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Global multidimensional poverty and COVID-19: A decade of progress at risk?

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Abstract

According to the global Multidimensional Poverty Index (MPI), an internationally comparable measure, poverty in developing countries has fallen substantially over the last 15 years. The COVID-19 pandemic and associated economic contraction are negatively impacting multiple dimensions of poverty and jeopardising this progress. This paper uses quantitative assessments of increases in food insecurity and out of school children made by UN agencies to inform microsimulations of potential impacts of the pandemic under six alternative scenarios. These simulations use the nationally representative datasets underlying the 2020 update of the global MPI. Because these datasets were collected between one and 12 years pre-pandemic, we develop models to translate the simulated impacts to 2020 while accounting for underlying poverty reduction trends and country-specific factors. Aggregating results across 70 countries that account for 89% of the global poor according to the 2020 global MPI, we find that the potential setback to multidimensional poverty reduction is between 3.6 and 9.9 years under the alternative scenarios.

Keywords: multidimensional poverty, global MPI, COVID-19, education, nutrition, microsimulations, poverty projections, developing regions

JEL classification: I32, C53

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1 Introduction

Recent decades have witnessed substantial global improvements in many development indicators, including neonatal and under-5 mortality (e.g., Lim et al., 2016), access to drinking water and sanitation (UNICEF and WHO, 2019), access to primary education (Friedman et al., 2020), and monetary poverty (World Bank, 2018) among others. Progress in multiple indicators simultaneously benefited many of the poorest households in the developing world; Alkire et al. (2020d) provide harmonized trends for 80 countries and find significant reduction of multidimensional poverty as measured by overlapping deprivations in the domains of health, education and living standards.

Further significant progress had been anticipated in the coming years (e.g., Bennett et al., 2018; Friedman et al., 2020), including continuing reductions of multidimensional poverty (Alkire et al., 2020e). However, the emergence of COVID-19 in late 2019 and its development into a global pandemic through 2020 has put both recent and anticipated progress at risk. With the demonstrated potential of COVID-19 to overwhelm even the most modern healthcare systems, governments have implemented varying and often harshly restrictive policy measures in an attempt to bring outbreaks under control (Hale et al., 2020). These policy measures have been implemented in a context of great uncertainty, whether regarding epidemiological characteristics of the pandemic, its transmission mechanisms (Lewis, 2020a,b; Mallapaty, 2020) or its general effects on the society at large (Altig et al., 2020). In these circumstances, policies have been country- and time-varying, with equally heterogeneous short-term effectiveness (e.g., the success of social distancing or the degree of compliance in wearing masks) (Anderson et al., 2020). As an example, an analysis of the extent to which such policy responses have varied in South American countries can be found in González-Bustamante (2021). Nevertheless, a broad pattern has emerged in which economic performance has been traded off against public health considerations, and poor people in countries across the globe have experienced disruptions to their livelihoods.

As the pandemic continues, information about the magnitude of the threat it poses in terms of reverting development progress is vital to design and implement public policies[1]. This paper seeks to contribute to the public debate on policy responses to COVID-19 by quantifying the potential impact on global multidimensional poverty as measured by the global Multidimensional Poverty Index (MPI) developed in Alkire and Santos (2014), which captures simultaneous or overlapping deprivations at the household level.[2]

Amidst the ongoing pandemic, data shortages, and rapidly evolving policy responses, it is impossible to evaluate the direct causal impacts on the global MPI. Nevertheless, it is important to evaluate the potential impacts of COVID-19 to inform the ongoing policy debate. This paper offers such an evaluation. We first apply microsimulation techniques to generate anticipated

[1] Few studies provide relevant prospective predictions, including the Bill & Melinda Gates Foundation Goalkeepers Report 2020, which documents possible reversal of decreasing trends in 18 SDG-related indicators (see Bill & Melinda Gates Foundation. [Internet.] Goalkeepers 2020 [Accessed Sep 15 2020]. Available from: `https://www.gatesfoundation.org/goalkeepers/`) and Sumner et al. (2020) who estimate that the pandemic will push between 420–580 more people below the 1.90$ monetary poverty threshold.

[2] Measures of multidimensional poverty capturing simultaneous deprivations (Tsui, 2002; Bourguignon and Chakravarty, 2003; Atkinson, 2003) are now acknowledged as useful complements to monetary poverty, accounting directly for critical shortfalls in dimensions of human well-being and the joint nature of deprivations (e.g., Pattanaik and Xu, 2018) and the UN Resolution about the Third Decade of Poverty Alleviation `https://undocs.org/A/RES/72/233`.

COVID-induced deprivations in the household level data underlying the actual global MPI estimations, under alternative scenarios. These scenarios draw on assessments by the World Food Programme (WFP) and the United Nations Educational, Scientific and Cultural Organization (UNESCO) that suggest substantial impacts of COVID-19 policy responses on food security and school attendance, respectively. Second, as the datasets were collected between one and 12 years before the pandemic, we develop and estimate a cross-country model of the simulated impacts then calibrate it at country level. This allows us to make country-specific adjustments to translate the simulated impacts to 2020 while accounting for underlying poverty reduction trends in a way that respects intrinsic country heterogeneities. Finally, we combine these simulation results with the country-specific multidimensional poverty trajectories calibrated by Alkire et al. (2020e). We aggregate results across 70 countries that account for 89% of the global population of poor people by the 2020 global MPI, to assess the setback in terms of poverty reduction at the global level. Our results suggest a potential setback in multidimensional poverty reduction of between 3.6 and 9.9 years across the alternative scenarios.

The paper is structured as follows. In section 2 we review the global MPI and its underlying datasets. In section 3 we present the microsimulations and discuss the results we obtain. In Section 4 we develop the model and apply it to translate the simulated impacts to 2020. In Section 5 we present and discuss our aggregate results, with concluding remarks in Section 6. The structure of the data sources and analysis in this paper is summarised in figure A.1.

2 Multidimensional poverty measurement and data

We measure multidimensional poverty using the global Multidimensional Poverty Index (MPI), an internationally-comparable index that has been published annually by the United Nations Development Programme (UNDP) and Oxford Poverty and Human Development Initiative (OPHI) since 2010 (UNDP, OPHI, 2020). This section describes the salient features of the index and the datasets from which it is estimated, which underlie our simulations and analysis of the impact of the COVID-19 pandemic on global multidimensional poverty.

Implementing the adjusted headcount ratio multidimensional measure developed by Alkire and Foster (2011), the global MPI (Alkire and Santos, 2014) aggregates information on deprivations in ten indicators to create a deprivation score, identifies who is poor using this score, then aggregates across sampled households to obtain population estimates.[3]

The ten deprivation indicators are organised in three dimensions: Health, Education, and Living Standards. While dimension and indicator choices were originally informed by the Millennium Development Goals (Alkire and Santos, 2014); recently five indicator definitions were revised to better align with the Sustainable Development Goals (Alkire and Kanagaratnam, 2020; Alkire et al., 2020a). Each indicator is a binary variable, taking a value of one if a critical threshold is not met. For example, a household is deprived in years of schooling if no eligible household member has completed at least six years of schooling, while it is deprived in sanitation if it has

[3]This order of aggregation (first across indicators and then across the population) reflects the joint distribution of deprivations in different indicators and (data permitting) allows the MPI to be disaggregated by population subgroups. This distinguishes it from, for example, the Human Development Index, which first aggregates across the population and second across indicators.

Table 1: Global MPI indicator definitions and weights

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 data and definitions see Alkire et al. (2020b)

no sanitation facility, or an inadequate (by SDG definitions) or shared facility. The eight remaining indicators are Nutrition, Child mortality, School attendance, Cooking fuel, Drinking water, Electricity, Housing and Assets; their deprivation thresholds are defined in Table 1. The three dimensions are assigned equal weights, reflecting a normative judgement of equal importance to capture multidimensional poverty; similarly, indicators are weighted equally within dimensions.

Following Sen (1976), poverty measurement requires both the identification of the poor and the aggregation of information about the poor. The global MPI is sensitive to the joint distribution of deprivations across dimensions through its *dual-cutoff* identification of poor households as proposed by Alkire and Foster (2011); a household and each of its members is multidimensionally poor if its sum of weighted deprivations is greater than or equal to 1/3. Thus ordinarily only households suffering from multiple overlapping deprivations are considered to be poor. The headcount ratio or *incidence* of multidimensional poverty H is the proportion of the population who are poor. A related concept is vulnerability to poverty. In the global MPI, a household is considered vulnerable if its sum of weighted deprivations is at least 1/5 but less than 1/3. Considering aggregation, Alkire and Foster (2011) introduced the *intensity* of multidimensional poverty, A, as the average share of weighted deprivations among the poor. If the poverty cutoff is 1/3 then the value of intensity lies between 1/3 and 1. The global MPI itself is then $M_0 = HA$, the *adjusted headcount ratio*. In this study, we will represent the global MPI with the simpler notation M, to permit subscripting by country.

