3

Beyond the Monetary Impacts of the Pandemic: A Lasting Legacy

Summary

The COVID-19 pandemic has affected many dimensions of human well-being. Among its negative consequences are lower incomes, higher mortality, school closures and interrupted learning, and disruptions of essential health services. Most countries have suffered multiple impacts across various dimensions, even if to different degrees. But how does one measure the combined extent of these impacts?

Poverty and Shared Prosperity 2018: Piecing Together the Poverty Puzzle *(World Bank 2018) introduced the World Bank's multidimensional poverty measure to account for certain nonmonetary dimensions of well-being such as access to education and to core services like electricity and sanitation. This chapter updates that measure with the latest available data, reviews historical changes, and uses it as a lens through which to explore the nonmonetary consequences of the pandemic period.*

The chapter then focuses on three dimensions severely affected by the pandemic: excess mortality, monetary poverty, and learning loss. For comparability, all three dimensions are expressed in terms of years of human life: excess mortality—loss of years of life; income loss—additional years spent in poverty over the 2020–21 period; and school closures—permanent learning losses that, if unaddressed, will reduce future earnings and prolong years spent in poverty.

From this analysis emerge two insights. First, losses of well-being from nonmonetary impacts—mortality and learning loss—are heterogeneous across countries but substantial. In fact, the analysis suggests that, for a range of valuations for years of life lost and years of life spent in poverty, the well-being losses from nonmonetary impacts could exceed the well-being losses solely from the current increases in monetary poverty in most countries. Second, the well-being losses are generally smallest on average for high-income countries and largest on average for middle-income countries.

Overall, this chapter confirms that monitoring well-being is a broader undertaking than monitoring monetary poverty alone. Moreover, the pandemic has brought to light potential trade-offs across dimensions of well-being that should be taken into account when calibrating policies. In particular, addressing recent learning loss is likely a key need for many countries, perhaps as important as protecting the poor and vulnerable from the income losses associated with the pandemic.

Chapter 3 online annexes available at http://hdl.handle.net/10986/37739:
3A. Estimating Multidimensional Poverty, circa 2018; **3B.** The Pandemic Shock through the Lens of the MPM: The Poverty-Adjusted Life Expectancy Measure; and **3C.** A Disaggregated Analysis of the Pandemic Shock.

Introduction

Although the extent and severity of the steep economic costs imposed on the world economy by the COVID-19 crisis have varied widely on the basis of local circumstances and local policy responses, nearly all countries across all income levels have felt these impacts. Many have yet to show signs of a significant recovery more than two years into the pandemic. However, because of the unique nature of the pandemic and the global response, including the adoption of social distancing measures, income losses are far from the only losses confronting policy makers in the recovery period.

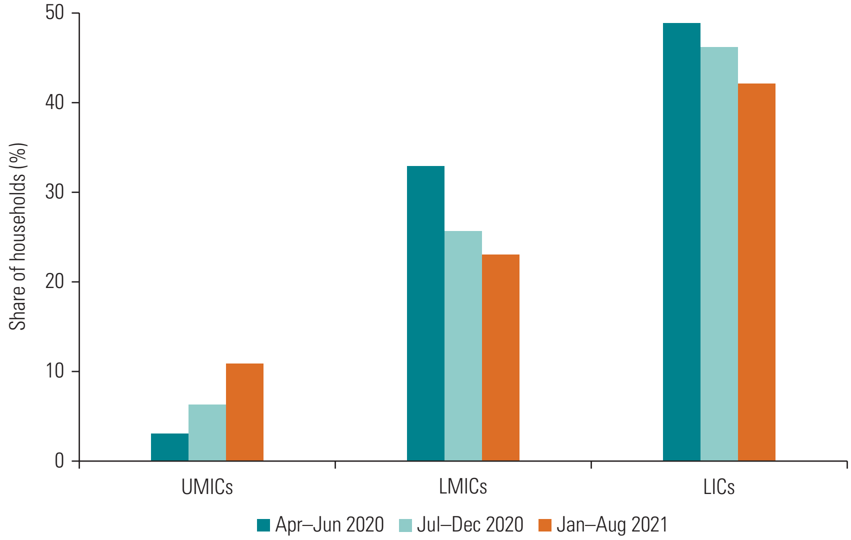
A variety of dimensions of human well-being have suffered since March 2020, perhaps none more than life itself. The impact of COVID-19 on excess mortality—mortality above what would be expected on the basis of prepandemic projections—has been so severe that global life expectancy declined for the first time since 1950, the first year for which the United Nations provided a global estimate (Heuveline 2022). The World Health Organization (WHO) estimates that approximately 14.9 million excess deaths occurred between January 1, 2020, and December 31, 2021. This excess mortality captures deaths directly from infection as well as from the widespread indirect impacts on society and health systems, including those from overburdened health systems unable to provide life-saving and life-extending care for other health conditions (WHO 2022a). For example, one analysis of dialysis patients in Rajasthan, India, revealed that, following a month of lockdown, mortality in May 2020 was 64 percent higher than in March 2020 (Jain and Dupas 2022). While this example provides evidence for just one type of health service interruption for a highly-vulnerable group, more generally, pandemic-related health service disruptions in 2020 were estimated to increase child and maternal mortality in 18 countries by 3.6 percent and 1.5 percent, respectively (Ahmed et al., 2022).

