



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 recent assessments of food insecurity and school closures made by UN agencies to inform microsimulations of potential short-term impacts of the pandemic under alternative scenarios. These simulations use the nationally representative datasets underlying the 2020 update of the global MPI. Because these datasets were collected in various years before the pandemic, we develop models to translate the simulated impacts to 2020. Our approach accounts for the country-specific joint distribution of deprivations in the simulations, recent poverty reduction trends, and resulting differences in the responsiveness of the global MPI to the scenarios. 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. We argue that the extent to which such disruptions result in persistent increases of poverty and deprivations may be attenuated by appropriate policy responses.

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 harmonised 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 (e.g., [Mallapaty, 2020](#)), its general effects on the society at large (e.g., [Altig et al., 2020](#)), or the short-term effectiveness of the implemented policy measure (e.g., [Anderson et al., 2020](#)).

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. This paper seeks to contribute to the public debate on policy responses to COVID-19 by quantifying the potential short-term impact of the pandemic on global multidimensional poverty as measured by the global Multidimensional Poverty Index

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(MPI). Developed by Alkire and Santos (2014), the global MPI captures simultaneous or overlapping deprivations at the household level. 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 at the global level, which provides several important insights while being feasible with the data currently available.

While this study is the first to address the potential impact of the COVID-19 pandemic on multidimensional poverty at the global level, other studies have assessed the potential impact on global monetary poverty. An early example is Sumner et al. (2020) who, considering hypothetical distribution-neutral contractions of the global economy by 5%, 10% or 20%, found that the pandemic would push 85 m, 182 m or 419 m people respectively below the \$1.90 monetary extreme poverty threshold. Lakner et al. (2020), updated by Mahler et al. (2021), utilise country-specific growth forecasts to find that the pandemic led to 97 m extra people being below the extreme poverty threshold in 2020, a setback of around 4.5 years. Lakner et al. also explored robustness to alternative distributional assumptions. The relationship between multidimensional poverty and growth is much less straightforward (Santos et al., 2019), so a different approach is needed for nowcasts and forecasts. Makdissi (2021) models the impact of the pandemic on the different dimensions of the Arab MPI (in one country, Iraq) independently, assuming stability of the multidimensional copula to account for the joint distribution when aggregating across dimensions. In contrast, we use a microsimulation-based approach to account for the joint distribution of deprivations, that is, their pattern of overlap across different dimensions.

More specifically, our approach is as follows. First, we apply microsimulation techniques to generate anticipated COVID-induced deprivations in the household level data of the actual global MPI estimations, and determine the resulting increase in multidimensional poverty, under alternative scenarios. The scenarios are informed by recent assessments of food insecurity and school closures by the World Food Programme (WFP) and the United Nations Educational, Scientific and Cultural Organization (UNESCO) respectively. This microsimulation approach allows us to account for each country's joint distribution of deprivations and demographic characteristics of the population. Consequently, the responsiveness of the global MPI may vary substantially across countries, even under the same scenario. Second, as the datasets were collected in various years before the pandemic, following Alkire et al. (2020e) we calibrate country-specific trajectories to nowcast multidimensional poverty in 2020, which allows us to take recent poverty reduction trends into account. Third, to combine shock simulations and nowcasts, we develop and estimate a cross-country model explaining the simulated impacts with measured (pre-simulation) levels of multidimensional poverty. This allows us to translate simulated impacts to 2020 by predicting the simulated impacts based on nowcasted multidimensional poverty. We calibrate this translation model to reproduce the simulated impact for each country, in order to account for the country-specific responsiveness of the global MPI to the simulated scenario. Finally, 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. We conclude that policy measures taking the joint distribution of deprivations into account are needed to prevent these deprivations from becoming persistent. 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 and apply the translation model for simulated impacts. 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.

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 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

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 <i>undernourished</i> .	SDG 2	$\frac{1}{6}$
	Child mortality	A child <i>under</i> 18 has <i>died</i> 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 <i>six years of schooling</i> .	SDG 4	$\frac{1}{6}$
	School attendance	Any school-aged child is <i>not attending school up to</i> the age at which he/she would complete <i>class 8</i> .	SDG 4	$\frac{1}{6}$
Living Standards	Cooking fuel	A household cooks using <i>solid fuel</i> , such as dung, agricultural crop, shrubs, wood, charcoal or coal.	SDG 7	$\frac{1}{18}$
	Sanitation	The household has <i>unimproved</i> or <i>no</i> sanitation <i>facility</i> or it is improved but <i>shared</i> with other households.	SDG 6	$\frac{1}{18}$
	Drinking water	The household's source of <i>drinking water</i> is <i>not safe</i> or safe drinking water is a <i>30-min walk</i> or <i>longer walk</i> from home, roundtrip.	SDG 6	$\frac{1}{18}$
	Electricity	The household has <i>no electricity</i> .	SDG 7	$\frac{1}{18}$
	Housing	The household has <i>inadequate</i> housing materials in <i>any</i> of the three components: <i>floor, roof, or walls</i> .	SDG 11	$\frac{1}{18}$
	Assets	The household does <i>not own more than one</i> 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).

uses the microdata that underlies the 2020 release of the global MPI (Alkire et al., 2020b,c); Table D.1 in the appendix presents a full list of datasets, their dates, and their use in our analysis. For our microsimulations, we use 97 out of 107 countries covered by the most recent available cross-section datasets ('global MPI'), excluding the 10 countries lacking the nutrition indicator which is essential for our simulations. For calibrating our trajectories, predicting the simulated shock in 2020, and the final aggregation to the global level, we use data of the 70 countries for which we have two intertemporally harmonised cross-sections ('Changes over time'); see also Figure A.1 on this. 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.