The global MPI itself and its associated incidence and intensity are estimated using nationally representative survey data, accounting for sampling weights and other aspects of complex survey design. This study uses the microdata that underlies the 2020 release of the global MPI (Alkire et al., 2020b,c). For our microsimulations, we use the most recent available cross-section datasets for each of 97 countries.[4] Forty-two of these datasets come from DHS surveys, 44 from MICS surveys, and 11 from national surveys. Meanwhile, we are able to calibrate dynamic models and thus predict pandemic impacts for 70 of these countries, for which two harmonized cross-sections are available (Alkire et al., 2020d)[5]. Across these 70 countries, the global MPI datasets collectively comprise a sample of 6.4 million individuals, representing a population of over 4.6 billion individuals. The full list of datasets, their dates, and their use in our analysis is presented in the Appendix (Table A.1).

3 Simulations of COVID-19 impact

The COVID-19 pandemic is impacting many of the indicators of the global MPI, both directly and through associated policy responses in countries across the globe. These policy responses include school closures, strict lock downs, restrictions to human mobility, as well as restrictions to local and international trade. In this section we implement microsimulations to ascertain the potential impact of increases in two indicators on the global MPI. We draw on analyses conducted by the World Food Programme (WFP) and the United Nations Educational, Scientific and Cultural Organization (UNESCO), on food security (and thus nutrition) and school attendance respectively, which highlight substantial impacts on these global MPI indicators. Our simulations are implemented with the datasets underlying the 2020 release of the global MPI and thus reflect impacts had the pandemic occurred in the year of the survey, between one and 12 years before 2020. We address this time discrepancy in the subsequent section.

3.1 Nutrition scenarios

The most recent World Food Programme (WFP) 2020 Global Report on Food Crises (WFP, 2020a, September release) is the latest and most comprehensive assessment of food insecurity threats pre- and during COVID-19. We will combine this information with our microdata to determine the potential increase in nutrition deprivations due to the pandemic and evaluate the magnitude of the induced changes in the global MPI. Ideally, we would rely on estimates of the expected COVID-19-induced increase in nutrition deprivation rates for every country in the global MPI. However, such information is unavailable at the time of writing, a situation that will most likely remain unchanged in the near future.[6] Therefore, our approach relies on the WFP pre-COVID-19 measured risk of food insecurity, which we assume may materialise in actual malnutrition among the poor and vulnerable due to pandemic response measures.

The WFP report contains detailed information on food insecurity for 55 countries in the developing world, with the aim to document the number of people living in food insecurity and malnutrition. In particular, it is estimated that 135 million people were in food crisis or worse

[4]The official global MPI 2020 covers 107 countries (Alkire et al., 2020b). Ten of these countries, however, lack the nutrition indicator, which is essential for our simulations: Afghanistan, Brazil, Colombia, Cuba, Dominican Republic, Indonesia, Papua New Guinea, Philippines, Ukraine and Viet Nam; data from the remaining 97 countries are the most recent available datasets for the global MPI and span 2008–19. We use all of the 97 available countries to improve the estimated adjustment model, which we use to predict the simulated shock in 2020.

[5]See 'Changes over Time' columns in Table A.1.

[6]Indeed, the on-going pandemic introduces new barriers into data collection, too. Among other things, many data collecting bodies suspended their in-person interaction thereby halting traditional household data collection (WFP, 2020b, p.2).

in 2019 (i.e. pre-COVID-19) according to the Integrated Food Security Phase Classification (IPC) methodology (or a compatible one when this analysis was not conducted). Fifty of those 55 countries are common between the WFP and the global MPI analyses, which are home to 122.8 million people in food crisis or worse according to the WFP. Although rich in information, the WFP report has two specific selection issues, (i) the countries that it includes, and (ii) the population covered within each country.

First, countries are covered by the WFP report if they asked for external food assistance in recent years or fulfill other criteria like hosting a refugee population assisted by UNHCR or WFP.[7] Given these inclusion criteria, one can expect people in these countries to be particularly vulnerable to nutrition deprivations. Indeed, using global MPI data, Figure 1 shows countries' nutrition deprivation rates sorted by incidence, and it reflects a clear selection procedure as countries covered by the WFP (bluish bars) tend to show up on the right. Moreover, the population-weighted average nutrition deprivation rate across all the global MPI countries for which this information is available is 30.4% (mid dotted line, Figure 1), whereas it is 34.4% for the 50 WFP-global MPI common countries (upper dotted line, Figure 1). The ratio of nutrition deprivation mean incidence over the whole set of global MPI countries relative to the WFG-global MPI common countries is 0.88, with a [0.74;1.11] 95% confidence interval. This ratio gauges the relative prevalence of nutrition problems in the global MPI countries compared with the WFP-global MPI common countries. Note, that the 95%-confidence interval does include 1, meaning we cannot reject equal prevalence. To better understand this result, it is important to notice, in particular, that populous countries with high nutrition deprivation rates, such as India (37.6%) and China (27.6%) are included in the global MPI analysis but not in the WFP report. Moreover, there are, in fact, several countries with relatively high nutrition deprivation according to the global MPI data but are yet not covered by the WFP report, such as Timor Leste, Nepal, or Benin.

Second, the IPC analysis first defines a reference population for each country, which sometimes comprises the entire population (e.g., in Malawi, Libya and Haiti), but in other countries only refers to a particular subpopulation unlikely to be representative of the whole population, such as refugees (e.g., in Bangladesh), migrants (e.g., in Ecuador and Colombia), or other minorities (e.g., in Mozambique and Angola). Moreover, in some countries, the reference population is not completely analysed. For instance, the WFP estimates for Bangladesh rely on an analysis of 3% of the reference population (Cox's Bazar and other refugee camps).

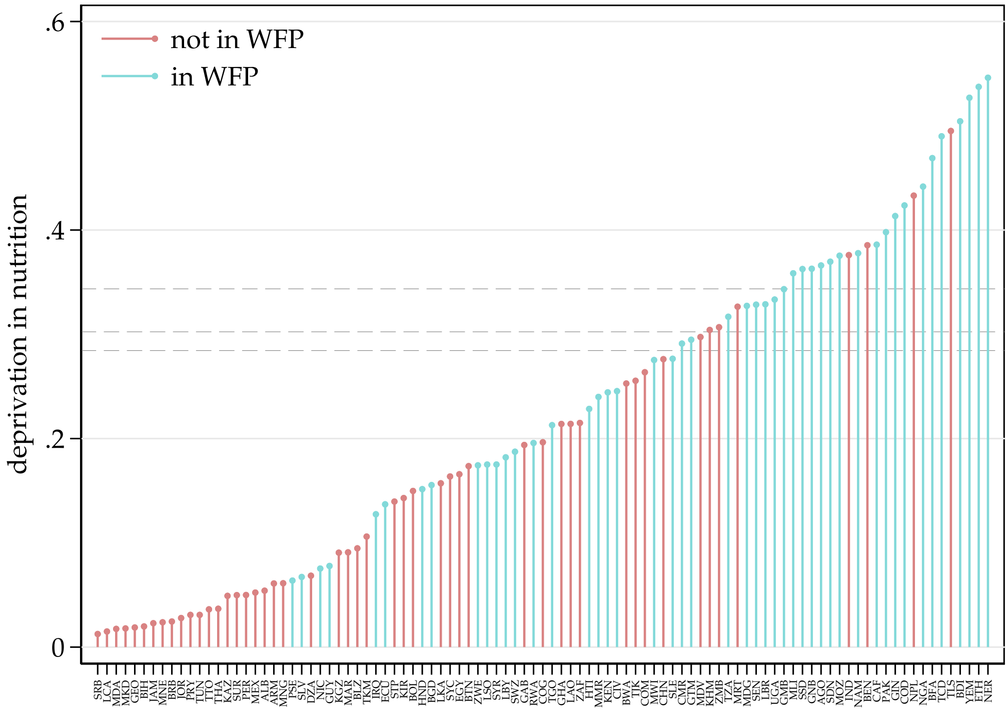
Because of these selection issues and the lack of data to assess their impact, we develop three plausible scenarios across which the likelihood of experiencing additional nutrition deprivations varies, rather than using a single point estimate.

3.1.1 Lower bound scenario

The WFP-estimated number of people living in food crisis or worse in the 50 WPF-global MPI common countries is 122.8 million, which clearly depicts a lower bound scenario due to the incomplete coverage of both countries and populations within countries. To simulate the materialization of food insecurity into nutrition deprivation, we need an estimate of the overall

[7] See WFP (2020a) p.13.