The health service disruptions widely documented worldwide have affected not only excess mortality but also many areas of health-related well-being. Essential health services in a large number of countries have experienced comprehensive and sustained disruptions during the pandemic. According to surveys by WHO, use of health services was disrupted in nearly all countries from May 2020 through November 2021. Disruptions in potentially life-saving emergency care and routine child immunizations were increasing toward the end of this period, suggesting that the duration and extent of the health impacts have not yet been fully captured. The predominant reasons reported for overall disruptions in each country were a roughly even mix of declines in spending, intentional service reductions, and fewer individuals seeking care (WHO 2022b). A review of several studies that focused on January–May 2020 found a 37 percent reduction in the use of health care services across 20 economies (Moynihan et al. 2021). Another review of studies investigating use of maternal and child health services in eight Sub-Saharan African countries found disruptions in all assessed countries between March and July 2020, especially in critical services such as child vaccination and antenatal care (Shapira et al. 2021).

School closures, one of the social distancing measures enacted in many countries to limit transmission of the virus, will likely have severe ramifications for the future human capital of current school-age children if not addressed by remedial policy. Two years into the pandemic, empirical studies have begun to document widespread instances of learning loss and dropouts. The magnitude of the documented learning loss, highly variable and at times lower than earlier predictions, is consistently concentrated among the poorest students, regardless of country income level (Moscoviz and Evans 2022). Estimates based on data from the World Bank's high-frequency phone surveys (HFPS) found that the average percentage of students who had stopped learning since school closures in low- and lower-middle-income countries (LICs and LMICs) was highest at the peak of the pandemic, in April–June 2020, and remained elevated, while declining, through August 2021 (figure 3.1). Learning interruptions in upper-middle-income countries (UMICs) over the same period were lower but also increased

FIGURE 3.1

Widespread learning losses were reported, especially among low-income countries during the COVID-19 crisis



Source: Original estimates based on data from World Bank COVID-19 high-frequency phone surveys.
Note: The figure shows the share of households with children who attended primary or secondary school before the COVID-19 crisis in each income category and calendar period that report children stopped learning during the crisis. To account for the fact that the sample of economies with observations changes for each period, the numbers presented are the predicted values from a regression with time dummies and economy-fixed effects (taking the average of the economy-fixed effects for each income category within each period). The sample includes 29 economies. Economies are weighted equally. LICs = low-income countries; LMICs = lower-middle-income countries; UMICs = upper-middle-income countries.

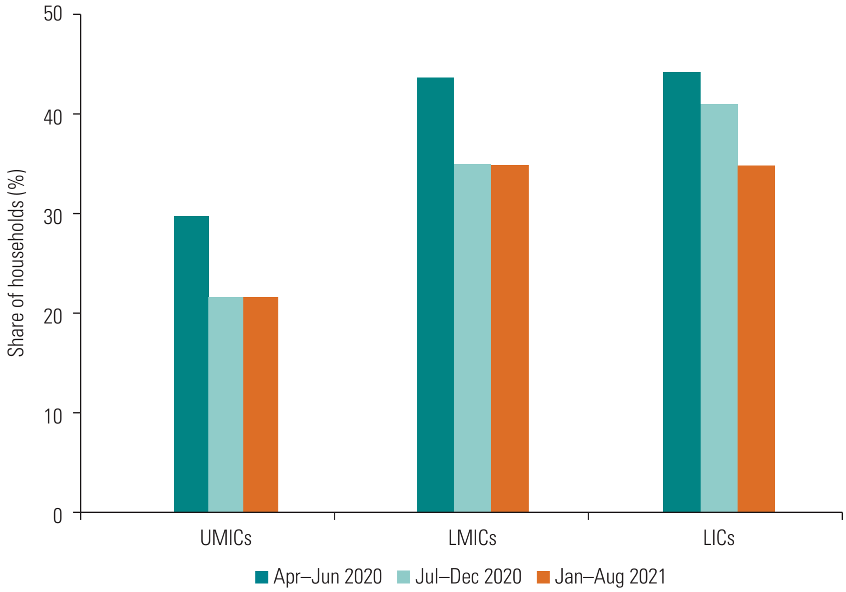
rather than decreased over time. Averaging across a range of countries reveals what seems to be a one-to-one correspondence between the duration of school closure and a measure of learning loss—that is, for every month of school closure there is a corresponding month lost in learning (World Bank 2022a).

