POVERTY AND SHARED PROSPERITY 2022

Chapter 3 Annex

WORLD BANK GROUP

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Annex 3A

Estimating Multidimensional Poverty, Circa 2018

Introduction

The estimates of multidimensional poverty in tables 3.1, 3.2, and 3.3 in chapter 3 and table 3A.2 in this annex are largely derived from household surveys included in the World Bank's Global Monitoring Database (GMD) circa 2018 (see chapter 3, note 1, for a full description of this data). These surveys account for most of the welfare aggregates included in recent years in the Poverty and Inequality Platform (PIP), the World Bank's online analysis tool. These harmonized surveys collect the information needed on total household consumption or income to estimate monetary poverty, as well as information on a host of other topics, including education enrollment, adult educational attainment, and access to basic infrastructure services, that permit construction of the multidimensional poverty measure (MPM).

The MPM has three dimensions: monetary poverty, education, and access to basic infrastructure (World Bank, 2018). Education and access to basic infrastructure are measured by individual indicators captured by the standardized household surveys. All indicators, once measured, are aggregated according to the weighting scheme in table 3A.1. Considerable heterogeneity across economies is found, however, in how the specific survey questions that record each indicator are worded, how detailed the response choices are, and how closely they match the standard definitions of access—for example, as defined by the Joint Monitoring Program for Water Supply and Sanitation (https://washdata.org/). Despite the effort to harmonize economy-specific questionnaires with the standard definitions, discrepancies with

TABLE 3A.1

Multidimensional poverty measure indicators and weights

Dimension	Parameter	Weight
Monetary poverty	Daily consumption or income is less than US$2.15 per person.	1/3
Education	At least one school-age child up to the (equivalent) age of grade 8 is not enrolled in school.	1/6
	No adult in the household (equivalent age of grade 9 or above) has completed primary education.	1/6
Access to basic infrastructure	The household lacks access to limited-standard drinking water.	1/9
	The household lacks access to limited-standard sanitation.	1/9
	The household has no access to electricity.	1/9

Source: World Bank 2018.

measures reported elsewhere could arise. Therefore, these estimates must be viewed as the best possible under the stringent data requirement of jointly observing the monetary and nonmonetary dimensions of well-being.

Both education indicators are household-level indicators (for example, the number of individuals living in a household in which one child is not attending school), meaning that each country's educational deprivations cannot be compared directly with official estimates of the United Nations Educational, Scientific and Cultural Organization, which are based on individual-level indicators. At the same time, not all indicators are applicable to every household. For example, not every household has at least one school-age child up to the (equivalent) age of grade 8 not enrolled in school (necessary for the school enrollment indicator). In these cases, the weight of the missing indicator is shifted to other indicators within the dimension so that each dimensional weight is unchanged. The same process occurs if the information on an indicator for a household is missing, even if the indicator is applicable.

Consequences of the reweighting process

Because of this reweighting process, few households are ignored because of missing data. Only households for which information is missing on all the indicators that constitute a dimension are not considered in the analysis. In addition to the economies included in the GMD, three—Germany, Israel, and the United States—are from the Luxembourg Income Study (LIS) Database. Including these economies improves the economy and data coverage for the analysis of multidimensional poverty. However, including them raises two issues. First, there is no information on the infrastructure variables in the LIS data. This is similar to the European Union Statistics on Income and Living Conditions (EU-SILC) data, which lack information on electricity. However, data from the World Bank's World Development Indicators (WDI)[1] suggest that 99 percent or more of the population in these economies had access to electricity, safely managed drinking water, and basic sanitation in the latest survey year (2016). So universal coverage is assumed for these economies in the infrastructure indicators. PIP uses LIS data for several additional economies. However, because their coverage in the WDI is lower than 99 percent or missing, they are not used in the MPM.

Second, school enrollment is not available in the LIS data because there is no education information for the 6–14 age group. Thus, in estimating the MPM the school enrollment indicator is set to "missing" and the weight of the education dimension is shifted to the educational attainment indicator. Because there is no schooling information for children younger than 15 from countries included in the EU-SILC data, the situation is handled in a similar manner.

Table 3A.2 presents the MPM estimates for 149 economies, leveraging the most recent survey year available for each economy listed.

TABLE 3A.2

Individuals in households deprived in each indicator, 149 economies, latest year available