Figure 1: 2020 WFP report Country selection



Notes: horizontal lines show from top to bottom population weighted average deprivation for countries covered by the WFP, all global MPI countries, and countries not covered by the WFP.

likelihood of added nutrition deprivations among the poor and vulnerable population. We focus on the poor and vulnerable because they endure simultaneous livelihood deprivations that make the translation of food crisis situation into actual nutrition deprivations more plausible. The estimated number of poor and vulnerable people in the WFP-global MPI common countries is 730.2 million, based on nationally representative samples (Alkire et al., 2020b). Thus, the possible increment of additional nutritional deprivations in these 50 countries, 122.8/730.2=16.8%. This is a lower bound. For example, this figure does not account for country selection issues in the WPF report. To extend our analysis to the entire set of global MPI countries, we adjust this likelihood by the relative prevalence of nutrition problems in the global MPI countries with respect to the WFP-global MPI common countries, the corresponding figure for the whole set of global MPI countries would approximately be between 12% and 19% with 95% confidence. We thus take 12% as our definitive lower bound for the likelihood of additional nutritional deprivations across all countries.

3.1.2 Upper bound scenario

The WFP report allows us to infer the proportion of people living in food crisis or worse among the reference population. This proportion ranges from <1% in Cote d'Ivoire, Liberia, Myanmar, Rwanda, and Nicaragua to >60% in Angola, Ecuador, and South Sudan. If one posits that the proportion of people in crisis or worse among the reference population can be directly extended to the entire population in each WFP-global MPI common country, the number of people living in food crisis or worse would be 328.6 million. This is clearly an upper bound due to the highly selected population subgroups within some countries in the WFP report, which are particularly at risk of food insecurity. For instance, they estimate that 51% of the population in the Pakistani areas of Balochistan and Sindh live in food crisis or worse. These are severely drought-affected regions in the country, so extending this proportion to the entire population yields a clear overestimation of food insecurity problems. In this scenario, after adjusting by the relative prevalence of nutrition problems in the global MPI countries with respect to the WFP-global MPI common countries, the likelihood of interest would be between 33% and 50% with 95% confidence. We thus take 50% as the definitive upper bound for the likelihood of additional nutritional deprivations across all countries.

3.1.3 Moderate scenario

While grounding the simulations on actually observed food insecurity in specific subpopulations clearly results in a lower bound scenario, extrapolating the observed likelihood of experiencing food insecurity to the entire population clearly results in a upper bound estimate. An intermediate approach is to extrapolate the observed likelihood only to a more plausible subset of the population, such as the global MPI-poor and vulnerable. Following this approach suggests that 169.5 million people live in food crisis or worse in the WFP-global MPI common countries. After adjusting by the relative prevalence of nutrition problems in the global MPI countries with respect to the WFP-global MPI common countries, the likelihood of interest would be between 17% and 26% with 95% confidence. We thus take the rounded mid point in this interval, 20%, as the moderate value for the uniform likelihood of additional nutritional deprivations across all countries.

3.2 School attendance scenario

UNESCO (2020) estimated that the education of around 1.3 billion learners worldwide was disrupted by the pandemic. UNESCO data suggest that school closures initially peaked in April 2020, with over 91% of the world's learners out of school. Subsequently, however, this proportion fell gradually to around 50% by the start of the Northern Hemisphere summer break in June-July 2020, with a similar proportion out of school at the conclusion of the break in September 2020. Following this trend, we assume that 50% of all primary school aged children (by national definitions), who were attending school, cease to attend school.

As school closures have been implemented geographically rather than by socioeconomic status, schooling shocks are likely to be uniformly distributed among countries' populations rather than concentrated among the poor. Therefore the increase in out-of-school children will affect three types of households in our analysis: (i) those who are already deprived in school attendance because at least one–but not all–primary school-aged children are out of school, (ii) non-poor and non-vulnerable households that have at least one school-aged child but not previously deprived in school attendance, and (iii) those who are poor or vulnerable and have at least one primary school-aged child, but not formerly deprived in school attendance. The MPI will increase if households that previously had deprivations in at least 16.7% of indicators but were not deprived previously in school attendance, because added schooling deprivations will either make them fall into poverty or exacerbate their poverty intensity.[8]

3.3 Implementation of simulations

In order to simulate the nutrition scenarios, for each country we randomly draw, in turn, 12% (lower bound scenario), 20% (medium scenario), and 50% (upper bound scenario) of those individuals who are either vulnerable to multidimensional poverty or are already multidimensionally poor, but are not nutrition-deprived. If an individual is selected to suffer from undernutrition, their entire household is considered to be deprived in the nutrition indicator, which follows the respective indicator definition of the global MPI (see Table 1).

To simulate the school attendance shock, for each country we randomly draw 50% of those children, who, given their age, should attend primary school. This procedure takes both country-specific entry age and duration of primary schooling into account. If a child is selected not to attend school, the entire household is considered deprived in school attendance, which also follows the indicator definition of the global MPI (Table 1).

The school attendance shock is simulated alongside each of the nutrition shock scenarios. However, as the impact on school attendance may be less persistent than the impact on nutrition, we also explore each of the nutrition shocks on their own, yielding a total of six scenarios. Simulation results for all 97 countries under each of the six scenarios are illustrated in figure 2, with selected countries highlighted. To fix notation, a simulated increase in global MPI M in country s is denoted $\Delta^* M_s$. Similarly, a simulated increase in incidence H in country s is denoted $\Delta^* H_s$.

3.4 Discussion of simulation results

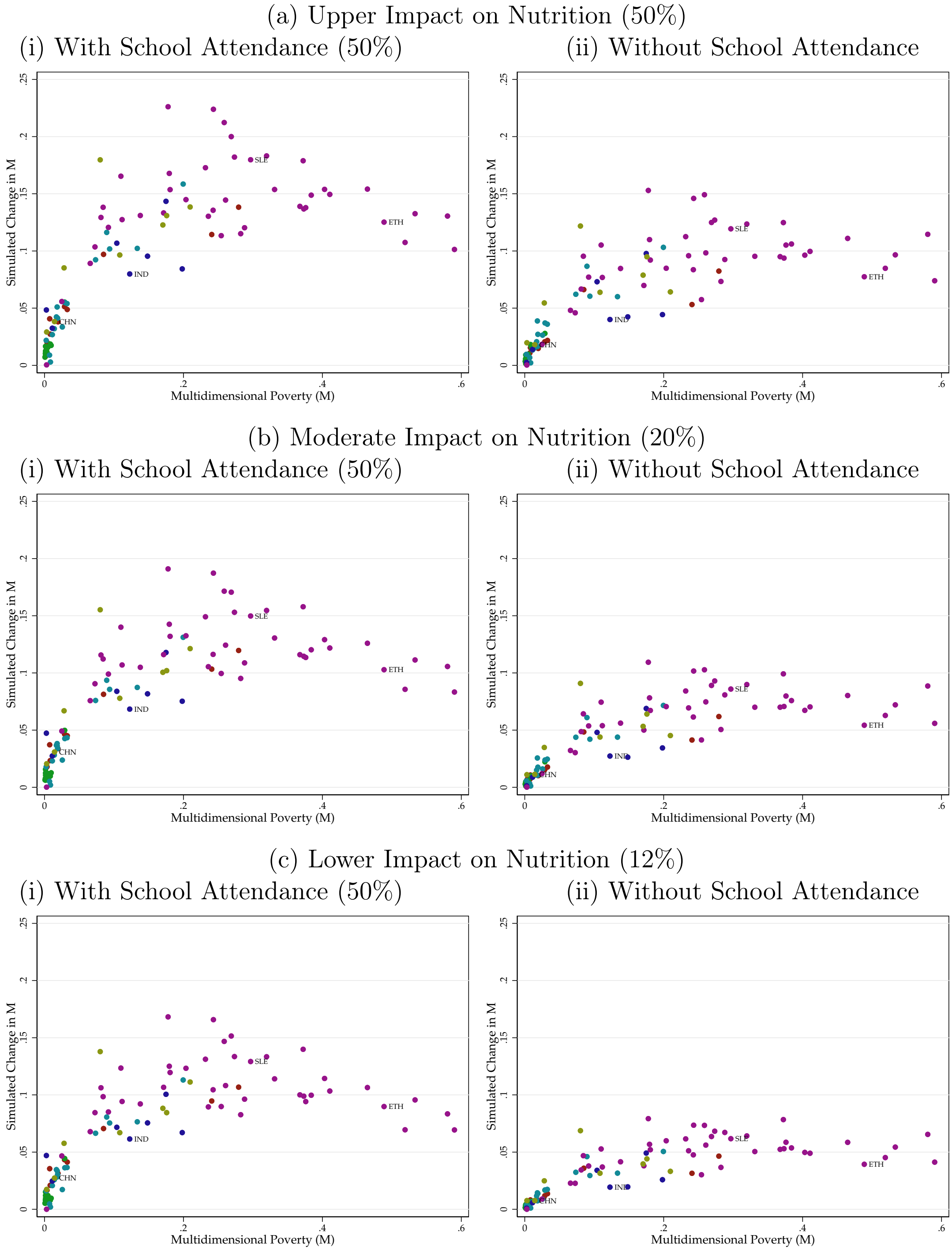
The simulation results illustrated in figure 2 demonstrate that, as expected, the magnitude of the simulated impact of the pandemic on multidimensional poverty is greater when the school attendance shock is included, and reflects the magnitude of the assumed nutrition impact.