The consequences of such learning loss, if unaddressed by public policy and the private efforts of families, are expected to be severe. Worldwide, school closures could result in an average lifetime reduction of 2–10 percent in annual expected earnings due to learning loss from a single missed academic year for those students affected. Globally, this earnings loss would equate to between US$10 trillion and US$21 trillion, depending on the extent of school closures and effectiveness of mitigation measures (Azevedo et al. 2021; Neidhöfer, Lustig, and Tommasi 2021; Psacharopoulos et al. 2021; Samaniego et al. 2022; World Bank 2022b). The most recent estimates predict losses even exceeding US$21 trillion—Samaniego et al. (2022) project a worst-case scenario of welfare declines due to learning loss equivalent to a one-time loss of 111 percent of current national income in high-income countries (HICs), 89 percent in middle-income countries, and 74 percent in LICs.

Another important dimension of well-being likely widely affected over the pandemic period is the food security of vulnerable households. Food security has been affected primarily by pandemic-induced loss of employment and income, as well as reduced mobility (mandatory or voluntary) and reduced food availability due to multiple supply constraints (Éliás and Jámbor 2021; Picchioni, Goulao, and Roberfroid 2021). Data from the World Bank's HFPS show that the average estimated percentage of adults who skipped one

FIGURE 3.2

Meals skipped were highest at the start of the COVID-19 crisis and in lower-income countries



Source: Original estimates based on data from World Bank COVID-19 high-frequency phone surveys.
Note: The figure shows the share of households in each income category and calendar period in which adults skipped a meal in the past 30 days. To account for the fact that the sample of economies with observations changes for each period, the numbers presented are the predicted values from a regression with time dummies and economy-fixed effects (taking the average of the economy-fixed effects for each income category within each period). The sample includes 29 economies. Economies are weighted equally. LICs = low-income countries; LMICs = lower-middle-income countries; UMICs = upper-middle-income countries.

meal in the past 30 days was highest across all country income levels at the peak of the pandemic (figure 3.2). HFPS data also show that households with children have fared worse by some measures of income loss and food insecurity. After controlling for proxies of welfare such as education level and location, 5–7 percent more households with children reported total income loss, and 4 percent reported an adult member who had gone a day without eating because of resource constraints (World Bank and UNICEF 2022). It is possible that more recent data may also indicate challenges with food security after the worldwide rise in food prices that began in March 2022. In addition to the higher risks posed for food intake and nutritional status, increases in intimate partner violence were documented in several countries in the early months of the COVID-19 crisis amid movement restrictions, reduced social support, increased tension, and other risk factors (De Paz Nieves, Gaddis, and Muller 2021; Lausi et al. 2021).

Multidimensional poverty on the eve of the pandemic

Multidimensional poverty outstripped monetary poverty

The recognition that monetary welfare measures are able to capture only a subset of well-being dimensions has spurred a wide body of research on multidimensional poverty measures (Alkire et al. 2015; Bourguignon and Chakravarty 1999). In 2018, the World Bank published its first estimates of a multidimensional poverty measure (MPM), grounded in the notion that a comprehensive view of well-being, even one centered on consumption like the World Bank measure, should include nonmarket goods measured consistently for the same unit of analysis (that is, the household) and in a wide range of countries. The first MPM figures were presented in *Poverty and Shared Prosperity 2018* (World Bank 2018), and subsequent reports update the MPM.