3. Simulations of COVID-19 impact

The COVID-19 pandemic is impacting multidimensional poverty 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 on the global MPI of increases in two indicators: nutrition and school attendance. We focus on these particular indicators because of their relatively larger weight in the global MPI, the availability of relevant data to inform scenarios, and the plausibility of short-term impacts.

The scenarios underlying our microsimulations are informed by recent assessments of food insecurity and school closures made by WFP and UNESCO, respectively. We implement the same scenarios in all countries, primarily in order to assess the *potential* impact on poverty at the global level (which strong policies might have averted). Furthermore, due to the lack of sufficiently detailed data and the staggered spread of the pandemic among the poorer populations around the world, we cannot measure the *actual* impact of the pandemic on poverty at country level. This remains an important area for future research as data becomes available.

3.1. Nutrition scenarios

The 2020 WFP Global Report on Food Crises (WFP (2020), September release) is the latest and most comprehensive assessment of food insecurity threats before the COVID-19 pandemic. While estimates of the expected pandemic-induced increase in nutrition deprivation rates for every country in the global MPI would be ideal, such information is unavailable at the time of writing. Therefore, our approach relies on assessing the risk that the poor and vulnerable will become nutritionally deprived, using the pre-COVID-19 WFP food insecurity information. In our simulations, we assume that this risk materializes in undernutrition. A detailed explanation of how the simulation parameters were derived is presented in Appendix B; the intuition is as follows. The WFP report documents the number of people living in food insecurity in areas of several countries. However, the report only covers countries with certain characteristics (e.g. recipients of food aid or significant refugee populations), resulting in an imperfect overlap with those covered by the global MPI. To address this issue, we estimate the prevalence of nutrition deprivations in (i) all the countries covered by the global MPI (30.4%) and (ii) the countries covered by both the global MPI and the WFP report (34.4%). We use the ratio of these prevalences as a correction factor enabling us to extend the risk of becoming nutritionally deprived to the full set of global MPI countries.

Furthermore, the WFP report only covers certain subpopulations within some of the included countries (e.g. refugee populations or drought-prone regions). To address this issue we make alternative assumptions regarding the extent to which non-represented populations experience similar food insecurity, to arrive at three scenario parameterizations (lower bound, moderate, and upper bound scenario). Combining each scenario with the correction factor presented above, our approach gives us alternative risks of 12%, 20% and 50% for the poor and vulnerable in each country to become nutritionally deprived.

3.2. School attendance scenario

A common response to curtail the spread of the coronavirus is to close schools. We use UNESCO (2021) data to motivate our scenario for the school attendance indicator of the global MPI. UNESCO reports since March 2020 for every country and day whether schools were *fully open*, *partially closed*, or *fully closed* due to pandemic responses, or closed for *academic breaks*. As we seek to simulate the short term effect on school attendance over the first year of the pandemic at the global level, we use these data to approximate the extent of classes canceled as experienced by learners around the world. More specifically, we calculate a simple

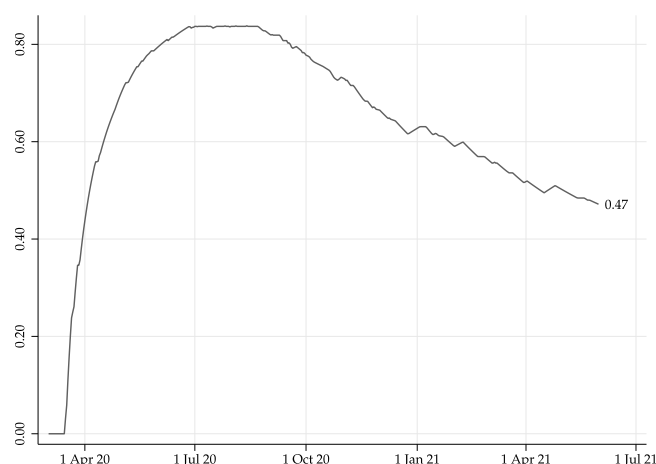


Fig. 1. Median loss of schooling. Notes: Data source: UNESCO; sample restricted to 97 countries covered in simulation; observation period March 2020 to May 2021.

'loss of schooling' measure as the share of days with closed schools (excluding academic breaks) since March 2020 on a per country basis. The category *partially closed* includes grade or region-specific school closures, and reduced in-person class time, and thus represents a very diverse status for which we lack further detail; we count such days as half a day of lost schooling.

