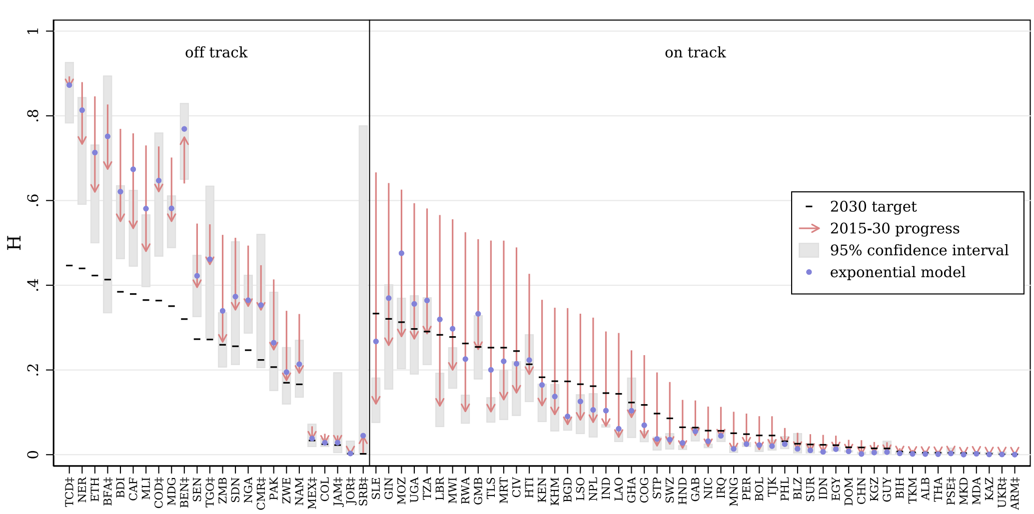


**Fig. 8.** Projections for incidence of poverty 2015–2030 (if observed trends continue).
Notes: Authors' calculations; target and progress are obtained using the logistic model; confidence intervals refer to logistic model; ‡ indicates that estimated change is not significantly different from 0. (For accurate rendering of coloured elements of this figure, the reader is referred to the web version of this article.)

**Table 6**
Results summary of on-track analysis (proportion of countries).

| World region | # countries | Headcount ratio ($H$) | | | | | | | Adjusted headcount ratio ($M$) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | meeting target by model | | same outcome both models | | projections (logistic) | | | projections (logistic) | |
| | | log. | exp. | target met | target not met | signif. exceeds target | target in 95% CI of proj. | different from exp. | meeting target | signif. exceeds target |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| AS | 5 | .6 | .6 | .6 | .4 | .4 | .8 | 0 | .6 | .4 |
| EAP | 8 | 1 | 1 | 1 | 0 | .88 | .25 | .13 | 1 | .75 |
| ECA | 11 | .91 | .91 | .91 | .09 | .55 | .55 | 0 | .91 | .55 |
| LAC | 12 | .75 | .67 | .67 | .25 | .5 | .58 | 0 | .75 | .5 |
| SA | 4 | .75 | .75 | .75 | .25 | .75 | .25 | 0 | .75 | .75 |
| SSA | 35 | .51 | .31 | .31 | .49 | .34 | .34 | .51 | .57 | .43 |
| Total | 75 | .68 | .57 | .57 | .32 | .48 | .43 | .25 | .71 | .51 |

Notes: Authors' calculation; cells contain proportions of countries and all projections are for 2030; in column (6), (7) and (10) statistical tests and 95-% confidence intervals are computed as detailed in appendix C; in column (8) models are considered different if projections differ by 5%-points or more; world regions are Arab States (AS), East Asia and the Pacific (EAP), Europe and Central Asia (ECA), Latin America and the Caribbean (LAC), South Asia (SA), Sub-Saharan Africa (SSA).

outcomes. We note that the exponential and logistic projections diverge most substantially for countries with relatively high poverty levels and relatively high projected poverty reduction. Additionally, visual inspection of the confidence intervals demonstrates the importance of sampling errors for the conclusions drawn.