Under each of the scenarios, there are small absolute increases in multidimensional poverty for countries whose baseline level of poverty is very low, for example China. This is natural, given the structure of the global MPI: a deprivation in just one of the indicators is not sufficient for a household to be considered multidimensionally poor. Furthermore, the simulated nutrition shocks are only applied to those who are already poor or vulnerable to poverty, so in the countries with the lowest incidence of multidimensional poverty, few households are recieve these shocks.

The magnitude of the simulated impacts rises sharply with the baseline level of multidimensional poverty, reflecting the greater incidence of existing deprivations and thus sensitivity of the global MPI to new deprivations in these poorer countries, for example Sierra Leone. However, the simulated impact levels off as baseline poverty increases further, with some suggestion of a decrease at the highest levels of baseline poverty, in countries such as Ethiopia. This reflects the already-high incidence of multidimensional poverty in households in the poorest countries, so additional deprivations mainly could affect poverty intensity. But if a primary-school aged

[8] Considering the substantive impact of the schooling shocks, children in better-off households are more likely to have access to alternative modes of education during school closures. While this is technically not relevant to the global MPI school attendance indicator, it is consistent with the concentration of the impact on households of type (iii).

Figure 2: Simulated Impact of COVID-19 on Multidimensional Poverty



Notes: Simulated increase in multidimensional poverty, $\Delta^* M_s$, under microsimulations implementing indicated scenarios. Selected countries labelled: China (CHN), India (IND), Sierra Leone (SLE) and Ethiopia (ETH). 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.

child is already out of school, then another simulated deprivation for a different child does not change the household's deprivation score. Also, if two persons are randomly assigned a status of undernutrition, the change in MPI is the same as if one persons was assigned that status. This tempers the measured impact of the pandemic on multidimensional poverty in very poor countries.

Despite the clear cross-country patterns described above, there is substantial cross-country variation in the simulated impact of the pandemic for countries at the same baseline levels of multidimensional poverty. This reflects variations in the underlying joint distribution of deprivations across countries. For example, in India, where the baseline incidence of undernutrition is high relative to its multidimensional poverty level (Alkire et al., 2020b), the simulated impact of the pandemic is lower than in other countries with a similar baseline multidimensional poverty level.

Note, however, that these raw microsimulation results represent the impact of the pandemic under the various scenarios, had it coincided with survey data collection in each country. In the next section we estimate cross-country models that enable us to compute country-specific adjustments to account for the time elapsed between survey data collection and incidence of the pandemic.

4 Translating simulated impacts from survey year to 2020

Our microsimulations necessarily capture the potential impact of the COVID-19 pandemic had it taken place at the same time as the survey in each of the 97 countries — between 2008 and 2019 — yet the pandemic took hold globally in the early months of 2020. Using data for 70 of these countries, in this section we account for the progress in poverty reduction that countries are projected to have made since the time of their surveys, acknowledging not only that baseline poverty levels (and the underlying distribution of deprivations) will have changed in each country, but also that the impact of the pandemic may be different from the result of our simulation as a result of these changes.

4.1 Baseline poverty and simulated impact

Figure 2 demonstrates that there is a systematic relationship between level of poverty and simulated impact of the pandemic. It is increasing over much of the domain, so most countries that have reduced poverty since their survey are likely to experience a smaller impact from the pandemic in 2020 than they would have done at the time of their survey. Conversely, at very high levels of multidimensional poverty the relation between level and simulated impact reverses.

To account for these effects, we start by choosing and estimating descriptive cross-country models of the relationship between the simulated impact of the pandemic and baseline (estimated) multidimensional poverty. We have one observation for each of the 97 countries for which we implemented the microsimulations. For each of the six simulation scenarios, we estimate simple parametric models for both the impact on multidimensional poverty, $\Delta^* M$, and the impact on its incidence, $\Delta^* H$.

Focusing on the scenario in which the pandemic has a moderate impact on nutrition (20% of the poor or vulnerable but not undernourished become undernourished) and an impact on school attendance (50% of primary aged children in school stop attending), we find that a quadratic specification in H,

$$\Delta^* H_s = \gamma_0 + \gamma_1 H_s + \gamma_2 H_s^2 + u_s, \tag{1}$$

captures the nonlinear relationship of the simulated impact with baseline intensity and global

MPI well, predicting 73% of the variation in $\Delta^* H$ across countries. The fit increases only marginally with more complex polynomials in H and A, so we select this quadratic model (1) for $\Delta^* H$; model selection regressions are reported the Appendix, Table A.2. Similar results are obtained under the remaining scenarios.

Despite the good fit, there remains important residual variation. Given parameter estimates $\hat{\gamma}_0$, $\hat{\gamma}_1$ and $\hat{\gamma}_2$, the residual for country s is

$$\hat{u}_s = \Delta^* H_s - \hat{\gamma}_0 - \hat{\gamma}_1 H_s - \hat{\gamma}_2 H_s^2. \tag{2}$$

The Breusch-Pagan test rejects the hypothesis of homoskedasticity ($p = 0.008$ for this scenario).

Continuing to focus on the scenario in which the pandemic has a moderate impact on nutrition (20% of the poor or vulnerable but not undernourished become undernourished) and an impact on school attendance (50% of primary aged children in school stop attending), we find that a linear function of H and HA,

$$\Delta^* M_s = \eta_0 + \eta_1 H_s + \eta_2 H_s A_s + v_s, \tag{3}$$

predicts the simulated impact on global MPI very well, reproducing 86% of the variation in $\Delta^* M$ across countries. There is no gain in terms of goodness-of-fit from including more complex terms in H and A, or powers of M itself, so we select this model (3) for $\Delta^* M$; model selection regressions are reported the Appendix, Table A.3. Similar results are again obtained under the remaining scenarios.

The residual variation is again important; given parameter estimates $\hat{\eta}_0$, $\hat{\eta}_1$ and $\hat{\eta}_2$, the residual for country s is

$$\hat{v}_s = \Delta^* M_s - \hat{\eta}_0 - \hat{\eta}_1 H_s - \hat{\eta}_2 H_s A_s. \tag{4}$$

The Breusch-Pagan test rejects the hypothesis of homoskedasticity ($p = 0.001$ for this scenario).

4.2 Trajectories of multidimensional poverty

In order to apply models (1) and (3) to translate the simulated impacts of the pandemic from the survey years to 2020, we need to know the counterfactual incidence and intensity of multidimensional poverty in each country in 2020 had the pandemic not occurred. As these counterfactuals cannot be observed, we utilise country-specific projections of the global MPI, building on related work by Alkire et al. (2020e). They identify logistic functions of time as the preferred trajectory models for intensity and incidence, in line with theoretical requirements, empirical evidence, and previous studies of other bounded development indicators (e.g., Klasen and Lange, 2012; Clemens, 2004). These trajectory models will also allow us to compute the setback to poverty reduction in section 5.

Specifically, Alkire et al. (2020e) identify the logistic function

$$H_s(t) = \frac{1}{1 + e^{-\alpha_s^{\mathrm{h}} + \beta_s^{\mathrm{h}} t}} \tag{5}$$

as the preferred trajectory model for the incidence of multidimensional poverty H in each country

s, and the transformed logistic function

$$A_s(t) = \frac{1 + 3e^{\alpha_s^{\mathrm{a}} - \beta_s^{\mathrm{a}} t}}{3(1 + e^{\alpha_s^{\mathrm{a}} - \beta_s^{\mathrm{a}} t})} \tag{6}$$

as the preferred trajectory model for the intensity A. The model for multidimensional poverty is then $M_s(t) = H_s(t)A_s(t)$. We calibrate these models using estimates of global MPI obtained by Alkire et al. (2020d) based on the intertemporally-harmonised ('Changes over Time') datasets documented in Table A.1, to obtain the logistic growth rates β_s^{h} and β_s^{a} for each of the 70 countries s for which data is available. We then re-calibrate the trajectories such that they coincide with the 2020 release global MPI estimates, yielding shift parameters α_s^{h} and α_s^{a} for each country.[9]

4.3 Predicting pandemic impacts in 2020

Direct application of the estimated models (1) and (3) to translate the simulated impacts of the pandemic from the survey years to 2020 would suppress the effect of country-specific factors in mediating the simulated scenarios to impacts on multidimensional poverty. Country-specific factors are fundamentally important in determining the impact of the pandemic: the existing joint distribution of global MPI indicators varies even across countries with the same global MPI levels, making poverty in some countries more sensitive than in others to the simulated scenarios. This is illustrated in Figure 2, which demonstrates moderate variation in simulated impacts across countries, conditional on the baseline level of poverty. Put differently, if the models were naively implemented to predict pandemic impacts at the time of the country's survey without any further adjustments, these predictions would not coincide with the simulated impacts.