We rely on the median of our loss of schooling measure, summarising the typical implementation of school closures, to inform our simulations of the potential impact of the pandemic. This approach takes into account the staggered spread of the pandemic (countries differ in their total loss of schooling over a given period, simply because they experienced different episodes of pandemic closures). Moreover, it is consistent with our strategy for undernutrition simulations to implement the same scenario in all countries.

Fig. 1 shows how the median loss of schooling since the onset of the pandemic evolves over time. We observe a sharp increase in late March 2020 quickly exceeding 60% in April and 80% from late June to end of September. Since then, the median loss of schooling has been declining steadily. This pattern largely reflects that full school closures were in most countries only applied initially, subsequently being replaced by more nuanced responses (figure D.1 in the appendix illustrates how frequencies of individual response categories change over time). By the end of the first year of the pandemic, this measure suggests that the median share of scheduled classes that had been canceled was around 50%. Therefore, in our simulation of the school attendance shock we assign a 50% probability to children of school age, not to attend school. Azevedo et al. (2021, p. 4), who assess the impact of school closures on learning outcomes, also cover schools closed for 50% of the school year as their intermediate scenario.

The increase in out-of-school children may affect households which have at least one school-aged child who so far has been attending school. Such a household would become deprived in school attendance, unless they were already deprived (with other school-aged children not attending school), demonstrating that the likelihood of consequences for a particular household depends on its demographic characteristics. The global MPI will increase if households become deprived that previously had deprivations in at least 16.7% of indicators but previously were not deprived in school attendance. Specifically, the added schooling

deprivations will either make them fall into poverty or exacerbate their poverty intensity.

3.3. Implementation of simulations

We implement the simulations using, for each country, the most recent available dataset as documented in Table D.1. In most developing countries suitable datasets are collected approximately every 3–5 years; the datasets we use date between 2008 and 2019. Without further adjustment, our simulations therefore reflect the impact of the scenarios, had the pandemic taken place at the same time as the survey in each country.

In order to simulate the nutrition scenarios, for each country we randomly draw, in turn, 12% (lower bound scenario), 20% (moderate 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).

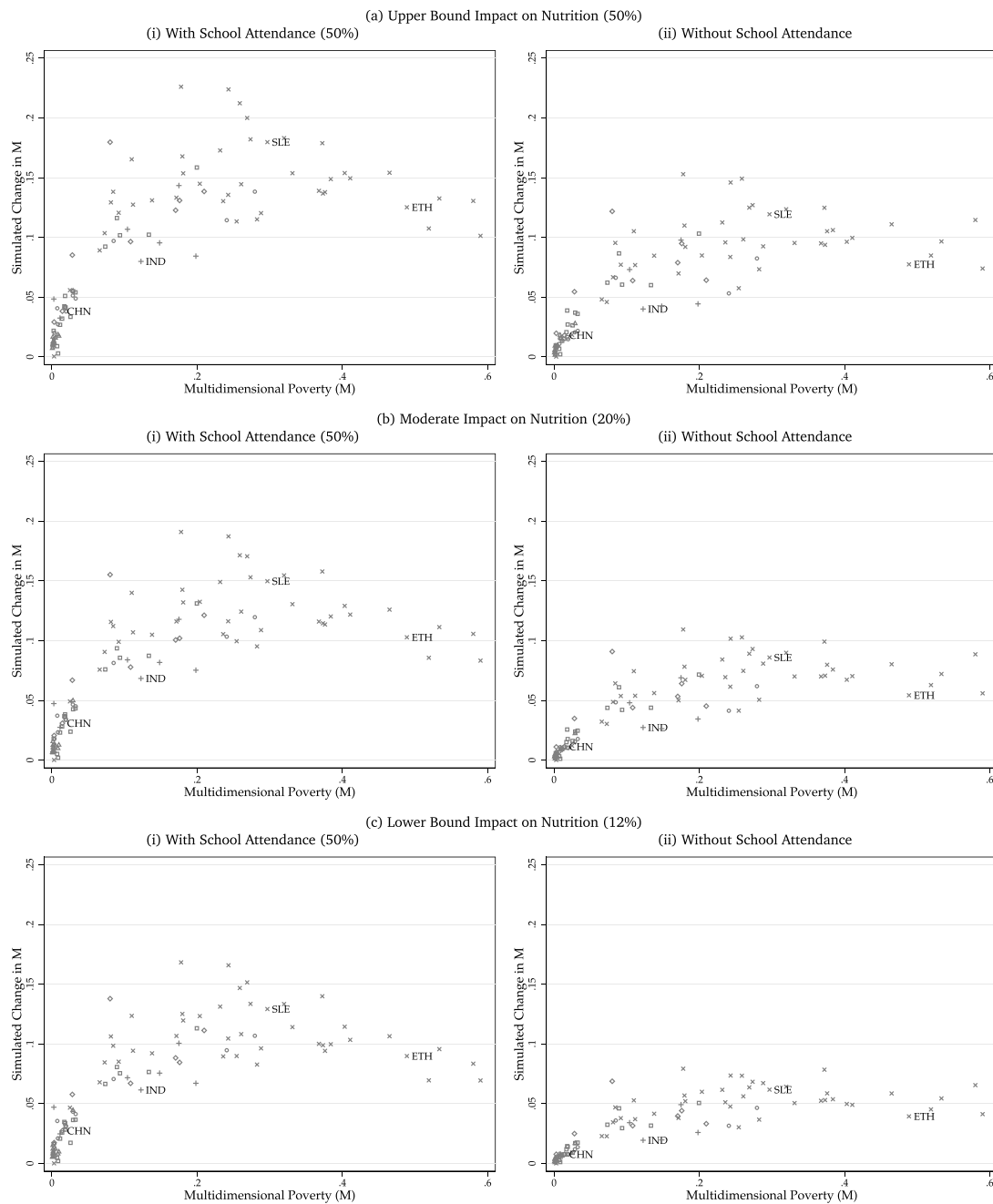
The school attendance shock is simulated alongside each of the nutrition shock scenarios. However, as the impact on school attendance may be less persistent than the impact on nutrition, we also explore each of the nutrition shocks on their own, yielding a total of six scenarios. Simulation results for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