These findings are also summarised in Table 6, which shows results by world region and for the entire set of countries in our analysis; for country-specific results see Table A.2. More specifically, we find that according to the logistic dynamic model (column 2), 51 countries around the world (68% of our countries) are on track to meet the target to cut poverty by half by 2030. The proportions vary from 51% of the countries being on track in sub-Saharan Africa to 100% in East Asia and the Pacific. As column (3) shows, we find that fewer countries are on track according to the exponential model (57%), which is theoretically expected because this model does not anticipate acceleration and deceleration phases for high-poverty countries' trajectories. Countries where each model suggests a different conclusion are either located in Latin America and the Caribbean or in sub-Saharan Africa. Considering both models together, columns (4) and (5) demonstrate that for 89% of the countries both give the same assessment of on track or not, whereas for 11% of the countries results are model-dependent, with discrepancies again only found in Latin America & the Caribbean and sub-Saharan Africa.

We now assess the extent to which sampling errors affect conclusions about whether a country is on track to meet its target. As the poverty observations for each country are in fact mean point estimates from survey data, they are subject to sampling error and thus so are our calibrated parameter values and projections. Our approach to inference for the projections respects the bounded nature of the variables and is detailed in Appendix C. Column 6 of Table 6 shows that only 36 countries (48% of our countries) are projected to achieve a poverty headcount ratio in 2030 significantly below (exceeding) their target (see Appendix C for more detail on this one-tailed test). Relatedly, the share of countries with projected headcount ratios significantly below their targets is also smaller in most world regions. In order to assess the importance of sampling errors for such an on track analysis more generally, Table 6 also reports the share of countries for which the interval estimates include the targets in column (7). For 43% of the countries we find the target to be within the 95% confidence interval of their projected value (irrespective of the projection itself being above or below the target).

Finally, to provide a sense of the magnitude by which projections by different models may diverge from one another, column (8) of Table 6 reports the proportions of countries for which the projected incidence of multidimensional poverty in 2030 differs by 5 percentage points or more between the logistic and the exponential models. While the two models suggest substantially different projections only for 27% of all countries (20 countries), this share increases to 51% (18 countries) in sub-Saharan Africa. The reason for this finding is simply that for low levels of poverty, the exponential model may serve as reasonable approximation of the logistic model. For high poverty countries, however, the two models project substantially different trajectories – crucially, the logistic model anticipates both acceleration and deceleration periods, whereas the exponential model does not.

We conclude this section by highlighting the value that the adjusted headcount ratio can add to the evaluation of poverty reduction goals. Like most development targets, SDG 1.2 is formulated in terms of a headcount ratio, that is, the proportion of people experiencing a certain condition. Headcount ratios suffer from well-known limitations as poverty measures (Sen, 1976), specifically that they obscure improvement (or deterioration) of conditions among those who remain poor. In the context of multidimensional poverty measurement, Alkire and Foster's (2011) adjusted headcount ratio, discussed in Section 3.1.1, addresses this by adjusting for the intensity of poverty among the poor. Our on-track analysis for the adjusted headcount ratio $M$ in columns (9) and (10) of Table 6 suggests very similar findings to those for the headcount ratio (for country-level findings see Fig. A.1). This is not surprising as, for most countries, the change in intensity of poverty between observations is smaller than the change in incidence. There are, however, notable exceptions. For example, we observe that Guinea and Ghana are on track to significantly exceed the $M$-target but not the $H$-target. Both exhibit significant and substantial intensity reductions, which are among the three largest that we observe in our data. This example demonstrates how intensity reductions play a critical role in explaining how countries may meet the $M$-target despite missing the $H$-target. Thus, formulating the poverty target in terms of $M$ – instead of or alongside $H$ – can make visible progress among the poor (even if they are still poor) and, moreover, entails the possibility to meet the poverty reduction target via reductions in poverty intensity. We show here that these reductions can be substantial, especially for some of the globally poorest countries, and that they will not be recognised while the focus remains exclusively on poverty incidence reductions.

### 4.2. Is cutting poverty by half a reasonable target?

In this section we revisit the previous results, taking a more reflective stance. In particular, we address the question of whether our by SDG 1.2-inspired poverty reduction target was feasible for all countries, and how far away countries are from meeting or failing to meet the target. To do so, we perform two exercises, focusing on the headcount ratio and the logistic dynamic model to facilitate the presentation.