We recover coincidence between predicted and simulated impacts at the survey time period by introducing country-specific scale factors,[10] so our country- and scenario-specific model for the impact of the pandemic on the incidence of multidimensional poverty is

$$\Delta^* \hat{H}_s(2020) = \hat{\phi}_s \left(\hat{\gamma_0} + \hat{\gamma_1} H_s(2020) + \hat{\gamma_2} \left(H_s(2020)\right)^2 \right), \tag{7}$$

with

$$\hat{\phi}_s = \frac{\Delta^* H_s}{\hat{\gamma_0} + \hat{\gamma_1} H_s + \hat{\gamma_2} H_s^2}.$$

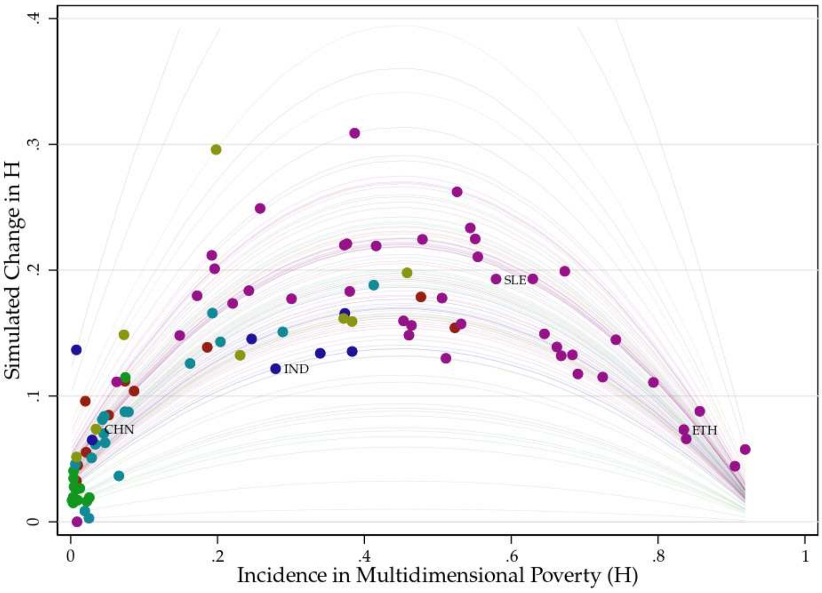
Figure 3 (a) illustrates such models for all countries under the scenario in which the pandemic causes a moderate impact on nutrition (20% of the poor or vulnerable but not undernourished become undernourished) and impacts on school attendance (50% of primary age children in school stop attending).

[9] Alkire et al. (2020e) calibrate all parameters for each country using the harmonised estimates. Effectively, this means that we use the same β_s^{h} and β_s^{a} and moreover, in many cases our α_s^{h} and α_s^{a} also coincide exactly with the parameters calibrated by Alkire et al. (2020e). Small discrepancies arise for 11 countries where the 2020 global MPI dataset is more recent than the harmonised Changes over Time data: Democratic Republic of the Congo, Gambia, Guinea, Kyrgyzstan, Lesotho, Mali, Mongolia, Suriname, Togo, Zambia and Zimbabwe. In other cases extremely small discrepancies arise where the intertemporal harmonisation process resulted in one or more minor discrepancies in indicator definitions between Alkire et al. (2020d) and the 2020 global MPI (Alkire et al., 2020b). The correlation between estimates of H and M in the 2020 global MPI and Alkire et al. (2020d) data is extremely high: 0.999 and 0.998 respectively across the 59 countries for which the same data source is used.

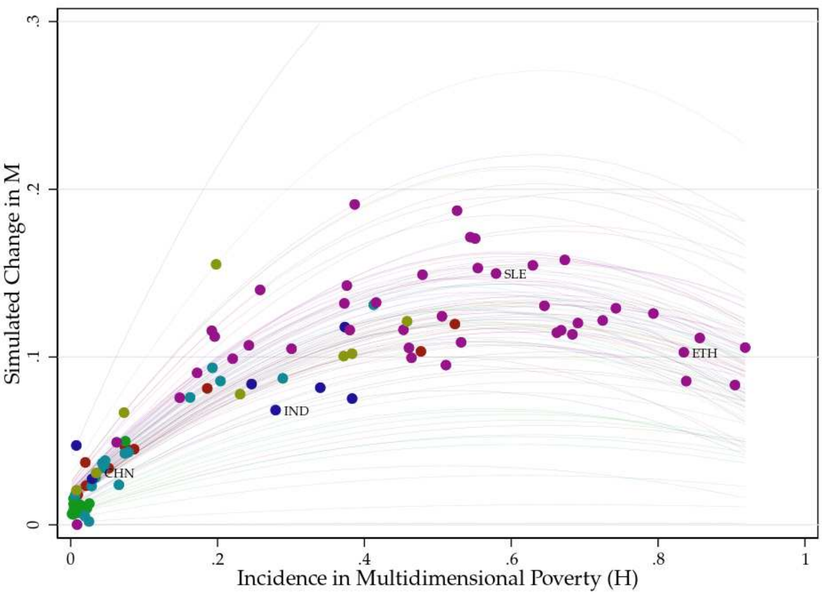
[10] An additive adjustment introducing the residuals (2) and (4) achieves a worse fit to the observations and, moreover, would allow the predicted impacts to be negative.

Figure 3: Country-Specific Models of Simulated Impact of COVID-19 on Multidimensional Poverty

(a) Simulated impact on incidence (H)



(b) Simulated impact on global MPI (M)



Notes: Simulated increase in (a) multidimensional poverty incidence (H) and (b) multidimensional poverty level (M) under microsimulations implementing the moderate nutrition (20%) and school attendance (50%) scenario. Fine lines represent the country- and scenario-specific models (7) and (8). Selected countries labelled: China (CHN), India (IND), Sierra Leone (SLE) and Ethiopia (ETH). 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.

Similarly, our country- and scenario-specific model for the impact of the pandemic on the level of multidimensional poverty M is

$$\Delta^*\hat{M}_s(2020) = \hat{\psi}_s\left(\hat{\eta_0} + \hat{\eta_1}H_s(2020) + \hat{\eta_2}H_s(2020)A_s(2020)\right), \tag{8}$$

with

$$\hat{\psi}_s = \frac{\Delta^* M_s}{\hat{\eta_0} + \hat{\eta_1}H_s + \hat{\eta_2}H_sA_s}.$$

Figure 3 (b) illustrates such models for all countries under the scenario in which the pandemic causes a moderate impact on nutrition (20% of the poor or vulnerable but not undernourished become undernourished) and impact on school attendance (50% of primary age children in school stop attending).

5 Aggregate results

To evaluate the potential global impact of the pandemic under our six scenarios, we now aggregate our adjusted simulated impacts on global MPI (8) and its incidence (7) across the 70 countries for which we are able to do so.[11] These 70 countries, collectively labelled S, account for 89% of the global poor by the 2020 global MPI.

Table 2: Summary of Aggregate Results

COVID-19 scenario		Aggregate Adjusted Simulation for 2020		
Selection probabilities		MPI (M)	Δ # poor	Setback
Nutrition	School attendance	$\hat{M}^*_S(2020)$	$\Delta^*\hat{Q}_S(2020)$	$(2020 - t^*)$
(%)		value	(million)	(years)
12	–	0.114	152	3.6
20	–	0.122	213	4.8
50	–	0.134	310	6.4
12	50	0.146	426	8.0
20	50	0.153	469	8.8
50	50	0.164	547	9.9

Notes: Authors' calculations; MPI values are population-weighted aggregates across the 70 countries, while the increases in number of poor are totals across the same countries. All calculations based on UN-DESA medium-fertility population projections.