3.4. Discussion of simulation results

The simulation results illustrated in Fig. 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. Similarly, we see a rising impact as the assumed risk of undernutrition increases.

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 nutrition or school attendance is not sufficient for a household to be considered multidimensionally poor (which would require this deprivation to overlap with others). 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 experience 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 responsiveness 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



Notes: Simulated increase in multidimensional poverty, Δ^*M_s , under microsimulations implementing indicated scenarios. Selected countries labelled: China (CHN), India (IND), Sierra Leone (SLE) and Ethiopia (ETH). Markers indicate countries' world region: \circ Arab States; \diamond East Asia and the Pacific; \triangle Europe and Central Asia; \square Latin America and the Caribbean; $+$ South Asia; \times Sub-Saharan Africa.

Fig. 2. Simulated Impact of COVID-19 on Multidimensional Poverty. Notes: Simulated increase in multidimensional poverty, Δ^*M_s , under microsimulations implementing indicated scenarios. Selected countries labelled: China (CHN), India (IND), Sierra Leone (SLE) and Ethiopia (ETH). Markers indicate countries' world region: \circ Arab States; \diamond East Asia and the Pacific; \triangle Europe and Central Asia; \square Latin America and the Caribbean; $+$ South Asia; \times Sub-Saharan Africa.

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 would mainly affect poverty intensity (the average deprivation among the poor) without pushing new

people into multidimensional poverty. Furthermore, if a primary-school aged 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 in the same household are randomly assigned a

status of undernutrition, the change in MPI is the same as if one person was assigned that status. This tempers the simulated 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. 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. More generally, our microsimulation results have demonstrated that the potential impact of the pandemic on multidimensional poverty varies substantially across countries, even having implemented the same scenarios in all countries. This is because our approach reflects, in important ways, the consequences of joint distributions of deprivations being country specific. In particular, countries differ in terms of which persons or households are susceptible to an increase in deprivations and poverty as a result of either of the shocks. Moreover, our microsimulation results also reflect the consequences of other cross-country differences such as primary school entry age and demographic differences, for example the pattern of household compositions.

In summary, we observe that the size of the simulated COVID-19 impact depends (i) non-linearly on the level of poverty and (ii) on the country-specific responsiveness of the global MPI to the implemented shocks. In the next section we develop an approach to translate these simulated impacts to 2020 in order to accommodate recent poverty reductions, while accounting for both of these features.

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 country — between 2008 and 2019 — yet the pandemic took hold globally in the early months of 2020.

In order to translate our simulation results to 2020, we first nowcast baseline multidimensional poverty levels in each country to 2020, to assess what the 2020 level of poverty would have been had the pandemic not occurred. This allows us to account for poverty reductions between the last survey year and 2020. We then develop and estimate a cross-country model that explains the simulated impacts with pre-simulation levels of multidimensional poverty. We calibrate this translation model to reproduce the simulated impact for each country, in order to account for the country-specific responsiveness of the global MPI to the simulated scenario, and use the calibrated model to predict impacts in 2020 on the basis of the nowcasted baseline poverty levels.

This approach allows us to account for two distinct consequences of the time elapsed between the survey and pandemic: the change in baseline poverty level (and underlying joint distribution of deprivations) in each country; and that the impact of the pandemic may be different from the result of our simulation as a result of these changes.

4.1. Nowcasting multidimensional poverty

In order to translate the simulated impacts of the pandemic from the survey years to 2020, we need to know the baseline incidence and intensity of multidimensional poverty in each country in 2020, had the pandemic not occurred. No straightforward relationship has been established between multidimensional poverty and more frequently observed economic variables such as growth (Santos et al., 2019), so we utilise country-specific projections of the global MPI based on recent poverty trends, building on related work by Alkire et al. (2020e). These

trajectory models will also allow us to compute the setback to poverty reduction in section 5.