Our first analysis focuses on those countries that would miss the target if recent trends continue. We ask whether, under an improved performance in poverty reduction, they would manage to meet the target. Our second analysis focuses on countries that *are* expected to meet targets under recent trends, and we ask whether falling back to

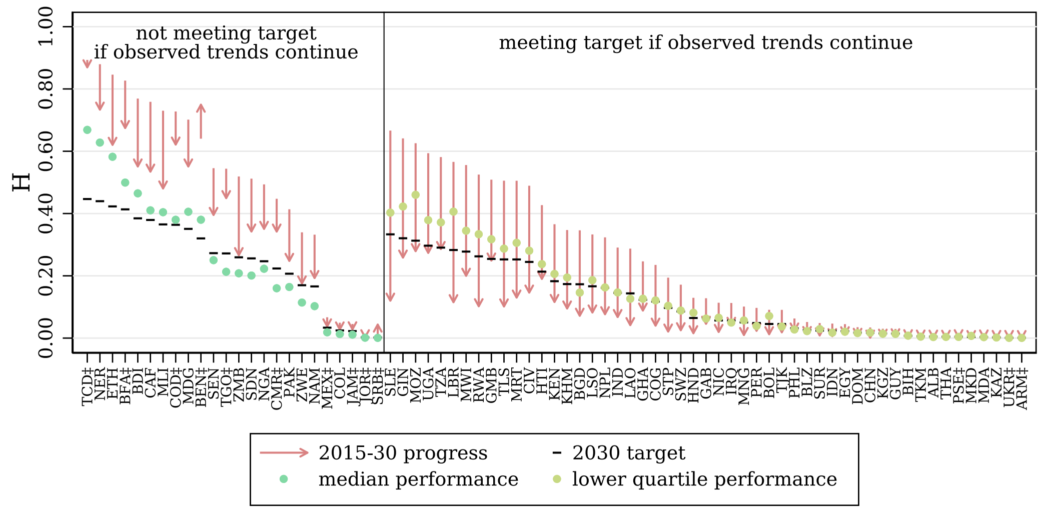


**Fig. 9.** Projections of the headcount ratio for 2015–2030 for alternative scenarios.
Notes: Authors' calculations; projected 2015–2030 progress is based on logistic model; ‡ indicates that the estimated change for a country is not significantly different from 0. (For accurate rendering of coloured elements of this figure, the reader is referred to the web version of this article.)

a poorer performance may result in missing the target. These analyses provide a sense of (i) what is feasible, in principle, (ii) the sensitivity of the target-achievement outcome to changes in observed pace of poverty reduction, and (iii) what changes in the magnitude of the $\check{\beta}_{hs}^{\log}$ mean. To choose meaningful counterfactual performances, we draw on the observed distribution of estimated coefficients. This ensures that counterfactual performances have been observed in other countries and thus are not entirely unfeasible. Specifically, we identify the median performance using the empirical distribution of $\check{\beta}_{hs}^{\log}$ across countries. Similarly, we also define 'poor' and 'good' performance based on the lower and upper quartiles of this distribution.

Fig. 9 shows the results of this counterfactual analysis for all 75 countries. We posit 'median' performance (green dots) as a meaningful benchmark for countries that are found to be off track according to projections obtained from the logistic dynamic model. This typically implies a moderate (i.e. realistic) improvement in their observed performance. For countries that are found to be on track according to logistic model-based projections, it is important to note that, typically, they already perform at a level corresponding to 'median' performance or better. Thus we consider 'lower quartile' performance as an appropriate counterfactual benchmark (yellow dots) for these countries.

In Fig. 9 we observe that more than a dozen of the 24 countries which are not on track to meet the target, would manage to achieve this goal if they boost their poverty reduction performance to a 'median' level (e.g., Senegal or Pakistan). Since slow trajectories of poverty reduction are not predetermined, the results show that there is a chance to increase the likelihood of halving poverty by 2030 if some of the countries shifted gear. However, Fig. 9 also reveals that the challenge is greater for some of the poorest countries, which are all in Africa, as these would not halve poverty by 2030, even if recent performance were boosted.

Conversely, we also find that several countries among the 51 that would be expected to meet the target according to the logistic model-based projections if observed trends continue are actually at risk of failing to halve poverty if their poverty reduction dynamics are interrupted (e.g., Malawi or Rwanda). These results are as important as the previous ones in that they offer compelling evidence of the need of continuity and sustainability of policy efforts in the quest to halve poverty by 2030.