The World Bank's MPM expands the definition of poverty beyond monetary deprivation to include five indicators of well-being under two additional dimensions: access to education and access to basic infrastructure. These indicators are used to produce a household-level multidimensional headcount ratio. The MPM is produced with data (primarily) from the harmonized household surveys in the Global Monitoring Database.[1] A household is considered to be multidimensionally poor if it is below the extreme poverty line or if it cumulates too many deprivations in education and basic infrastructure. For education, the two deprivation indicators are whether a child is not enrolled in school and whether no adult in the household has completed a primary education. For basic infrastructure, the three deprivation indicators are no access to electricity, no access to limited-standard drinking water, and no access to limited-standard sanitation. The methodology for constructing the MPM was documented in detail in the 2018 and 2020 *Poverty and Shared Prosperity* reports (World Bank 2018, 2020) and is summarized in online annex 3A.

As noted, the MPM provides insight into the extent of poverty not captured solely by standalone monetary measures. Table 3.1 summarizes the global and regional multidimensional poverty headcount ratios for 2018, the most recent year there is total population data coverage of at least 50 percent. However, as indicated in the table, the East Asia and Pacific and South Asia regions do not reach the 50 percent threshold.

Worldwide, the 2018 multidimensional poverty headcount ratio was 14.7 percent, which is a 65 percent increase over the monetary poverty measure of 8.9 percent. By comparing the monetary poverty dimension with indicators from other dimensions, it is possible to form a picture of how many multidimensionally poor are not captured by monetary poverty, as well as which indicator deprivations most affect well-being in the different regions. Indeed, almost four out of 10 (39 percent) multidimensionally poor persons are not captured by monetary poverty because they are deprived in nonmonetary dimensions alone. Figure 3.3 depicts the extent of the overlap in deprivation across the three dimensions for the world circa 2018 among those who are multidimesionally poor. Almost one out of three (28 percent) is deprived in all three dimensions.

In terms of deprivations in individual indicators, the most prevalent is clearly sanitation, with 22.8 percent of the covered population living with less than adequate sanitation. After sanitation, the most prevalent deprivations occur with adult educational attainment (12.9 percent) and access to electricity (12.7 percent). Consistent with the observations from previous *Poverty and Shared Prosperit*y reports (World Bank 2018, 2020), multidimensional poverty in 2018 was concentrated in Sub-Saharan Africa and South Asia. In Sub-Saharan Africa, just over half of all households experienced multidimensional poverty. Sub-Saharan Africa and South Asia have, respectively, the highest and second-highest percentage of population experiencing each of the individual deprivations, except for drinking water. For this indicator, the East Asia and Pacific region has the second-worst performance (although this regional comparison may be complicated by the relatively low population coverage of the East Asia and Pacific and South Asia regions).

TABLE 3.1

Deprivations in education and infrastructure raise the multidimensional poverty measure above monetary poverty

	Deprivation rate (% of population)								
Region	**Monetary**	**Educational attainment**	**Educational enrollment**	**Electricity**	**Sanitation**	**Drinking water**	**Multidimensional poverty headcount ratio (%)**	**Number of economies**	**Population coverage (%)[a]**
East Asia and Pacific	3.8	8.7	1.7	6.6	15.9	8.2	6.0	14	30
Europe and Central Asia	0.3	0.9	2.2	1.7	7.1	4.5	2.1	25	89
Latin America and the Caribbean	3.8	9.4	1.6	1.0	16.6	2.9	4.6	14	87
Middle East and North Africa	1.7	8.6	2.8	0.5	3.1	1.4	2.4	5	51
South Asia	8.2	20.5	19.1	14.8	35.5	5.3	17.4	5	22
Sub-Saharan Africa	32.4	35.7	23.0	48.7	65.1	28.9	52.6	35	73
Rest of the world	0.7	1.0	2.2	0.0	0.2	0.5	1.4	25	78
All regions	**8.9**	**12.9**	**9.7**	**12.7**	**22.8**	**10.1**	**14.7**	**123**	**51[b]**

Source: World Bank, Global Monitoring Database.