Consistent with theoretical constraints and previous studies (Clemens, 2004; Klasen and Lange, 2012) on trajectories of bounded development indicators, Alkire et al. (2020e) identify logistic functions of time as the preferred trajectory models for intensity and incidence of multidimensional poverty. With only two harmonised observations available for each country in their study, they rely on cross-country empirical evidence, which strongly supports the choice of logistic over linear or constant-relative-change trajectories to project recent poverty trends.

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

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

as the preferred trajectory model for the incidence of multidimensional poverty H in each country s , and the transformed logistic function

$$A_s(t) = \frac{1 + 3e^{\alpha_s^a - \beta_s^a t}}{3(1 + e^{\alpha_s^a - \beta_s^a t})} \quad (2)$$

as the preferred trajectory model for the intensity A . The trajectory model for multidimensional poverty is then $M_s(t) = H_s(t)A_s(t)$.

We calibrate these models using global MPI estimates obtained by Alkire et al. (2020d) based on the intertemporally-harmonised datasets documented in Table D.1, to obtain the logistic growth rates β_s^h and β_s^a for each of the 70 countries s for which two cross-sections are 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. Alkire et al. (2020e) calibrate all parameters using the harmonised estimates, so our β s coincide exactly with theirs, while in many cases (where the 2020 global MPI matches the second harmonised estimate) so do our α s.

4.2. Cross-country model for simulated impacts

In section 3 we found a systematic non-linear relationship between the baseline measured (pre-simulation) level of multidimensional poverty and the responsiveness of multidimensional poverty to the simulated scenarios. It follows that the impact of each scenario in 2020 is likely to be different from the simulated impact, because the baseline level of poverty and underlying distribution of deprivations in each country will have changed over the time elapsed between the survey and 2020.

In order to translate the simulated impacts to 2020, we start by choosing and estimating descriptive cross-country models of the relationship between the simulated impact of the pandemic and baseline (pre-simulation) 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, Δ^*M , and the impact on its incidence, Δ^*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 baseline incidence H ,

$$\Delta^*H_s = \gamma_0 + \gamma_1 H_s + \gamma_2 H_s^2 + u_s, \quad (3)$$

captures the nonlinear relationship of the simulated impact to baseline multidimensional poverty well, predicting 73% of the variation

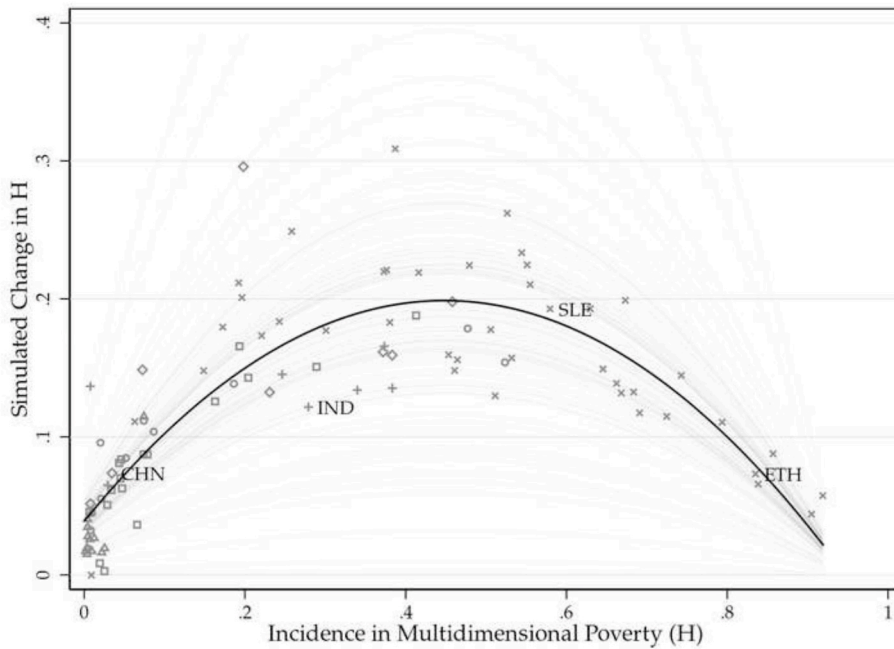


Fig. 3. Translation Model for Simulated Impact of COVID-19 on Multidimensional Poverty Simulated impact on incidence (H). Notes: Simulated increase in multidimensional poverty incidence (H) under microsimulations implementing the moderate nutrition (20%) and school attendance (50%) scenario. Heavy line represents the estimated cross-country translation model (3). Fine lines represent the country-specific calibrations (5). Selected countries labelled: China (CHN), India (IND), Sierra Leone (SLE) and Ethiopia (ETH). Markers indicate countries' world region: \circ Arab States; \diamond East Asia and the Pacific; \triangle Europe and Central Asia; \square Latin America and the Caribbean; $+$ South Asia; \times Sub-Saharan Africa.

in Δ^*H across countries. The fit increases only marginally with more complex polynomials in H and A , so we select this quadratic model (3) for Δ^*H ; model selection regressions are reported the Appendix, Table D.2. The estimated model is represented by the heavy curve in Fig. 3. Similar results (available on request) are obtained under the remaining scenarios and also when the sample is restricted to the 70 countries for which we have nowcasts and can thus translate the simulated impacts to 2020.