In our second exercise, we calculate the required performance to meet the goal in 2030 for each country and the additional years needed to achieve the target under the actually observed performance. This analysis provides additional information to assess the feasibility of the targets, and to obtain a sense for the magnitude of $\check{\beta}_{hs}^{\log}$. Fig. 10 shows the *actual* and the *needed* $\check{\beta}_{hs}^{\log}$ to achieve the target in 2030, and the years needed to achieve the target under the actual $\check{\beta}_{hs}^{\log}$. Several interesting insights emerge. First, we observe that a dozen or so countries, shown on the left of the figure, would need 10 or more additional years to reach the target, given their recent performance. Seven of those countries would, in fact, need some 20 years or more. Conversely, 10 countries appear to trivially achieve the targets about 10 years earlier, and another 8 countries 9 years earlier. Given that the SDG target period for halving poverty incidence is 15 years, we conclude that setting a uniform 'cutting poverty by half' target results in unrealistically ambitious targets for many countries and entirely unambitious targets for many others. We note that both overly ambitious and unambitious targets are problematic. Over-ambitious targets may be discouraging from the outset and even remarkable progress (including substantial accelerations in poverty reduction) may appear as entire failures. Meanwhile, unambitious targets would neither direct any attention to the underlying problem, nor induce policy changes and are, therefore, essentially ineffective and irrelevant.

Turning to the actual and needed $\check{\beta}_{hs}^{\log}$, we observe that among those countries that would need some additional 10 or more years to achieve the target if recent trends continue, several countries would require a $\check{\beta}_{hs}^{\log}$ of 0.7–0.8 (e.g., Cameroon, Nigeria or Senegal), which is in fact less than the global median performance ($\check{\beta}_{Q_{50}}^{\log} = 0.098$). This observation is important as it suggests that the required empirical performance is feasible, at least in the mid-run, because it has been observed in many other countries. In other cases, however, such as Chad or Niger, the required $\check{\beta}_{hs}^{\log}$ suggest that these countries would need to deliver better than the upper quartile performance ($\check{\beta}_{Q_{75}}^{\log} = 0.128$). While all required performances are at least empirically observed, the needed performance would, however, make those countries top-performing in poverty reduction by global standards, which appears very unrealistic again. Finally, how unrealistic these targets may be is also evidenced by the case of Ethiopia, which delivers a relatively good performance within the group of high poverty countries ($\check{\beta}_{hs}^{\log} = 0.081$), which is also close to global median performance. And yet Ethiopia would fail to meet the target of halving poverty by some 10 years.

In summary, three main conclusions emerge from this section. First, our results suggest that plausible variation of the $\check{\beta}_{hs}^{\log}$ may affect target achievement for both better or worse: a change of policy in either direction can make a difference. Second, for many countries, their targets appear to be either too ambitious or too unambitious and, thereby, cast doubt on a one-size fits all approach to setting poverty

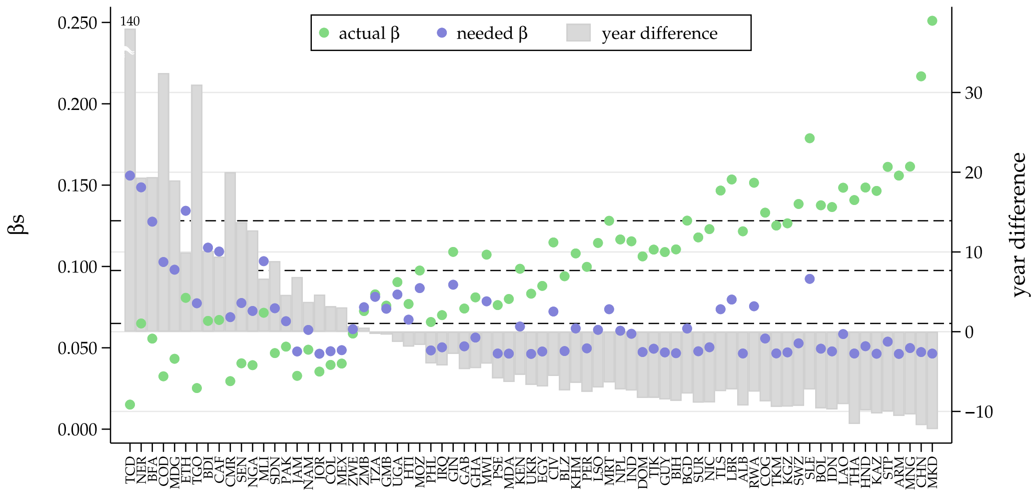


**Fig. 10.** Actual and required performance to meet targets.
Notes: Authors' calculations; countries with observed increases of poverty omitted (Benin and Serbia); dashed lines indicate upper quartile ($\beta_{Q75} = 0.128$), median ($\beta_{Q50} = 0.098$), and lower quartile ($\beta_{Q25} = 0.065$) performance; countries are sorted by difference between actual and needed $\beta$s. (For accurate rendering of coloured elements of this figure, the reader is referred to the web version of this article.)