Economy	Survey year	Deprivation rate (% of population)						Multi-dimensional poverty headcount ratio (%)
		Monetary	Educational attainment	Educational enrollment	Electricity	Sanitation	Drinking water	
Albania	2018	0.0	0.2	—	0.1	6.6	9.6	0.3
Angola	2018	31.1	29.8	27.4	52.6	53.6	32.1	47.2
Argentina	2020	1.1	1.4	0.7	0.0	0.8	0.1	1.1
Armenia	2020	0.4	0.1	1.9	0.0	0.8	1.6	0.4
Australia	2018	0.5	1.7	—	0.0	0.0	—	2.2
Austria	2019	0.7	0.0	—	0.0	0.8	0.7	0.7
Bangladesh	2016	13.5	22.0	8.4	23.6	54.5	2.8	20.5
Belarus	2019	0.0	0.0	—	—	4.6	3.3	3.2
Belgium	2019	0.2	0.6	—	0.0	0.7	0.4	0.8
Benin	2018	19.9	50.2	31.5	54.3	80.0	22.1	53.3
Bhutan	2017	0.9	40.8	4.1	1.9	14.3	0.4	3.3
Bolivia	2020	3.1	14.1	2.1	4.4	17.9	6.6	6.6
Botswana	2015	15.0	8.2	4.2	35.5	52.0	3.7	20.8
Brazil	2019	5.4	15.0	0.4	0.2	34.3	1.8	6.1
Bulgaria	2019	0.9	0.6	—	0.0	13.2	7.4	1.4
Burkina Faso	2018	30.5	56.4	50.9	47.2	69.6	19.7	60.4
Burundi	2013	65.1	66.3	18.9	91.8	94.3	20.6	85.2
Cabo Verde	2015	4.6	11.7	2.7	9.9	30.2	11.1	7.6
Cameroon	2014	25.7	24.4	15.9	1.2	38.9	23.2	37.5
Chad	2018	30.9	69.0	34.9	90.0	87.0	34.8	79.3
Chile	2020	0.7	3.4	3.3	—	1.4	0.8	1.0
Colombia	2019	5.3	5.1	2.8	1.3	8.2	2.4	5.9
Comoros	2014	18.6	15.3	7.3	28.5	67.2	6.4	26.3
Congo, Dem. Rep.	2012	69.7	22.5	8.0	83.0	80.0	47.9	78.3
Congo, Rep.	2011	35.4	13.4	2.3	29.9	47.3	23.4	41.6
Costa Rica	2020	2.2	3.9	0.5	0.1	1.4	0.1	2.3
Côte d'Ivoire	2018	11.4	48.6	30.4	18.1	64.4	20.7	37.3
Croatia	2019	0.3	0.3	—	0.0	1.4	0.9	0.6
Cyprus	2019	0.2	1.1	—	0.0	0.4	0.5	1.2
Czech Republic	2019	0.0	0.0	—	0.0	0.3	0.2	0.0
Denmark	2019	0.5	0.5	—	0.0	0.5	2.0	0.9
Djibouti	2017	19.1	30.1	18.0	34.2	45.4	7.1	29.3
Dominican Republic	2020	1.1	13.1	8.8	0.6	5.7	5.2	2.9
Ecuador	2020	6.5	3.8	2.3	2.8	4.8	4.6	6.9
Egypt, Arab Rep.	2017	2.5	10.6	4.2	0.5	3.2	0.8	3.5

(continued)

TABLE 3A.2

Individuals in households deprived in each indicator, 149 economies, latest year available *(continued)*

Economy	Survey year	Deprivation rate (% of population): Monetary	Educational attainment	Educational enrollment	Electricity	Sanitation	Drinking water	Multidimensional poverty headcount ratio (%)
El Salvador	2019	1.4	24.8	3.9	2.1	9.4	3.1	4.4
Estonia	2019	0.7	0.1	—	0.0	3.9	5.2	0.8
Eswatini	2016	36.1	10.7	0.3	35.7	46.5	27.9	40.8
Ethiopia	2015	27.0	66.7	31.2	64.1	95.9	42.7	72.7
Fiji	2019	2.0	0.6	1.9	4.5	5.1	12.0	2.2
Finland	2019	0.0	0.9	—	0.0	0.3	0.3	1.0
France	2018	0.1	1.6	—	0.0	0.5	0.5	1.7
Gabon	2017	2.5	11.3	7.9	8.6	68.2	11.5	8.4
Gambia, The	2015	13.4	29.9	6.1	8.0	58.2	8.2	18.3
Georgia	2020	5.8	0.1	1.2	0.0	9.5	5.7	5.8
Germany	2018	0.1	2.7	2.5	0.0	0.0	—	0.2
Ghana	2016	25.3	15.1	9.0	19.5	79.9	40.8	32.9
Greece	2019	1.0	2.0	—	0.0	0.3	0.1	3.0
Guatemala	2014	9.5	24.8	18.3	16.5	46.7	8.4	22.2
Guinea	2018	13.8	61.3	25.0	56.4	71.1	21.0	51.7
Guinea-Bissau	2018	21.7	41.0	30.1	42.1	63.0	21.6	46.1
Haiti	2012	29.2	23.2	9.0	64.3	68.8	33.5	46.8
Honduras	2019	12.6	10.1	10.0	6.7	5.8	5.7	14.8
Hungary	2019	0.3	0.0	—	0.0	1.6	1.6	0.4
Iceland	2017	0.2	0.0	—	0.0	0.0	0.2	0.2
Indonesia	2021	3.6	3.8	1.2	0.8	11.6	6.5	4.1
Iran, Islamic Rep.	2019	1.1	4.4	0.8	0.0	1.9	1.6	1.2
Iraq	2012	0.5	13.6	22.7	0.1	0.9	10.0	5.8
Ireland	2018	0.0	0.7	—	0.0	0.2	0.2	0.7
Israel	2018	0.4	0.7	—	0.0	0.0	—	1.1
Italy	2018	1.6	1.3	—	0.0	0.8	0.7	2.9
Japan	2013	0.7	8.8	0.5	0.0	0.0	—	0.8
Jordan	2010	0.0	1.8	3.0	0.0	0.0	0.2	0.3
Kazakhstan	2018	0.0	0.0	—	0.0	0.5	0.7	0.0
Kenya	2015	29.4	22.5	6.1	56.9	69.0	32.2	45.4
Kiribati	2019	1.7	0.6	6.0	—	83.8	17.1	21.0
Korea, Rep.	2016	0.1	0.0	—	0.0	0.0	—	0.1
Kosovo	2017	0.4	0.5	23.6	0.2	1.4	0.7	0.8
Kyrgyz Republic	2020	1.3	0.0	0.1	0.0	0.1	4.6	1.3
Lao PDR	2018	7.1	12.8	5.7	1.7	22.5	7.8	10.3
Latvia	2019	0.5	0.1	—	0.0	7.9	8.9	0.6