To evaluate the potential impact of the pandemic on the total number of people living in multidimensional poverty across the 70 countries, we combine our adjusted simulated impacts on incidence with the UN-DESA medium-fertility population projections. Given population projections $N_s(t)$ for each country s at times t, we may compute the predicted increase in the number of multidimensionally poor people in country s in the year 2020, under any of the scenarios, as $\Delta^*\hat{Q}_s(2020) = N_s(2020)\Delta^*\hat{H}_s(2020)$, where $\Delta^*\hat{H}_s(2020)$ is our country- and scenario-specific prediction for the impact of the pandemic on the incidence of multidimensional

[11] Those for which data is available such that both (i) we were able to simulate pandemic impacts as described in section 3, and (ii) Alkire et al. (2020e) were able to calibrate logistic growth rates.

poverty (7). The aggregate predicted increase in the number of multidimensionally poor people across the 70 countries $s \in S$ is then simply

$$\Delta^* \hat{Q}_S(2020) = \sum_{s \in S} \Delta^* \hat{Q}_s(2020) = \sum_{s \in S} N_s(2020) \Delta^* \hat{H}_s(2020). \tag{9}$$

Results under each of the six scenarios are reported in Table 2. The increases in the number of multidimensionally poor people under the different scenarios vary between 152m (in the low impact on nutrition only scenario) and 547m (in the high impact on nutrition and impact on school attendance scenario). These results should be interpreted in relation to a baseline projected total number of people living in poverty in 2020 across the 70 countries of $\sum_{s \in S} N_s(2020) H_s(2020) = 941$m, based on the countries' pre-pandemic calibrated trajectory models (5).

To evaluate the potential impact of the pandemic on the aggregate value of the global MPI across the 70 countries, we first combine the country- and scenario-specific adjusted predicted impacts of the pandemic $\Delta^* \hat{M}_s(2020)$ (8) with the country-specific calibrated projection in the absence of the pandemic, $M_s(2020) = H_s(2020) A_s(2020)$ (5 and 6), to obtain country- and scenario-specific adjusted predicted global MPI levels

$$\hat{M}_s^*(2020) = M_s(2020) + \Delta^* \hat{M}_s(2020).$$

The scenario-specific population-weighted aggregate value of global MPI across the 70 countries is then

$$\hat{M}_S^*(2020) = \frac{\sum_{s \in S} N_s(2020) \hat{M}_s^*(2020)}{\sum_{s \in S} N_s(2020)}. \tag{10}$$

Results under each of the six scenarios are reported in Table 2. The aggregate value of global MPI under the different scenarios varies between 0.114 (in the low impact on nutrition only scenario) and 0.164 (in the high impact on nutrition and impact on school attendance scenario). It is informative to compare these aggregate simulated projections under the different scenarios to the aggregate projection in the absence of the pandemic,

$$M_S(2020) = \frac{\sum_{s \in S} N_s(2020) M_s(2020)}{\sum_{s \in S} N_s(2020)} = 0.095.$$

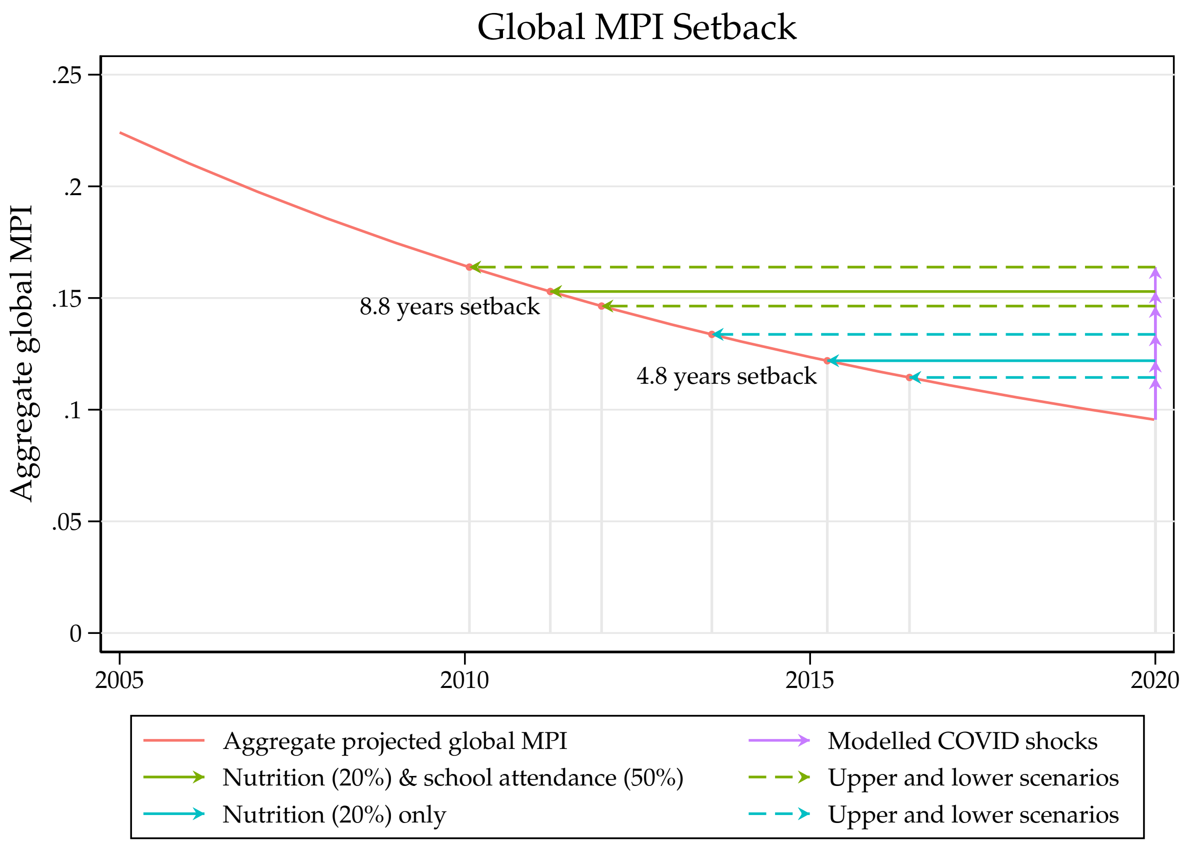
In relative terms, the simulated impacts of the pandemic on the value of global MPI under the various simulations are larger than the impacts on number of people living in multidimensional poverty. This reflects the fact that simulated impacts increase the intensity as well as the incidence of multidimensional poverty, in aggregate.

In order to further interpret our results, we determine the date to which multidimensional poverty reduction has been set back under each scenario, by numerically finding the value t^* that solves

$$\hat{M}_S^*(2020) = M_S(t^*) = \frac{\sum_{s \in S} N_s(t^*) M_s(t^*)}{\sum_{s \in S} N_s(t^*)}. \tag{11}$$

As the right hand side of equation (11) (aggregate projected global MPI for the 70 countries) may only be evaluated on an annual basis, we interpolate linearly to solve for non-integer t^*.

Figure 4: Setbacks in multidimensional poverty reduction due to COVID-19



This analysis is illustrated in Figure 4; as is clear from that figure, the curvature of the aggregate projection within-year is negligible. The number of years by which multidimensional poverty reduction is set back under a particular scenario is then $2020 - t^*$.

We find that under the moderate impact on nutrition and impact on school attendance scenario, in which the aggregate MPI value rises to 0.153 and the number of people in poverty increases by 469 million, our results correspond to an 8.8-year setback to achieved progress in multidimensional poverty reduction. Under the moderate impact on nutrition and no impact on school attendance scenario, the setback is still 4.8 years. The worst-case setback (upper bound impact on nutrition and impact on school attendance) is 9.9 years, while the most conservative setback (lower bound impact on nutrition only) is 3.6 years. These results are also reported in Table 2 and are illustrated in Figure 4.

6 Concluding remarks

Policy makers around the world face great challenges in responding optimally to the currently raging COVID-19 pandemic for several reasons. First is lack of information; many critical pieces of objective evidence to inform efficient policymaking are still missing, including real-time data on trends in multidimensional and monetary poverty and in their underlying components, details of transmission mechanisms of SARS-CoV-2, the hierarchy of factors impeding or accelerating its spread, the causes behind the profoundly different disease courses COVID-19 can take, immunity cycles, and even possible long-term effects for survivors. Consequently, many questions regarding both the effectiveness and appropriateness of policy measures remain. Yet, policy action needs to take place amid such an adverse context for effective planning. Second, the trade-off that policy makers have to deal with is certainly both ethically demanding and comes at great cost in either direction. Among the few things that are clear are (i) the potential of COVID-19 to easily overwhelm modern health care systems and (ii) that blunt measures like country-wide lockdowns come at considerable cost as well.

This paper seeks to bridge, partially, an informational gap which is vital for timely and effective policymaking against the negative effects of COVID-19: how multidimensional poverty may have increased across developing regions. We draw on assessments made by UN agencies of pandemic impacts relevant to selected indicators of the global MPI and offer an estimate of potential setback in global multidimensional poverty reduction under several plausible scenarios. For a combined school attendance and moderate nutrition shock, we find that around 8 years of poverty reduction would be undone. This result corresponds to 426 million extra people entering multidimensional poverty, which demonstrates the magnitude of the problem that policymakers are currently facing.