reduction targets in relative terms. Third, the $\check{\beta}^{\log}_{hs}$ offer a convenient way to assess performance in poverty reduction, as they are comparable across countries and prevailing levels of poverty.

## 5. Discussion

### 5.1. Implications for setting poverty targets

The previous section casts doubt on the usefulness of a one-size fits all approach to set poverty reduction targets, such as cutting poverty by half on the national level. Given this, how can poverty reduction targets be reasonably set? Indeed, many other development targets are set in a similar way, and this practice has been criticised from various directions. More specifically, previous research emphasises that in order to obtain feasible targets, initial conditions of a country have to be taken into account. Initial levels of the indicator are prominently discussed in the literature (Easterly, 2009), as is initial inequality in the case of (monetary) poverty targets (Allwine et al., 2015) and also, less prominently, historical trajectories or recent trends (Ranganathan et al., 2017).

Besides having different initial conditions among countries, political priorities may vary, too. In fact, even the SDG framework states that targets are universally applicable "taking into account different national realities, capacities and levels of development and respecting national policies and priorities" (UN, 2015, p. 3). Consequently, there is no purely technical way to derive definitive poverty targets. Nonetheless, our analysis entails several implications for the process to arrive at feasible and yet ambitious poverty reduction targets. In this context, business-as-usual projections may serve a useful reference, as they suggest a feasible outcome given the recently observed trends. We begin our discussion with two important considerations for these business-as-usual projections, followed by a suggestion about how to arrive at more ambitious goals.

First, our results suggest that in order to appropriately account for the initial conditions of a country, one has to consider *both initial levels and recent trends* of poverty (or development indicators more generally)—initial levels alone, which have been emphasised in previous research, are insufficient.

Intuitively, this insight follows from the fact countries may actually follow very different trajectories despite exhibiting a similar headcount ratio at one particular point of time. Fig. 11 provides empirical evidence in support of this idea (cf. also Fig. 7 above). The important observation is that for every given level of the headcount ratio, the observed value of $\check{\beta}^{\log}_{hs}$ may vary widely. For instance, we find that several countries with relatively high poverty headcount ratios of, say 60%, exhibit a performance level that is outside of the interquartile range on both sides (e.g., Madagascar or Togo on the one side with Liberia or Rwanda on the other). This means that some of those countries are truly 'top'- and 'bottom' performers by global standards. In fact, the very same observation also applies for poverty rates below, say 10%, too. Even for countries with very high poverty rates (80%+), we find performance differences in the same magnitude of the interquartile range (e.g., Chad and Ethiopia), even though all of them show below-median performance.[10] Therefore, for identifying feasible poverty targets both current levels and recent changes have to be taken into account. Only together do they reflect the initial conditions experienced by a country to the extent they are already embodied in the available data.

While accounting for initial conditions (including recent trends) is critical for arriving at a reasonable business-as-usual projection, it is also important to do so *using the appropriate model*. The projections for 2030 as discussed in Section 4.1 may also be interpreted as such business-as-usual projections. Recall that according to Table 6, for 17% of the countries around the world logistic and exponential (constant relative change) dynamic models result in significantly different projections for 2030. This share even increases to 26% for sub-Saharan Africa, where most of the highest poverty countries are found. In line with our theoretical discussion, the logistic and exponential models imply different projections particularly for countries with higher levels of poverty. In contrast, for lower levels of poverty, the exponential model may well be viewed as a reasonable approximation of the logistic model. Naturally, whether the choice of projection model makes a real difference in a particular case depends on several factors, including sample size, the country's position on its trajectory, and the period over which the target applies.

Country-specific projections based on the logistic dynamic model and recently observed trends may be understood as the outcome under continued efforts or business as usual. They can thus be deemed feasible given the currently available evidence. However, identifying more ambitious targets may be desirable to mobilise additional efforts and

[10] That we do not observe top-performers for very high levels of poverty follows from the fact such performance results in quickly graduating from such very high incidences.