Continuing to focus on the same scenario, we find that a linear function of H and HA ,

$$\Delta^*M_s = \eta_0 + \eta_1 H_s + \eta_2 H_s A_s + v_s, \quad (4)$$

predicts the simulated impact on global MPI very well, reproducing 86% of the variation in Δ^*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 (4) for Δ^*M ; model selection regressions are reported the Appendix, Table D.3. With two explanatory variables, this model is less easy to illustrate graphically. Similar results are again obtained under the remaining scenarios and restricted sample.

Despite the good fit of both models, there remains important residual variation (\hat{u}_s and \hat{v}_s) that reflects the variation in responsiveness of global MPI to simulated scenarios across countries with similar baseline poverty levels, due to variations in countries' joint distribution of deprivations and demographic characteristics. The Breusch-Pagan test rejects the hypothesis of homoskedasticity of the residuals, with $p = 0.008$ and $p = 0.001$ respectively for the two models reported.

4.3. Translating simulated impacts to 2020

Direct application of the estimated models (3) and (4) to translate the simulated impacts of the pandemic from the survey years to 2020 would suppress the variation across countries in responsiveness of the global MPI to the simulated scenarios. Country-specific factors are fundamentally important in mediating the scenarios' impacts on multidimensional poverty: the existing joint distribution of global MPI indicators and demographic characteristics vary even across countries with the same global MPI levels, so poverty in some countries is more responsive than in others to the simulated scenarios.

In order to address this, we calibrate the translation model to

reproduce the simulated impact for each country, by transforming the residuals into scale factors. Note that we do not simply calibrate by adding the residuals, as that achieves a worse fit to the heteroskedastic observations and, moreover, would allow the predicted impacts to be negative. Meanwhile, we did not estimate the models with multiplicative errors (as is conventional in welfare analysis, for example Glewwe and Dang, 2011), in order to retain linearity in parameters given our model specification.

Our calibrated model that translates the simulated impact on the incidence of multidimensional poverty H to 2020 in country s is thus

$$\widehat{\Delta^*H_s}(2020) = \hat{\varphi}_s (\hat{\gamma}_0 + \hat{\gamma}_1 H_s(2020) + \hat{\gamma}_2 (H_s(2020))^2), \quad (5)$$

with

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

(Note that, if we had observed (pre-pandemic) levels of H and A for some country in 2020, the translated impact for that country would coincide exactly with the simulated impact.)

Table 2
Summary of aggregate results.

COVID-19 scenario		Aggregate Adjusted Simulation for 2020		
Selection probabilities		MPI (M)	Δ # poor	Setback
Nutrition		$\widehat{M}_s(2020)$	$\widehat{\Delta^*Q_s}(2020)$	$(2020 - t^*)$
School attendance				
(%)		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.

The model is estimated and calibrated separately for each implemented scenario. Fig. 3 illustrates the calibrated model for all countries (fine curves) 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).

Similarly, our calibrated model that translates the simulated impact on the level of multidimensional poverty M to 2020 in country s is

$$\widehat{\Delta^* M_s}(2020) = \widehat{\psi}_s(\widehat{\eta}_0 + \widehat{\eta}_1 H_s(2020) + \widehat{\eta}_2 H_s(2020) A_s(2020)), \quad (6)$$

with

$$\widehat{\psi}_s = \frac{\Delta^* M_s}{\Delta^* M_s - \widehat{v}_s} = \frac{\Delta^* M_s}{\widehat{\eta}_0 + \widehat{\eta}_1 H_s + \widehat{\eta}_2 H_s A_s}.$$

5. Aggregate results

In this section we aim to assess the potential short-term global impact of the pandemic on multidimensional poverty, evaluating the potential increase in the number of poor people, increase in the aggregate global MPI, and the corresponding setback to multidimensional poverty reduction, under each of our six scenarios. In order to do so, we aggregate our translated simulated impacts on global MPI (6) and its incidence (5) across the 70 countries for which we were able both to simulate pandemic impacts and to calibrate trajectory models. All aggregation calculations rely on the UN-DESA medium-fertility population projections and are detailed in Appendix C.

To evaluate the potential increase in the total number of people living in multidimensional poverty across the 70 countries, $\widehat{\Delta^* Q_S}(2020)$, we combine our translated simulated impacts on incidence with the population projections. 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 152 m (in the lower bound nutrition only scenario) and 547 m (in the upper bound 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 941 m, based on the countries' pre-pandemic calibrated trajectory models (1).

To evaluate the potential impact of the pandemic on the aggregate

value of the global MPI across the 70 countries, $\widehat{M_S}(2020)$, we combine each country's simulated impact translated to 2020 with its projection in the absence of the pandemic, and aggregate. 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). These results should be interpreted relative to aggregate projection of global MPI in the absence of the pandemic of 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 t^* to which multidimensional poverty reduction has been set back under each scenario. As the aggregate projected global MPI for the 70 countries in the absence of the pandemic may only be evaluated on an annual basis, we interpolate linearly within each year to solve for non-integer t^* . This analysis is illustrated in Fig. 4, which makes clear that the curvature of the aggregate projection within-year is negligible, although there is significant convexity over the period of our computed potential setbacks. The number of years by which multidimensional poverty reduction is set back 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 Fig. 4.