(continued)

TABLE 3A.2

Individuals in households deprived in each indicator, 149 economies, latest year available *(continued)*

Economy	Survey year	Deprivation rate (% of population)						Multi-dimensional poverty headcount ratio (%)
		Monetary	Educational attainment	Educational enrollment	Electricity	Sanitation	Drinking water	
Lebanon	2011	0.0	9.2	2.3	0.9	30.7	0.9	0.7
Lesotho	2017	32.4	18.1	4.8	58.7	55.1	13.7	40.7
Liberia	2016	27.6	30.5	54.1	79.7	61.8	25.7	56.6
Lithuania	2019	0.6	0.4	—	0.0	7.6	7.2	1.0
Luxembourg	2019	0.4	0.5	—	0.0	0.1	0.1	0.9
Madagascar	2012	80.7	49.0	34.7	13.0	76.9	59.9	82.9
Malawi	2019	70.1	54.3	3.7	88.8	75.1	11.4	78.3
Malaysia	2015	0.0	0.7	0.6	0.6	13.2	1.6	0.2
Maldives	2019	0.0	0.0	1.9	1.9	4.8	0.0	0.0
Mali	2018	14.8	66.6	28.2	23.9	51.9	23.8	43.7
Malta	2019	0.3	0.1	—	0.0	0.1	0.0	0.4
Marshall Islands	2019	0.9	1.0	3.4	1.1	29.0	1.7	1.1
Mauritania	2014	6.5	54.3	8.3	54.1	49.3	38.6	45.7
Mauritius	2017	0.1	7.2	0.2	0.2	—	—	0.4
Mexico	2020	3.1	3.8	2.5	0.2	1.3	3.9	3.4
Micronesia, Fed. Sts.	2013	16.0	8.7	28.0	23.6	42.8	5.2	22.7
Moldova	2019	0.0	2.5	0.5	0.0	25.5	16.9	0.8
Mongolia	2018	0.7	2.7	3.2	0.2	10.4	13.0	2.0
Montenegro	2014	0.0	0.1	—	1.4	2.5	1.2	1.2
Morocco	2013	1.4	12.7	6.8	2.4	12.9	8.7	5.8
Mozambique	2014	64.6	54.9	33.3	14.6	71.3	41.1	73.7
Myanmar	2017	2.0	28.0	6.8	50.9	9.7	20.6	15.4
Namibia	2015	15.6	11.3	6.1	53.8	68.3	9.2	27.5
Nauru	2012	1.4	15.2	4.2	0.8	22.5	3.8	1.8
Nepal	2010	8.2	28.6	9.5	31.5	66.7	16.8	26.5
Netherlands	2019	0.2	1.6	—	0.0	0.0	0.1	1.8
Nicaragua	2014	3.9	14.1	8.1	20.0	42.7	12.5	15.6
Niger	2018	50.6	79.7	28.0	78.7	85.2	37.5	80.0
Nigeria	2018	30.9	17.6	20.3	39.4	44.9	27.5	41.8
North Macedonia	2018	3.4	0.4	—	0.0	5.1	—	3.7
Norway	2019	0.3	1.7	—	0.0	0.0	0.5	2.0
Pakistan	2018	4.9	21.1	28.8	9.3	24.8	6.5	16.7
Papua New Guinea	2009	39.7	22.2	9.0	82.6	79.8	69.2	74.7
Paraguay	2020	0.8	4.9	2.0	0.3	6.8	1.6	1.3
Peru	2020	5.8	4.8	1.2	3.7	11.5	5.5	7.0
Philippines	2015	6.5	4.0	0.0	9.1	16.4	9.7	8.2

(continued)

TABLE 3A.2

Individuals in households deprived in each indicator, 149 economies, latest year available *(continued)*