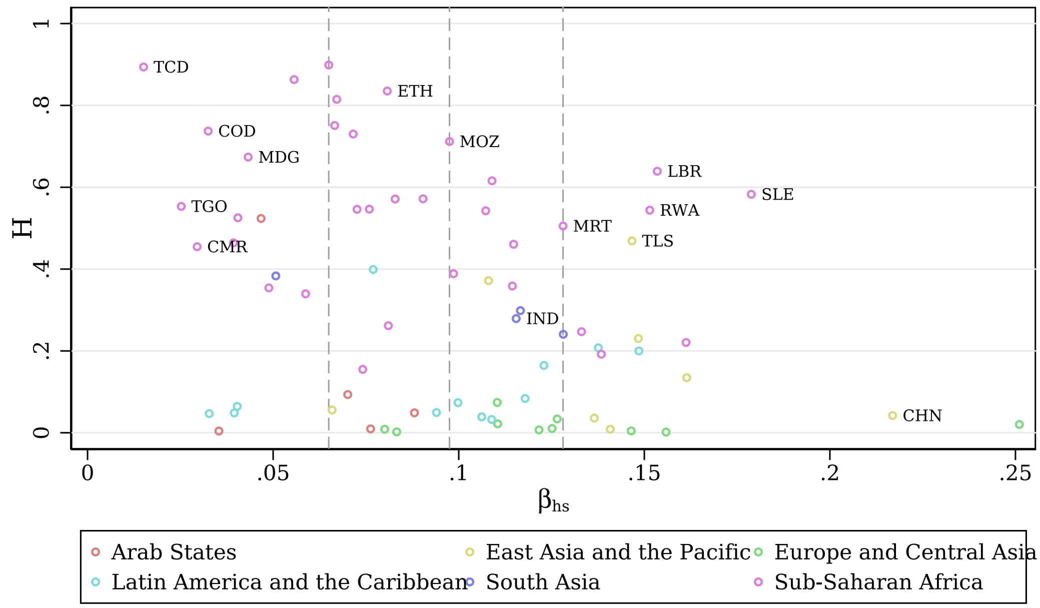


**Fig. 11.** Headcount ratios and calibrated $\check{\beta}^{log}_{hs}$.
Notes: Authors' calculations; dashed lines indicates lower quartile, median and upper quartile performance. (For accurate rendering of coloured elements of this figure, the reader is referred to the web version of this article.)

resources, calling for policy adjustments. In contrast, both overly ambitious and unassuming targets entail non-negligible costs. The question is, therefore, how to identify more *ambitious and yet feasible targets*.

One promising way forward is to revert to the observed logit rates of change and screen which other countries or sub-national regions of the same country were able to achieve targets. Recall that the $\check{\beta}^{log}_{hs}$ describe the entire trajectory of a country, including acceleration and slow down. Therefore, valid comparisons can be made for countries at different points in their trajectory; comparisons need not be limited to countries with similar poverty levels. For example, our results suggest that Mozambique and Kenya are following a very similar trajectory in poverty reduction, despite having a difference in the headcount ratio of around 30 percentage points in their first year of observation. Similar comparisons of simple absolute or relative changes would be misleading, since both are expected to vary over the entire trajectory for theoretical reasons, as shown and discussed in Section 3.1.3. In short, our argument is that comparing $\check{\beta}^{log}_{hs}$ across different countries or subnational regions provides critical evidence for feasibility assessments. Finally, we note that while arriving at sensible targets requires a careful analysis and choice of the $\check{\beta}^{log}_{hs}$, the actual formulation of the target may well be translated into an absolute or relative change, or even a level-end target to be achieved in a given year, which is easier to communicate to the interested public.

Finally, in many cases it may be preferable to formulate the target in terms of the adjusted headcount ratio ($M$). As discussed in Section 4.1, progress among the poor may go unnoticed due to well-known limitations of the headcount ratio ($H$), in particular in countries with relatively high poverty levels. A natural follow up question is then how reasonable poverty targets in terms of the adjusted headcount ratio may be set. One option is to choose $\check{\beta}^{ml}_{as}$ in a similar way to $\check{\beta}^{log}_{hs}$, to represent realistic ambitions in terms of reductions in poverty intensity as well as incidence, and then derive the respective target value of $M$ as the product of the implied target values of $H$ and $A$. Naturally, the resulting $M$ target should be carefully formulated and explained in the most communicable way. Alternatively, targeting a particular incidence reduction together with an unchanged intensity may also be sensible. Indeed, this approach implicitly mandates policymakers to promote improvements among both the least poor and the poorest of the poor. The reason for this is that if only the least poor were to exit poverty, intensity (which is average deprivation among the poor) would increase.