6. Concluding remarks

One of the great challenges that policy makers around the world face in responding optimally to the raging COVID-19 pandemic is lack of

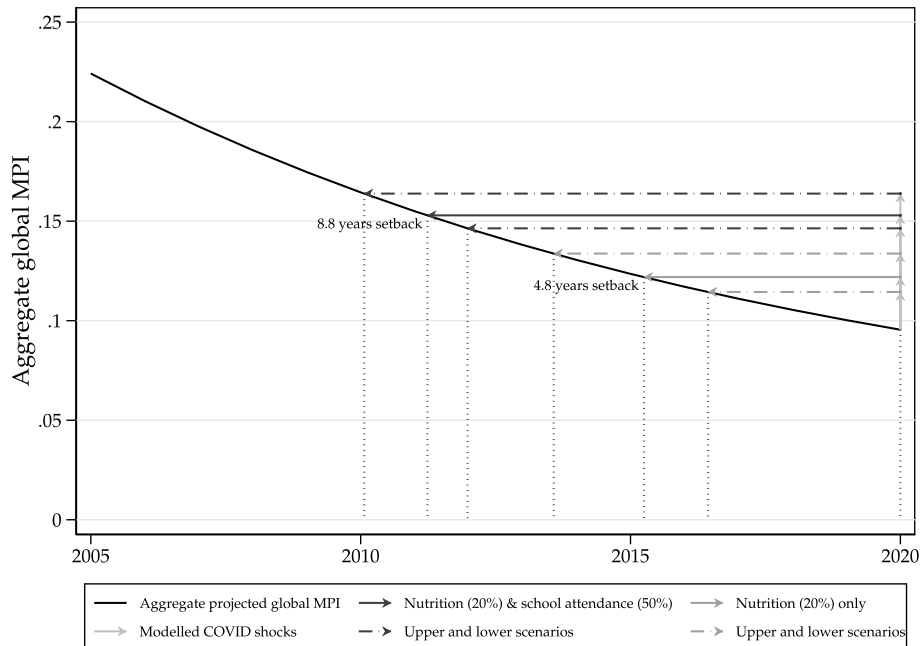


Fig. 4. Setbacks in multidimensional poverty reduction due to COVID-19.

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, epidemiological characteristics of the pandemic, and their interaction with policy measures impeding or accelerating its spread. Consequently, many questions remain, regarding both the effectiveness and appropriateness of policy measures. Yet, policy action needs to take place amid such an adverse context for effective planning. This paper seeks to bridge, partially, an informational gap which is vital for timely and effective policymaking against the negative effects of COVID-19: the extent to which multidimensional poverty may potentially have increased across the developing world. Our analysis of a combined school attendance and moderate nutrition shock suggests that 8.8 years of poverty reduction could be undone. This result corresponds to 469 million extra people entering multidimensional poverty, which demonstrates the magnitude of the problem that policymakers are currently facing.

Our analysis relies on several key assumptions that we highlight here, acknowledging the resulting limitations and suggesting directions for future work. First, in this paper we limit ourselves to analyze the potential short-term effect on global multidimensional poverty under plausible scenarios, which is feasible with the data currently available. As more data (comparable across countries) become available, however, future research may account for country- or region-specific differences in the COVID-19 spread and related policy responses, and their varying dynamic nature. Second, our simulations allow us to evaluate the *potential* impact of COVID-19 on poverty, which is crucial to provide timely information for policy makers and inform the policy debate now, but is 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. 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. Third, one of our key assumptions, namely that observed food insecurity manifests in malnutrition, may be revised in light of detailed evidence about where and how disruptions to food security strike, which would allow refined simulations, even if careful ex-post evaluations remain beyond reach. Finally, our analysis relies on nowcasts of multidimensional poverty that are based on the assumption of continuation of recent trends, in some cases over many years since the survey year. More frequent collection of multidimensional poverty data, or the development of effective methods for nowcasting that make better use of available data, would allow us to relax this assumption in future analyses.

To conclude, despite these limitations, there are three important implications of our results that we wish to highlight. The first is 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 (Santos et al., 2019). Thus complementary action and specific policy strategies are needed to fulfill the SDG mandate of leaving no-one behind. A second implication follows from the wide range of potential setbacks to poverty reduction under alternative plausible scenarios revealed by our analysis, 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 prevent excessive damage to people's lives and livelihoods. There is opportunity to mitigate drastic reversals in multidimensional poverty reduction, if impacts are illuminated and policy margins become visible.