Economy	Survey year	Deprivation rate (% of population): Monetary	Educational attainment	Educational enrollment	Electricity	Sanitation	Drinking water	Multidimensional poverty headcount ratio (%)
Poland	2019	0.0	0.0	0.4	0.0	1.0	0.1	0.0
Portugal	2019	0.1	1.5	—	0.0	0.6	0.6	1.7
Romania	2018	0.0	0.2	1.8	0.1	18.0	1.0	0.1
Russian Federation	2020	0.0	0.9	0.7	5.1	7.7	8.6	5.0
Rwanda	2016	52.0	36.9	4.3	64.0	28.1	24.5	57.4
São Tomé and Príncipe	2017	15.6	19.5	4.3	31.2	62.0	8.2	24.9
Senegal	2018	9.3	42.0	31.9	26.6	37.4	15.2	32.3
Serbia	2019	0.0	1.7	0.7	0.1	1.5	0.1	0.2
Seychelles	2018	0.5	0.4	—	0.0	0.2	5.5	0.9
Sierra Leone	2018	26.0	28.7	18.7	68.7	87.2	33.8	54.0
Slovak Republic	2019	0.1	0.0	—	0.0	1.0	0.7	0.1
Slovenia	2019	0.0	0.0	—	0.0	0.1	0.1	0.0
Solomon Islands	2012	26.6	11.4	13.5	53.8	58.5	25.5	38.7
Somalia	2017	70.7	59.2	56.3	50.6	39.4	11.8	83.8
South Africa	2014	20.5	2.3	2.3	4.1	35.2	10.4	21.7
South Sudan	2016	67.3	39.3	62.2	—	88.1	13.9	84.9
Spain	2019	0.9	2.7	—	0.0	0.4	0.2	3.6
Sri Lanka	2016	1.3	3.8	4.0	2.5	0.8	12.5	1.7
Sudan	2014	15.3	40.2	22.7	48.5	92.9	44.9	52.5
Sweden	2019	0.6	2.0	—	0.0	0.0	0.1	2.5
Switzerland	2018	0.2	0.0	—	0.0	0.1	0.1	0.2
Taiwan, China	2016	0.1	0.9	1.2	0.0	0.0	—	0.1
Tajikistan	2015	6.1	0.3	26.8	2.0	3.5	39.4	7.0
Tanzania	2018	44.9	13.2	19.5	44.3	71.5	29.2	54.6
Thailand	2020	0.0	13.4	0.5	0.1	0.2	0.5	0.2
Timor-Leste	2014	8.0	21.1	16.4	27.4	39.6	22.1	23.5
Togo	2018	28.1	32.7	14.0	47.4	83.7	25.3	46.4
Tonga	2015	1.1	1.9	0.8	8.3	0.4	0.1	1.1
Tunisia	2015	0.1	20.2	2.1	0.2	6.5	2.1	1.5
Türkiye	2019	0.4	3.3	3.0	0.0	5.3	0.1	0.6
Tuvalu	2010	3.6	4.5	6.1	9.2	11.5	2.4	4.3
Uganda	2019	42.2	31.4	11.8	41.3	71.1	23.7	52.3
Ukraine	2020	0.0	1.6	—	0.0	12.4	0.0	1.7
United Kingdom	2015	0.7	0.5	—	0.0	0.4	0.6	1.2

(continued)

TABLE 3A.2

Individuals in households deprived in each indicator, 149 economies, latest year available *(continued)*

Economy	Survey year	Deprivation rate (% of population)						Multidimensional poverty headcount ratio (%)
		Monetary	Educational attainment	Educational enrollment	Electricity	Sanitation	Drinking water	
United States	2019	1.0	0.2	—	0.0	0.0	—	1.1
Uruguay	2019	0.1	2.0	0.7	0.1	1.0	0.5	0.1
Vanuatu	2019	10.0	25.7	13.4	1.4	43.0	11.8	15.4
Vietnam	2018	1.2	11.8	1.7	0.4	11.1	4.7	2.5
West Bank and Gaza	2016	0.5	1.2	5.8	0.0	0.1	3.2	0.6
Yemen, Rep.	2014	19.8	16.0	44.5	33.9	41.2	14.0	35.4
Zambia	2015	61.4	24.4	30.4	69.2	60.0	34.4	66.5
Zimbabwe	2019	39.8	0.9	6.0	38.0	38.3	19.3	42.4

Source: World Bank, Global Monitoring Database.
Note: Estimates are based on harmonized household surveys in 149 economies that are part of the Global Monitoring Database. This table includes the 123 economies that are analyzed in chapter 3, given the 2018 line-up year, as well as the most recent data after 2009 for additional economies in the database not included in the analysis of 123 economies but present in earlier years. Definitions of the indicators and the deprivation thresholds are as follows. *Monetary poverty:* a household is deprived if income or expenditure, in 2017 purchasing power parity US dollars, is less than US$2.15 per person per day. The estimates in this table for Australia, Canada, Germany, Israel, Japan, the Republic of Korea, and the United States are based on the microdata available from the Luxembourg Income Study Database. *Educational attainment:* a household is deprived if no adult (grade 9 equivalent age or older) has completed a primary education. *Educational enrollment:* a household is deprived if at least one school-age child up to the (equivalent) age of grade 8 is not enrolled in school. *Electricity:* a household is deprived if it does not have access to electricity. *Sanitation:* a household is deprived if it does not have access to limited-standard sanitation. *Drinking water:* a household is deprived if it does not have access to limited-standard drinking water. The data reported refer to the percentage of people living in households deprived according to each indicator. — = not available.

Note

1. The World Bank's World Development Indicators database (https://wdi.worldbank.org/) is a compilation of relevant, high-quality, and internationally comparable statistics on global development and the fight against poverty.

Reference

World Bank. 2018. *Poverty and Shared Prosperity 2018: Piecing Together the Poverty Puzzle.* Washington, DC: World Bank.

Annex 3B

The Pandemic Shock through the Lens of the MPM: The Poverty-Adjusted Life Expectancy Measure

Introduction

Box 3.1 in chapter 3 uses poverty-adjusted life expectancy (PALE), based on the multidimensional poverty measure (MPM), to aggregate estimated well-being losses over the pandemic period arising from three sources: excess mortality, additional extreme poverty, and school closures. Aggregating the three sources with PALE helps determine the relative sizes of the impacts of each source as well as a comparison of impacts across countries.