### 5.2. *Testing for changes of trajectory*

A country's projected trajectory of poverty reduction, which is summarised by the rate of change parameter $\beta$ of the selected dynamic models (the $\check{\beta}^{log}_{hs}$) is not irrevocably determined. It can change for several reasons, including shocks and policy reforms. Therefore, one may also be interested in establishing whether a change of trajectory has effectively taken place. We argue that, in general, an appropriate modelling of the outcome variable is critical to test for the existence of such changes. Let us then explain what, exactly, adopting an exponential (constant relative change) or a logistic dynamic model entails.

For the sake of the argument we consider the case of a simple before-after comparison for a single country, for which we have an extensive time series of multidimensional poverty observations. If the trajectory of an outcome $y_t$ follows the exponential dynamic model, we may formulate the econometric model to test for a trajectory change as follows

$$\ln y_t = \alpha^{crc} + \delta_1^{crc} D_t + \beta^{crc} t + \delta_2^{crc} D_t \times t + e_t, \tag{8}$$

where $D_t = 0$ for all periods before the assumed change and $D_t = 1$ for all periods after it.

If we were able to reject $H_0 : \delta_2^{crc} = 0$, we may conclude that the country effectively experienced a change of trajectory. Moreover, in the exponential model it holds that $\beta^{crc} = \frac{\dot{y}}{y}|_{D=0}$ and $\beta^{crc} + \delta^{crc} = \frac{\dot{y}}{y}|_{D=1}$. Therefore, in the exponential model, an equivalent approach to test for changes in the trajectory is to calculate the average relative rates of change for both periods (before and after the potential structural break) and subsequently test the null of equality between them: $H_0 : \frac{\dot{y}}{y_t}|_{D=0} = \frac{\dot{y}}{y_t}|_{D=1}$.

If the trajectory of an outcome $y_t$ follows instead the logistic dynamic model, we may formulate the econometric model to test for a trajectory change as follows

$$\ln\left(\frac{y_t}{1-y_t}\right) = \alpha^{log} + \delta_1^{log} D_t + \beta^{log} t + \delta_2^{log} D_t \times t + e_t.$$

We infer a change of trajectory if we are able to reject $H_0 : \delta_2^{log} = 0$. In the logistic model, however, testing for differences in the relative rates of change before and after the potential change of trajectory is no longer an equivalent approach. Specifically, even if the country remains on the exact same trajectory ($\delta_2^{\log} = 0$), we actually expect the relative rates of change to decrease from a theoretical perspective, as $\frac{\dot{y}}{y} = -\beta^{\log}(1 - y_t)$. Therefore, testing for changes in the average relative change may be highly misleading if the true modelling framework is actually a logistic one.

In principle, this conclusion applies to all bounded variables, and thus some of the most popular development indicators. And yet, the exponential model is most often applied in the academic literature (e.g., Fukuda-Parr et al., 2013; French, 2015; Jacob, 2017; McArthur and Rasmussen, 2018; Ahimbisibwe and Ram, 2018), and it implicitly underlies assessments by practitioners (e.g., WHO-UNICEF, 2017). The extent to which this makes a difference in practice depends on the empirical distribution of the underlying indicator. More specifically, for an indicator such as a poverty headcount ratio, where lower values are better, the exponential model may be considered a reasonable approximation of the logistic model only for low levels of poverty. This is not true for high indicator levels.

## 6. Concluding remarks

In this paper, we develop a modelling framework for computing projections of global multidimensional poverty at the country level to offer a more detailed account of the evolution of multidimensional poverty over time. Thereby, we seek to lay the foundation for better methods to address highly relevant questions in practice, such as whether countries are on track to meet their poverty reduction targets, how to set such targets in the first place, and how to test for changes in the underlying trajectory.