There are two further implications of our results that we wish to highlight. First, our analysis reveals the wide range of potential setbacks to poverty reduction under alternative plausible scenarios, ranging approximately between 3 and 10 years. This finding underscores the central role of informed and well-judged political decisions in the COVID-19 response, to address the public heath exigencies while preventing excessive damage to people's lives and livelihoods. There is opportunity to prevent drastic reversals in multidimensional poverty reduction, if impacts are illuminated and policy margins become visible. Second, our results suggest that COVID-19 responses may result in large increases of multidimensional poverty, which are at risk of being overlooked. The pressing challenges policymakers must face are manifold, and societies around the globe are bracing for dangerous GDP contractions, which are rightfully attracting serious attention from policymakers. However, actions taken against GDP contraction may not necessarily spill over to prevent setbacks in multidimensional poverty reduction. Thus complementary action and specific policy strategies are needed to fulfill the SDG mandate of leaving no-one behind.

To conclude, let us make two final remarks. This paper is a first rather than final projection of COVID-19 impacts on the global MPI, and as such is constrained in several ways. For example, First, we note that our results refer to an aggregate level of multidimensional poverty and we do not provide country-specific increments in the number of poor. This is because while we account for country heterogeneity arising from differences in underlying patterns of deprivations across multiple indicators, other sources of heterogeneity are not covered due to lack of information. These include country- and region-specific differences in COVID-19 spread, in the related policy responses which are still being revised on a regular basis, and in people's behaviour and reactions to the pandemic itself and to the related policy measures and policies. Second, our simulations allow us to evaluate potential impacts of COVID-19 on poverty, which is crucial to provide timely information for policy makers and inform the policy debate now, but are not to be confused with an ex-post evaluation. After all, the pandemic is still in progress, and related policy responses are still in flux and in some actions, we hope, will have prevented the simulated increases in deprivation. As further information becomes available, it will be possible to refine this simulation-based analysis and update our evaluation of the anticipated impact of the pandemic on global multidimensional poverty.

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A Appendix

Figure A.1: Flowchart of analysis

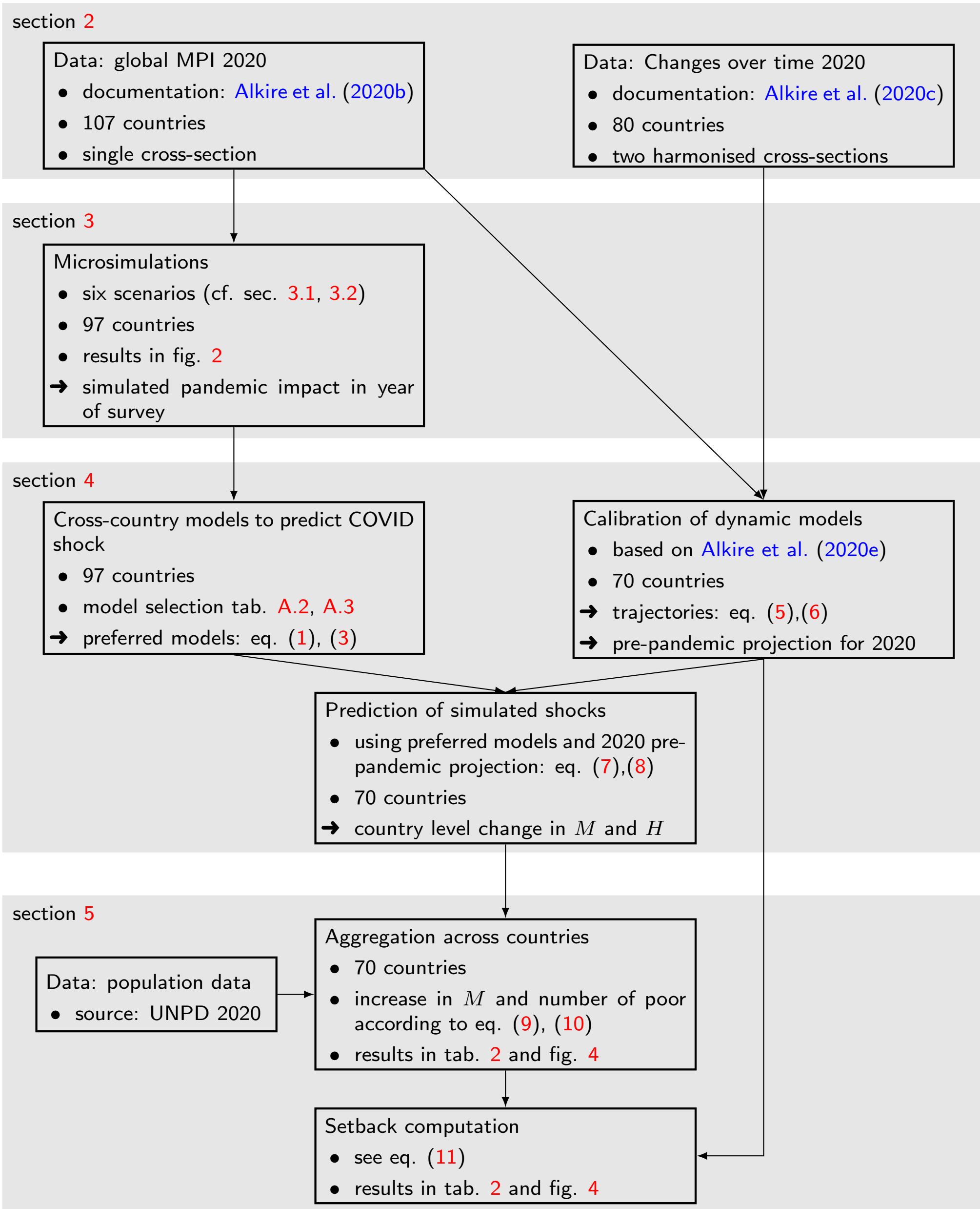

Table A.1: Survey datasets

		Changes over Time t_1		Changes over Time t_2		Global MPI		Analysis	
Code	Name	Survey	Year	Survey	Year	Survey	Year	Simulation	Aggregate
AFG	Afghanistan	MICS	2010/11	DHS	2015/16	DHS	2015/16		
AGO	Angola					DHS	2015/16	•	
ALB	Albania	DHS	2008/09	DHS	2017/18	DHS	2017/18	•	•
ARM	Armenia	DHS	2010	DHS	2015/16	DHS	2015/16	•	•
BDI	Burundi	DHS	2010	DHS	2016/17	DHS	2016/17	•	•
BEN	Benin	MICS	2014	DHS	2017/18	DHS	2017/18	•	•
BFA	Burkina Faso	MICS	2006	DHS	2010	DHS	2010	•	•
BGD	Bangladesh	DHS	2014	MICS	2019	MICS	2019	•	•
BIH	Bosnia and Herzegovina	MICS	2006	MICS	2011/12	MICS	2011/12	•	•
BLZ	Belize	MICS	2011	MICS	2015/16	MICS	2015/16	•	•
BOL	Bolivia	DHS	2003	DHS	2008	DHS	2008	•	•
BRA	Brazil					PNAD	2015		
BRB	Barbados					MICS	2012	•	
BTN	Bhutan					MICS	2010	•	
BWA	Botswana					BMTHS	2015/16	•	
CAF	Central African Republic	MICS	2000	MICS	2010	MICS	2010	•	•
CHN	China	CFPS	2010	CFPS	2014	CFPS	2014	•	•
CIV	Côte d'Ivoire	DHS	2011/12	MICS	2016	MICS	2016	•	•
CMR	Cameroon	DHS	2011	MICS	2014	MICS	2014	•	•
COD	Congo, DR	DHS	2007	DHS	2013/14	MICS	2017/18	•	•
COG	Congo	DHS	2005	MICS	2014/15	MICS	2014/15	•	•
COL	Colombia	DHS	2010	DHS	2015	DHS	2015/16		
COM	Comoros					DHS	2012	•	
CUB	Cuba					ENO	2017		
DOM	Dominican Republic	DHS	2007	MICS	2014	MICS	2014		
DZA	Algeria					MICS	2012/13	•	
ECU	Ecuador					ECV	2013/14	•	
EGY	Egypt	DHS	2008	DHS	2014	DHS	2014	•	•
ETH	Ethiopia	DHS	2011	DHS	2016	DHS	2016	•	•
GAB	Gabon	DHS	2000	DHS	2012	DHS	2012	•	•
GEO	Georgia					MICS	2018	•	
GHA	Ghana	MICS	2011	DHS	2014	DHS	2014	•	•
GIN	Guinea	DHS	2012	MICS	2016	DHS	2018	•	•
GMB	Gambia	MICS	2005/06	DHS	2013	MICS	2018	•	•
GNB	Guinea-Bissau					MICS	2014	•	
GTM	Guatemala					DHS	2014/15	•	
GUY	Guyana	DHS	2009	MICS	2014	MICS	2014	•	•
HND	Honduras	DHS	2005/06	DHS	2011/12	DHS	2011/12	•	•
HTI	Haiti	DHS	2012	DHS	2016/17	DHS	2016/17	•	•
IDN	Indonesia	DHS	2012	DHS	2017	DHS	2017		
IND	India	DHS	2005/06	DHS	2015/16	DHS	2015/16	•	•
IRQ	Iraq	MICS	2011	MICS	2018	MICS	2018	•	•
JAM	Jamaica	JSLC	2010	JSLC	2014	JSLC	2014	•	•
JOR	Jordan	DHS	2012	DHS	2017/18	DHS	2017/18	•	•
KAZ	Kazakhstan	MICS	2010/11	MICS	2015	MICS	2015	•	•
KEN	Kenya	DHS	2008/09	DHS	2014	DHS	2014	•	•
KGZ	Kyrgyzstan	MICS	2005/06	MICS	2014	MICS	2018	•	•
KHM	Cambodia	DHS	2010	DHS	2014	DHS	2014	•	•
KIR	Kiribati					MICS	2018/19	•	
LAO	Lao PDR	MICS-DHS	2011/12	MICS	2017	MICS	2017	•	•
LBR	Liberia	DHS	2007	DHS	2013	DHS	2013	•	•
LBY	Libya					PAPFAM	2014	•	
LCA	Saint Lucia					MICS	2012	•	
LKA	Sri Lanka					SLDHS	2016	•	
LSO	Lesotho	DHS	2009	DHS	2014	MICS	2018	•	•