Extending the MPM to the pandemic setting

The monetary poverty impact of the pandemic period is directly accounted for under the official definition of the MPM. However, the definition of the education dimension must be revised slightly to account for school closures. “School enrollment” does not capture school closures well because children can be administratively enrolled even when schools are closed. To overcome this limitation, any household with a school-age child who is not enrolled in a school or who is out of school because of school closure is considered deprived. This new definition does not affect the prepandemic MPM rate, but it does capture the specific impact of the pandemic on education. In addition, although mortality does not enter the definition of the MPM, mortality can be taken into account by means of PALE as explained in box 3.1.

Instantaneous impact at the peak of the pandemic

The timing of the pandemic has been heterogeneous across countries, with some countries such as China already affected in late 2019, and others such as India experiencing their greatest impact on mortality in 2021. To account for this heterogeneity when comparing countries, the analysis looks at a country’s hypothetical “worst period of time.” This approach is not intended to sum over time the pandemic’s total well-being losses (in contrast with the perspective taken later in this chapter). Instead, this approach assesses the size of the maximal reduction of PALE that countries may have experienced.

To apply this approach to a large set of countries, the analysis makes the following strong assumptions about the maximal impact the pandemic has had on each source. For mortality, the analysis considers for each country the largest shock to life expectancy at birth estimated over 12 months from 2020 to the end of 2021. This information is contained in the all-cause excess mortality estimates of Heuveline (2022), who estimates the shock to life expectancy in 98 countries. For low-income countries not included in this set, Heuveline provides estimates based on the same method. As Heuveline warns, the latter estimates are less precise because of the lack of recent mortality data in most low-income countries.

For monetary poverty, the largest nowcasted shock experienced by a country (in either 2020 or 2021) is taken as the magnitude of change in the monetary poverty dimension. The monetary poverty estimates considered are the same as those presented in chapter 1.

For school closures, all schools are assumed closed during this hypothetical worst period. This assumption is likely to overestimate the pandemic's impact on education. Although school closures have been widespread, the duration and severity of such closures are highly variable. Data from the United Nations Educational, Scientific and Cultural Organization suggest that most countries, even most low-income countries, closed or partially closed their schools for at least half a school year. Many countries did so for more than a year, and several even for an entire two school years. Table 3B.1 presents summary statistics on school closures. Note that a very large increase in the share of households deprived in the school enrollment indicator does not automatically lead to a very large increase in the share of households considered multidimensionally poor. The reason is that being deprived in school enrollment alone is not sufficient to be deemed multidimensionally poor. Given the value of the weight attributed to this indicator, only households that already suffer from deprivations in other dimensions enter multidimensional poverty when they become deprived in school enrollment (if not already multidimensionally poor).

The joint distribution of increases in monetary poverty and school closures

One key attraction of multidimensional poverty measures like the MPM is that they capture overlaps in deprivations. Some deprivations such as school enrollment, when taken in isolation, may not be deemed sufficiently strong to confer MPM poverty status. However, when an individual adds this deprivation to other deprivations, well-being may be sufficiently affected for that the individual to be identified as multidimensionally poor. By contrast, monetary poverty at the international US$2.15 line for low-income groups is considered a harsh enough form of deprivation that, on its own, confers multidimensional poverty status.

Because the joint distribution of deprivations affects the rate of multidimensionally poor, the impact that the extreme poverty shock and school closures have on the MPM rate depends on

TABLE 3B.1

Many countries have experienced a year or more of school closure

Country income group	No. of typical school years for which schools are closed or partially closed: 20th percentile	50th percentile	80th percentile
Low income	0.5	0.7	1.2
Lower-middle income	0.4	0.9	1.6
Upper-middle income	0.6	1.4	1.7
High income	0.4	0.9	1.4
All countries	**0.5**	**0.9**	**1.5**

Sources: United Nations Educational, Scientific and Cultural Organization (UNESCO) map on school closures (October 2021); UNESCO Institute of Statistics (UIS) via World Bank Databank (April 2021).
Note: This table conveys the number of typical school years for which schools were fully or partially closed, by country income group and the world, at the 20th, 50th (median), and 80th percentiles of distribution for each income category. The share of school years is expressed for the total portion of a typical school year falling between February 16, 2020, and October 31, 2021.

the other deprivations faced by affected individuals. For example, the MPM rate is not affected by an individual who becomes poor if that person was already multidimensionally poor due to deprivations in education and infrastructure. Also, a non-multidimensionally-poor individual who becomes deprived in school enrollment will become multidimensionally poor only if already deprived in other indicators. Because most economies do not have MPM data that cover the pandemic period 2020–21, the analysis considers for each economy the most recent year of MPM data and then assesses the impact that the monetary poverty shock and school closures have on the MPM rate for that year. Because the pandemic's impact on monetary poverty is nowcasted, the analysis ignores whether those individuals pushed into extreme poverty were already multidimensionally poor.