Our empirical analysis of the global MPI for 75 countries suggests that 51 countries were on track to reduce the proportion people living in multidimensional poverty by half between 2015 and 2030 (before the outbreak of the COVID-19 pandemic). Accounting for sampling error, 36 of those countries were on track to significantly exceed the target, reducing poverty incidence by significantly more than half. Our results also indicate that for projection purposes, choosing a logistic instead of an exponential dynamic model makes a difference—in particular for countries with high levels of poverty, most of which are located in sub-Saharan Africa. Taking a more reflective stance, our subsequent analysis questions the appropriateness of a one-size-fits-all approach to target setting, as it results in both hardly feasible targets for some countries and entirely unambitious targets for many others. More specifically, we find around a dozen countries that require 10 or more (and sometimes more than 20) additional years to meet the target if they continue their observed trajectories. At the same time, around 20 countries would reach the target about 10 years earlier than the deadline. Our results also suggest that using the headcount ratio to measure progress towards a poverty reduction target may obscure improvements achieved among the poor, in particular for the poorer countries. Refined measures such as the adjusted headcount ratio are one way to overcome this limitation.

Furthermore, we argue that business-as-usual projections may play an important role in setting feasible and yet ambitious targets. In this context, we emphasise that our modelling framework makes possible meaningful international or subnational performance comparisons, as well as comparisons over time, providing additional guidance on the feasibility of more ambitious targets. As the discussed implications essentially follow from the bounded nature of our outcome variables, they are also applicable to most other development indicators. In particular, the practice of inferring different trajectories from different relative change rates turns out to be potentially problematic. Future research should take this into account and revisit related empirical analyses, paying due attention to the double-bounded nature of the underlying outcome variables.

Projections based on observed recent trends naturally ignore the manifold effects of shocks, such as the recently unfolding COVID-19 pandemic, for global poverty trends. Even though data availability is improving, it remains hard to quantify all relevant implications for updated trajectories for several reasons. These include the fact that reliable and fully comparable data on how the pandemic and related policy-responses have affected the lives of the poor remain scarce. A first attempt to assess the potential increase of global multidimensional poverty due to COVID-19 was conducted by Alkire et al. (2021). That study uses simulation techniques which are informed by assessments of UN agencies about food insecurity and school closures. Their results suggest that a decade of progress in poverty reduction might be undone. However, the study is not an ex-post evaluation, and it is unclear to what extent this increase translates into persistent deprivation (policymakers still seek to attenuate the effects). Accordingly, it also remains unclear whether the pandemic and related responses affect only the levels or also the slopes of poverty reduction trajectories around the world.

This paper represents a step forward towards a comprehensive analysis of multidimensional poverty trends, and it manages to accommodate important current data limitations. However, future research in this direction will require more and better data, which would allow the introduction of complementary statistical approaches, including non-parametric techniques, to assess the role played by covariates of multidimensional poverty for its trajectories. Having several rounds of data or subnational data, would permit the estimation of longitudinal models and allow, for instance, accounting for projection errors. Future research may also seek to identify and analyse different profiles underlying the overall trajectories (e.g., in terms of the underlying subindices of incidence and intensity of poverty or the underlying indicator trajectories), and to incorporate shock simulations into projections.

In his last book, *Measuring Poverty Around the World*, Atkinson aimed to “provide the evidence about the extent and nature of poverty that is necessary to spur action and to design effective policies” (Atkinson, 2019). Recognising that exercises related to global poverty may be highly controversial, and flawed, but nonetheless useful, this paper has sought to complement efforts to improve the analysis of global poverty, by developing a modelling framework to project multidimensional poverty trajectories. Given the relevance and level of complexity as well as current data limitations, this paper is a first rather than a last word on the subject. The aim, through critical exchange, is to strengthen the methods available in ways that might spur both discussion and action.

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## CRediT authorship contribution statement

**Sabina Alkire:** Conceptualisation, Writing – original draft, Writing – review & editing, Funding acquisition. **Ricardo Nogales:** Conceptualisation, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing. **Natalie Naïri Quinn:** Conceptualisation, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing, Visualisation. **Nicolai Suppa:** Conceptualisation, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing, Visualisation, Funding acquisition.

## Data availability

The data underlying this article can be freely downloaded from the website of the Oxford Poverty and Human Development Initiative (OPHI) under https://ophi.org.uk/data-tables-do-files-2020-archive/ as “Table 6: Changes over Time”.

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## Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2023.103150.

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