... Table A.1 continued.

Code	Name	Changes over Time t_1		Changes over Time t_2		Global MPI		Analysis	
		Survey	Year	Survey	Year	Survey	Year	Simulation	Aggregate
MAR	Morocco					PAPFAM	2011	•	
MDA	Moldova	DHS	2005	MICS	2012	MICS	2012	•	•
MDG	Madagascar	DHS	2008/09	MICS	2018	MICS	2018	•	•
MDV	Maldives					DHS	2016/17	•	
MEX	Mexico	ENSANUT	2012	ENSANUT	2016	ENSANUT	2016	•	•
MKD	North Macedonia	MICS	2005/06	MICS	2011	MICS	2011	•	•
MLI	Mali	DHS	2006	MICS	2015	DHS	2018	•	•
MMR	Myanmar					DHS	2015/16	•	
MNE	Montenegro	MICS	2005/06	MICS	2013	MICS	2018	•	
MNG	Mongolia	MICS	2010	MICS	2013	MICS	2018	•	•
MOZ	Mozambique	DHS	2003	DHS	2011	DHS	2011	•	•
MRT	Mauritania	MICS	2011	MICS	2015	MICS	2015	•	•
MWI	Malawi	DHS	2010	DHS	2015/16	DHS	2015/16	•	•
NAM	Namibia	DHS	2006/07	DHS	2013	DHS	2013	•	•
NER	Niger	DHS	2006	DHS	2012	DHS	2012	•	•
NGA	Nigeria	DHS	2013	DHS	2018	DHS	2018	•	•
NIC	Nicaragua	DHS	2001	ENDESA	2011/12	DHS	2011/12	•	•
NPL	Nepal	DHS	2011	DHS	2016	DHS	2016	•	•
PAK	Pakistan	DHS	2012/13	DHS	2017/18	DHS	2017/18	•	•
PER	Peru	DHS-Cont	2012	DHS	2018	ENDES	2018	•	•
PHL	Philippines	DHS	2013	DHS	2017	DHS	2017		
PNG	Papua New Guinea					DHS	2016/18		
PRY	Paraguay					MICS	2016	•	
PSE	Palestine, State of	MICS	2010	MICS	2014	MICS	2014	•	•
RWA	Rwanda	DHS	2010	DHS	2014/15	DHS	2014/15	•	•
SDN	Sudan	MICS	2010	MICS	2014	MICS	2014	•	•
SEN	Senegal	DHS	2005	DHS-Cont	2017	DHS	2017	•	•
SLE	Sierra Leone	DHS	2013	MICS	2017	MICS	2017	•	•
SLV	El Salvador					MICS	2014	•	
SRB	Serbia	MICS	2010	MICS	2014	MICS	2014	•	•
SSD	South Sudan					MICS	2010	•	
STP	Sao Tome and Principe	DHS	2008/09	MICS	2014	MICS	2014	•	•
SUR	Suriname	MICS	2006	MICS	2010	MICS	2018	•	•
SWZ	eSwatini	MICS	2010	MICS	2014	MICS	2014	•	•
SYC	Seychelles					QLFS	2019	•	
SYR	Syria					PAPFAM	2009	•	
TCD	Chad	MICS	2010	DHS	2014/15	DHS	2014/15	•	•
TGO	Togo	MICS	2010	DHS	2013/14	MICS	2017	•	•
THA	Thailand	MICS	2012	MICS	2015/16	MICS	2015/16	•	•
TJK	Tajikistan	DHS	2012	DHS	2017	DHS	2017	•	•
TKM	Turkmenistan	MICS	2006	MICS	2015/16	MICS	2015/16	•	•
TLS	Timor-Leste	DHS	2009/10	DHS	2016	DHS	2016	•	•
TTO	Trinidad and Tobago	MICS	2006	MICS	2011	MICS	2011	•	
TUN	Tunisia					MICS	2018	•	
TZA	Tanzania	DHS	2010	DHS	2015/16	DHS	2015/16	•	•
UGA	Uganda	DHS	2011	DHS	2016	DHS	2016	•	•
UKR	Ukraine	DHS	2007	MICS	2012	MICS	2012		
VNM	Vietnam	MICS	2010/11	MICS	2014	MICS	2013/14		
YEM	Yemen	MICS	2006	DHS	2013	DHS	2013	•	
ZAF	South Africa					DHS	2016	•	
ZMB	Zambia	DHS	2007	DHS	2013/14	DHS	2018	•	•
ZWE	Zimbabwe	DHS	2010/11	DHS	2015	MICS	2019	•	•

Notes: Displayed countries are either included in global MPI or in changes over time or both. *Simulation* indicates countries analysed in sections 3 and 4.1, *Aggregate* indicates countries covered by the analysis in sections 4.2, 4.3, and 5.

Table A.2: COVID-19 Model Selection for H

	(1)	(2)	(3)	(4)	(5)
H	0.121***	0.714***	0.955***	1.487***	1.043***
	(4.95)	(15.61)	(8.92)	(14.44)	(5.41)
H^2		-0.797***	-1.586***		-0.552**
		(-13.64)	(-4.90)		(-2.70)
H^3			0.625*		
			(2.48)		
A				0.404*	-0.170
				(2.17)	(-0.61)
HA				-2.570***	-0.813
				(-13.26)	(-1.20)
Constant	0.0868***	0.0389***	0.0302***	-0.107	0.104
	(9.02)	(5.89)	(4.12)	(-1.49)	(1.00)
Observations	97	97	97	97	97
Adj. R^2	0.196	0.727	0.742	0.728	0.745

Notes: Dependant variable is $\Delta^* H$ in all models, moderate Nutrition (20%) and Education (50%) Scenario. Own calculations, t-statistics in parentheses, 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 A.3: COVID-19 Model Selection for M

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
H	0.147***	0.437***	0.855***	0.762***	0.858***			
	(11.84)	(17.45)	(16.51)	(7.62)	(16.54)			
H^2		-0.389***		-0.116				
		(-12.17)		(-1.09)				
A			0.117	-0.00367				
			(1.24)	(-0.03)				
HA			-1.288***	-0.920*	-1.240***			
			(-13.22)	(-2.62)	(-13.83)			
M						0.228***	0.741***	1.086***
						(9.36)	(17.12)	(11.89)
M^2							-1.127***	-3.003***
							(-12.62)	(-6.61)
M^3								2.384***
								(4.20)
Constant	0.0367***	0.0134***	-0.0279	0.0163	0.0167***	0.0451***	0.0208***	0.0136***
	(7.51)	(3.70)	(-0.78)	(0.30)	(5.26)	(8.61)	(5.54)	(3.52)
Observations	97	97	97	97	97	97	97	97
Adj. R^2	0.592	0.840	0.865	0.865	0.864	0.474	0.803	0.832

Notes: Dependant variable is $\Delta^* M$ in all models, moderate Nutrition (20%) and Education (50%) Scenario. Own calculations, t-statistics in parentheses, 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.