For the sake of simplicity, the analysis assumes that additional monetary poverty is distributed independently of other forms of deprivations—that is, any individual who was not monetarily poor has the same probability of becoming poor, regardless of whether that person was deprived in education or in infrastructure. This assumption is clearly wrong, but it has little consequence because the results suggest that the pandemic has, in most countries, a relatively smaller impact on PALE through extreme poverty than through school closures or excess mortality (see table 3B.2). This assumption is likely to err on the side of increasing the pandemic's impact on the MPM rate, at least if people with other forms of deprivations are, in practice, more likely to become extremely poor than individuals not affected by other forms of deprivations.

The analysis does not need to make similar assumptions for school closures. Indeed, the exercise assumes that *all* households with school-age children are deprived in school enrollment because of school closures. There is no need to worry about the distribution of this additional deprivation because all of these households are affected.

The analysis makes a final joint distribution assumption for countries that do not report school enrollment (mostly high-income countries—see the discussion in annex 3A). For these countries, virtually all children are enrolled in school, and the official MPM rate is computed by transferring the weight of school enrollment to the other indicator of the education dimension, "primary school completion." In practice, this means that any

TABLE 3B.2

The reduction in poverty-adjusted life expectancy was driven by learning loss in lower-income countries and by increased mortality in higher-income countries

Country income group	MPM baseline (pp)	PALE baseline (years)	Shocks to PALE during COVID-19 pandemic: Increase in MPM due to school closure (pp)	Change in extreme poverty (pp)	Decrease in life expectancy (years)	PALE, pandemic (three sources, years)	Proportional PALE shock (three sources, %)
Low income	54.9	28.7	8.5	2.7	2.3	21.5	0.72
Lower-middle income	20.8	55.4	6.9	1.3	3.0	47.7	0.85
Upper-middle income	4.3	71.9	2.2	0.0	3.8	66.7	0.93
High income	0.4	80.5	0.3	0.0	1.4	78.8	0.98
All countries	**18.2**	**61.0**	**4.2**	**0.9**	**2.6**	**55.8**	**0.88**

Sources: Original calculations based on MPM data from World Bank, Global Monitoring Database; mortality estimates from Heuveline 2022.
Note: Table quantifies the shocks to the multidimensional poverty measure (MPM) and poverty-adjusted life expectancy (PALE) from three sources, by country income group and the world. Shocks during the pandemic represent the peak value occurring between 2020 and 2021. Average values for economies within the sample group are not weighted for population. pp = percentage point.

individual living in a household deprived in primary school completion is identified as multidimensionally poor.

The results suggest that in many high-income countries, mortality has a larger impact on PALE than school closures. For this finding to be robust to alternative assumptions, the following two-step approach provides an upper bound on the impact that school closures can have on the MPM rate in these countries. First, a counterfactual baseline MPM rate is computed by assuming that these countries do report school enrollment and that this report is a confirmation that all children are enrolled into a school. This assumption implies a lower MPM rate than the official MPM rate because individuals living in households deprived in primary school completion are not multidimensionally poor under this assumption unless they cumulate other deprivations. Second, the MPM rate corresponding to the case in which all households with school-age children are school enrollment deprived is simulated.

There is no need to draw any assumption on the distribution of excess deaths in order to assess the impact that the mortality shock has on PALE. Again, this follows from the exclusive nature of mortality, which implies that individuals cannot be dead and simultaneously suffer another form of deprivation.

Shapley type decomposition of the shock to PALE

PALE is not additively decomposable. Thus, comparison of the impacts of the three sources of deprivation on PALE will depend on the decomposition method selected—in this case, the well-established decomposition method proposed by Shorrocks (1999), which is known as the Shapley-Owen-Shorrocks (SOS) decomposition. The SOS method decomposes the difference between the baseline PALE value and the PALE estimate accounting for the three shocks. This decomposition is conducted by attributing to each shock its average impact on PALE when considering all possible orderings in which the three shocks are applied when moving from the baseline value to the final value. For example, one order is to first apply the monetary poverty shock, then the education shock, and finally the mortality shock. Because three sources are considered, six different orderings can be explored. The SOS decomposition has two attractive features. First, it is symmetric because it does not depend on the order considered (it takes an average over all possible orders). Second, decomposition is exact in the sense that the sum of the impacts attributed to each shock exactly yields the total shock.

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Annex 3C

A Disaggregated Analysis of the Pandemic Shock

Introduction

This annex explains in more detail the methods used in the disaggregated welfare analysis of the pandemic period 2020–21 presented in chapter 3.

The framework considered is an extension of the one considered by Decerf et al. (2021) and Ferreira et al. (2021), who provide more details. In this framework, the three sources of the well-being losses stemming from the pandemic are expressed in the same unit: years of human life.

The remaining lifetime well-being of a population I in year T is given by

$$W = \sum_{i \in I} \sum_{t=T}^{d_i} u(s_{it}),$$

where $s_{it} \in \{P, NP\}$ is the poverty status of person i in year t (poor or nonpoor), d_i is the year in which i dies, and u is the period utility function, with $u(NP) \geq u(P) \geq 0$. Thus, W is the weighted sum of years spent in poverty and years spent out of poverty.

It is assumed that the pandemic starts in year T and can affect individual i's lifetime utility in three ways:

1. The pandemic's economic impact may change the individual's status from $s_{it} = NP$ to $s_{it}' = P$ for one or two of the years t during the pandemic (in this case for $t = 2020$ and $t = 2021$). The total current poverty impact is the sum over all individuals of their additional number of years spent in poverty. CPY denotes the total number of additional current poverty years.