The third implication is the need for effective policy interventions to ensure that the potential short-term impact of the pandemic and related responses does not manifest in *persistent* deprivation. In the case of school attendance several factors support the concern of persistence, including (i) previous studies on school closures due to epidemics and other shocks finding lower school enrollment rates after schools reopened; (ii) the risk of some schools closing down entirely (for lack of revenue or public investment cuts); (iii) contemporaneous income shocks exacerbating the risk of school dropouts especially for poorer families and (iv) that disadvantaged people – precisely those multiply deprived that the global MPI seeks to capture – tend to be hit disproportionately by shocks, are less likely to return to school, and are harder to reach with policy measures (e.g., Bandiera et al., 2019; World Bank, 2020; Azevedo et al., 2021). On the other hand, certain policy measures have been shown to be effective in mitigating the effect of school closures on school dropouts in similar settings. The benefits of measures to prevent and reduce school dropout both during and after school closures (such as re-enrollment campaigns, various incentive schemes) are much-discussed in the literature (e.g., Bandiera et al., 2019; World Bank, 2020), as is the importance of early intervention to mitigate nutrition deprivations (e.g., Heckman, 2011; Dercon and Porter, 2014). All in all, this strengthens our case that there is a real risk that deprivations become persistent, generating negative effects for many people many years in the future. Even though a wide range of policy measures fuels hope that relief is feasible, we emphasize that recovery strategies must take multiply deprived households explicitly into account in order to prevent these deprivations from becoming entrenched.

Credit author 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 Nairi 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.

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Appendix A. Overview of the analysis

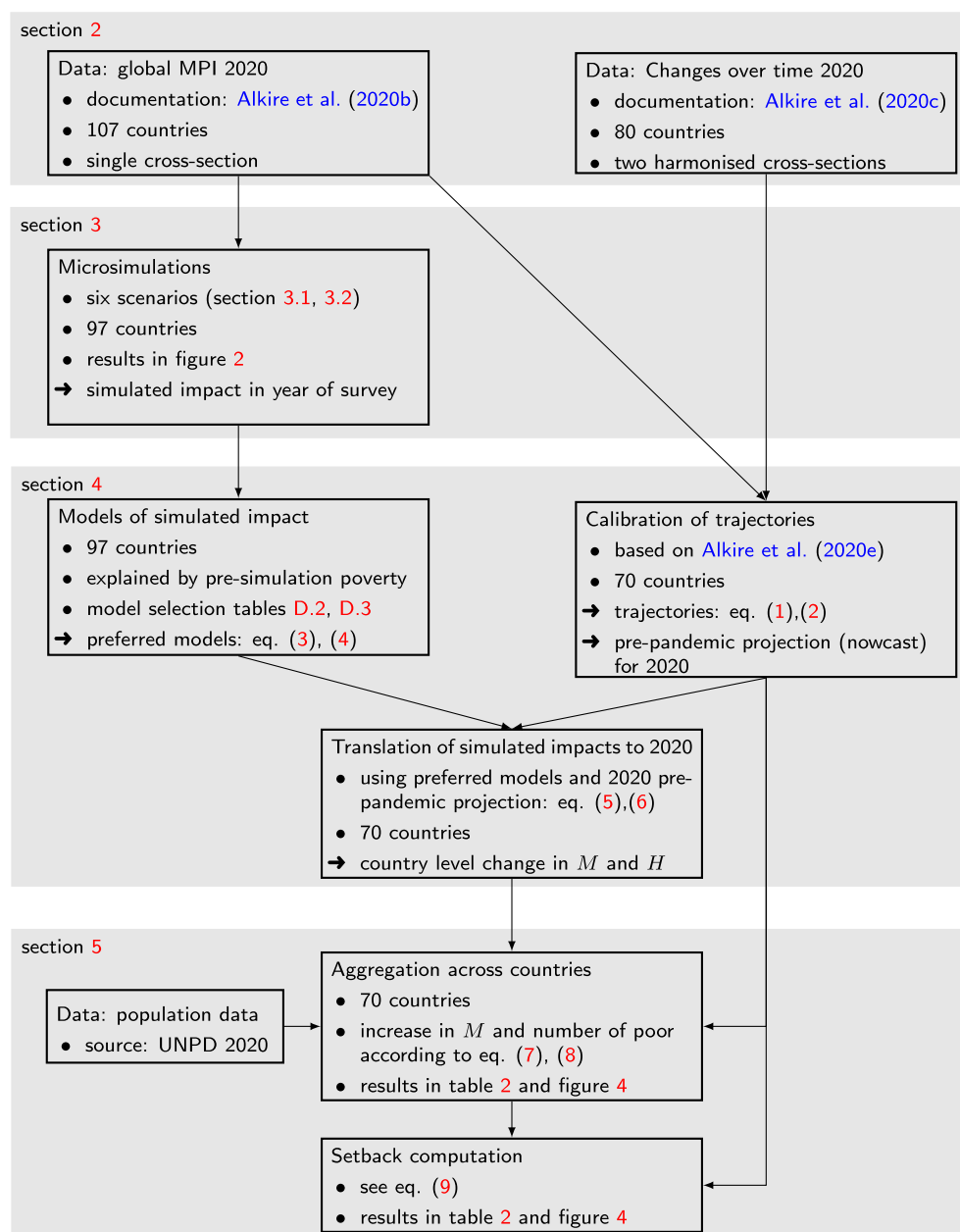


Fig. A.1. Flowchart of analysis.

Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.socscimed.2021.114457>.

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