2. The learning losses generated by school closures may reduce economic growth over the coming decades, at least during the three decades corresponding to the work lives of children affected by school closures. This reduced growth may change individual i's postpandemic status from $s_{it} = NP$ to $s_{it}' = P$ for several years t following school closures. The total future poverty impact is the sum over all individuals of the additional number of years spent in poverty. FPY denotes the total number of additional future poverty years.

3. The excess mortality associated with the pandemic can advance the year of individual i's death to an earlier calender year $d_i' \leq d_i$, where $d_i' = 2020$ or $d_i' = 2021$. The total mortality impact is the sum of all years of life lost over all individuals who die as a result of the excess deaths during the pandemic. YLL denotes the total number of lost years due to the pandemic.

The period utility loss from becoming poor for one year is $\Delta u_p = u(NP) - u(P)$, and Δu_d denotes the period utility loss of losing one year due to excess mortality.[1] Both Δu_p and Δu_d are assumed to be constant over time and across individuals and thus have no i or t subscripts.

The total well-being loss of the pandemic is $WL = \Delta W = W - W'$, where W' denotes the remaining societal well-being under the pandemic. This total well-being loss can be expressed as

$$\frac{\Delta W}{\Delta u_p} = \frac{\Delta u_d}{\Delta u_p} YLL + CPY + FPY,$$

where parameter $\alpha = \Delta u_d / \Delta u_p$, which can be interpreted as the number of current poverty years having the same impact on societal well-being as one year lost. WL is therefore proportional to

$$\alpha YLL + CPY + FPY.$$

Estimation methods

YLL, CPY, and FPY are estimated for 61 countries. Estimates for FPY are more demanding because they require conducting simulations with a long-term growth model (LTGM), whereas estimates for YLL and CPY can be obtained simply by combining data from other sources.

Number of current poverty years

The adopted poverty line is the societal poverty line anchored to its 2019 value.

For each country, estimation of the increased poverty rate in 2020 is determined using the findings of Mahler, Yonzan, and Lakner (forthcoming). The authors triangulate various data sources to obtain a global picture of the impact of the pandemic on poverty in 2020. They use as their starting point welfare distributions for 2019 covering 168 countries from the World Bank's Poverty and Inequality Portal (PIP). To derive estimates for 2020, those authors use published household surveys where available and complement them with simulation exercises based on high-frequency phone surveys for 46 countries. In each country, the authors produce a distribution of economic welfare in 2020. One advantage of their methodology is that, to some extent, their estimation accounts for changes to the within-country inequality that occurred in 2020. To isolate the impact of the COVID-19 pandemic, they compare their 2020 distribution with a counterfactual 2020 distribution, created by assuming that countries in 2020 would experience the growth expected by growth forecasts conducted before the pandemic. The estimation of the increased poverty rate in 2021 is obtained by further building on the distribution of economic welfare in 2020 of Mahler, Yonzan, and Lakner (forthcoming). A distribution for 2021 is scaled from the distribution in 2020 using the reported growth rate. Again, the impact of the pandemic is estimated from a counterfactual distribution for 2021 constructed by the same method as in Mahler, Yonzan, and Lakner (forthcoming).

The estimation here of CPY directly follows from the additional poverty rates estimated for 2020 and 2021. From these additional poverty rates and population numbers, the analysis computes how many additional individuals were poor in 2020 and 2021. Summing these two numbers provides an estimate of CPY, as one additional individual spending one year in poverty constitutes one poverty year—that is,

$$CPY = \sum\nolimits_{t=2020}^{2021} (H_t^{estimation} - H_t^{counterfactual}) * Pop,$$

where H_t is the societal poverty rate at time t and Pop is the size of the population in 2019.

Number of lost years due to premature mortality

The analysis starts from estimates of the number of excess deaths for the period January 1, 2020, to December 31, 2021, in 191 countries, economies, and territories computed by Wang et al. (2022). To produce their estimates, these authors collect all-cause mortality reports for 74 countries and territories as well as 266 subnational locations, including 31 locations in low- and middle-income countries, that reported all-cause mortality both before and during the pandemic. Their final estimates of the number of excess deaths are based on a set of six models.

In each country, the analysis estimates the number of years of life lost taken from the number of excess deaths (Wang et al. 2022). There is no country-specific information on the age at which these excess deaths take place. As a result, the analysis cannot compute the residual life expectancy at the age at which these excess deaths occur. Instead, the analysis assumes that the all-cause excess mortality has the same age structure as the excess mortality from COVID-19. This assumption should approximately hold in countries for which most of the excess mortality is directly due to the disease. Clearly, this assumption will not hold in countries where excess deaths are largely driven by other factors (increased food insecurity, lack of access to medical care, and so on). Because COVID-19 mortality mostly applies to older individuals, this assumption tends to lead to an underestimation of YLL, at least in low-income countries.

In practice, in each country YLL is estimated as

$$YLL = D * PAYLL,$$

where D is the number of excess deaths in the period 2020–21 and $PAYLL$ is the population average years of life lost due to COVID-19. PAYLL represents the average country-specific residual life expectancy of individuals dying from COVID-19 in 2020 in the country.

The analysis relies on the estimates that Heuveline (2021) provides for 2020 for a large set of countries. To estimate PAYLL, one needs an estimate of the age distribution of COVID-19 deaths. When not available in a given country, Heuveline (2021) relies on a reference age distribution provided by the US Centers for Disease Control and Prevention. Use of the US age distribution as a reference leads to an underestimation of PAYLL, and thus of YLL, in countries for which the (unknown) age distribution of COVID-19 deaths is "younger," as could be expected in low-income countries (Demombynes et al. 2021).

Heuveline's estimates of PAYLL range from about 10 years to 25 years. Typically, the PAYLL estimated for high-income countries is smaller because of the share of older ages in their populations, which implies a larger average age at death from COVID-19 than in low-income countries. This effect often seems to dominate the larger residual life expectancy at a given age enjoyed in high-income countries, which in isolation would imply larger PAYLL.

Overall, the assumptions on which the YLL estimates rely are such that YLL would likely underestimate the true number of years of life lost, at least in low-income countries.

Number of future poverty years

For 61 countries,[2] the FPY could be generated by estimating the impact that the learning losses associated with the period when schools were closed are expected to have on future incomes over the period 2020–50. This period corresponds approximately to the majority of the working life of affected school-age children—the relevant period to assess the economic losses generated by these school closures.

In practice, the analysis adopts a country-specific LTGM to simulate two growth paths for GDP per capita over that period: one baseline growth path (without school closures) and one alternative growth path (with school closures). The difference between the two is that the alternative path assumes that school-age children in 2020 (and potentially 2021) have suffered a certain loss in their learning-adjusted years of schooling (LAYS), a standard measure of human capital (Kraay 2018). In the LTGM, the LAYS loss generates a smaller accumulation of human capital and therefore smaller growth rates. One advantage of this macroeconomic approach is that it accounts for general equilibrium effects, such as the slower accumulation of capital following from the smaller human capital generated by the LAYS loss. At the same time, this approach may underestimate the human capital consequences of the pandemic because it does not consider the human capital loss from preschool closures or loss in work experience from extended unemployment.

To estimate LAYS losses, the analysis assumes that students learn nothing when schools are not open, a finding in World Bank (2022) that summarizes the recent evidence of school closures on learning. For each country, the analysis assumes that the LAYS loss corresponds to the number of school years during which the country's schools have been closed, or partially closed, multiplied by the quality of the country's school system. Table 3C.1 lists the countries that inform the analysis. Decerf et al. (forthcoming) provide more information on the LTGM and the calibration used.

Starting from the country's economic welfare distribution in 2020 and using distribution-neutral forecasts, the analysis uses the two growth paths to compute the distribution of economic welfare in each year in the period. From these distributions, each year the additional poverty generated by school closures is defined as the difference in the fraction of poor between the baseline and the pandemic scenario. The total poverty impact of school closures is obtained by summing the poverty impact over all years in the period. Poverty is again assessed using the societal poverty line anchored to its 2019 value in the country. The estimates of FPY are thus given by

$$FPY = \sum_{t=2021}^{2050} (H_t^{scenario} - H_t^{baseline}) * Pop$$

where H_t is the poverty rate at time *t*, and *Pop* is the size of the population in 2019. Thus, the analysis assumes that the size of the population stays constant, which underestimates FPY for countries in which the population is projected to grow rapidly.

The estimation of the impact that school closures have on future poverty is likely conservative for the following additional reasons. First, the analysis assumes that the future incomes of all school-age cohorts are affected in the same proportion, even though there is evidence in many countries that vulnerable individuals have suffered heavier learning losses than their well-off peers. This finding suggests that future incomes in the bottom of the distribution

TABLE 3C.1

Countries used in the disaggregated analysis of the pandemic shock

Country income group	Countries
Low-income countries	Burkina Faso; Congo, Dem. Rep.; Ethiopia; Haiti; Madagascar; Mali; Mozambique; Nepal; Niger; Tanzania; Uganda; Yemen, Rep.
Lower-middle-income countries	Bangladesh; Bolivia; Egypt, Arab Rep.; Ghana; India; Indonesia; Kenya; Morocco; Myanmar; Nigeria; Pakistan; Philippines; Sudan; Tunisia; Uzbekistan; Vietnam
Upper-middle-income countries	Argentina; Brazil; China; Colombia; Dominican Republic; Ecuador; Guatemala; Iran, Islamic Rep.; Kazakhstan; Lebanon; Malaysia; Mexico; Peru; Romania; Russian Federation; Serbia; South Africa; Thailand; Türkiye
High-income countries	Australia; Chile; Croatia; France; Germany; Greece; Italy; Japan; Korea, Rep.; Poland; Saudi Arabia; Spain; United Kingdom; United States

Source: World Bank.

should be more than proportionally affected, pointing toward larger future impacts on poverty. Second, the analysis does not account for the possibility of higher school dropout rates, which may generate much larger LAYS losses. Indeed, a child who drops out of school four years earlier than expected because of the pandemic suffers more learning loss than a child who misses school during the year schools were closed.

Notes

1. It is assumed that the utility loss for one year of life is the same for an individual who would have been poor as for an individual who would not have been poor.
2. The set of 61 countries intentionally includes relatively populous countries that are largely representative of both world regions and country income groups.

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