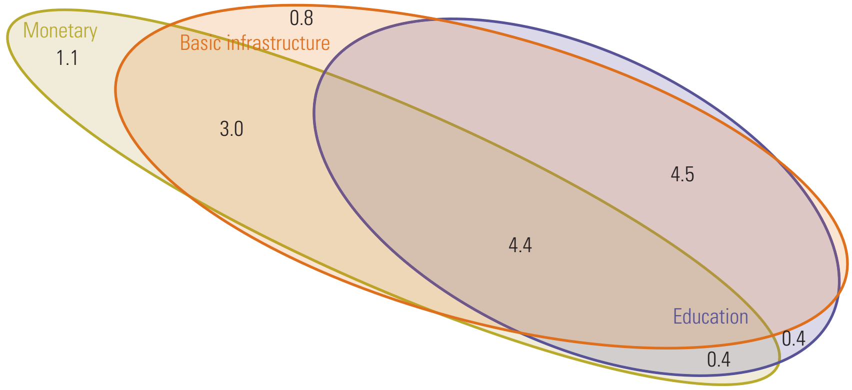
Note: The table presents the multidimensional poverty headcount ratio and share of population deprived in each indicator by region and rest of the world circa 2018. “Multidimensional poverty headcount ratio” is the share of the population in each region defined as multidimensionally poor. “Number of economies” is the number of economies in each region for which information is available in the window between 2015 and 2019 for a circa 2018 reporting year. The monetary headcount is based on the international poverty line. Regional and total estimates are population-weighted averages of survey year estimates for 123 economies and are not comparable with those presented in the previous section. The coverage rule applied to the estimates is identical to that used in the rest of the chapter. Details can be found in online annex 3A. Regions without sufficient population coverage are highlighted in purple.

a. Data coverage differs across regions. The data cover as much as 89 percent of the population of Latin America and the Caribbean and as little as 22 percent of the population of South Asia. The coverage for South Asia is low because no household surveys are available for India between 2014 and 2021. Regional coverage is calculated using the same rules as in the rest of this chapter (see online annex 3A). Thus, because of the absence of data on China and India, coverage of the East Asia and Pacific and South Asia regions is insufficient.

b. The table conforms to both coverage criteria for global poverty reporting. Both the global population coverage and the coverage for low-income and lower-middle-income countries are 51 percent.

FIGURE 3.3

Almost 40 percent of the multidimensionally poor are not monetarily poor



Source: World Bank estimates based on data from World Bank, Global Monitoring Database.

Note: The figure shows the share of population that is multidimensionally poor and the dimensions in which they are deprived. For example, the numbers in the yellow oval add up to 8.9 percent, which is the monetary headcount. Adding up all numbers in the figure results in 14.7 percent, which is the proportion of people who are multidimensionally deprived. Estimates are based on harmonized household surveys in 123 economies, circa 2018.

Before the pandemic, declining trends in multidimensional poverty mirrored declines in monetary poverty

The significant progress in poverty reduction achieved before the onset of COVID-19 applies to nonmonetary dimensions as well. Table 3.2 summarizes the MPM from 2015 to 2018. In parallel with the declines in monetary poverty, the MPM and each individual indicator displayed strong declines at the global level. The overall multidimensional poverty headcount ratio fell 2.9 percentage points from 2015 to 2018, while the monetary poverty figure linked to the same countries fell 2.3 percentage points. Progress was observed in each of the individual dimensions as well. For example, the rate of deprivation in sanitation fell from 25.5 percent to 22.8 percent.

One interpretive difficulty with table 3.2 is that the underlying composition of economies was not constant over the four-year period. For example, the share of the global population covered declined from 57 percent to 51 percent. Therefore, some of the improvements in poverty and multidimensional well-being may be attributable to the changing composition of economies. However, when the analysis is restricted to a smaller set of seven countries in Latin America and the Caribbean that contribute regular and complete data to the estimation of multidimensional poverty, the declining trends in all assessed dimensions remain. Table 3.3 depicts the MPM and the incidence of each indicator as measured annually from 2012 to 2019 for these seven Latin American countries. The monetary poverty rate declined from 5.7 percent to 3.5 percent, while the MPM poverty rate declined from 7.8 percent to 4.6 percent. Gains in other dimensions include a reduction in the proportion of the population deprived of electricity from 4.5 percent to 2.2 percent and the proportion deprived of adequate access to water, falling from 7.9 percent to 4.2 percent.

Finally, in the years before the COVID-19 crisis hit, the world benefited not only from sustained reductions in monetary poverty but also from gains in access to key goods not typically provided through market purchase such as primary education and sanitation services.

TABLE 3.2

Multidimensional poverty declined in recent years, along with monetary poverty

Reporting year	Deprivation rate (% of population)						Multidimensional poverty headcount ratio (%)	Population coverage (%)
	Monetary	Educational attainment	Educational enrollment	Electricity	Sanitation	Drinking water		
2015	11.2	13.8	10.3	14.3	25.5	13.1	17.6	57
2016	9.7	13.4	10.5	12.6	24.2	11.5	15.9	56
2017	9.6	13.5	10.4	12.9	24.5	11.0	16.0	54[a]
2018	8.9	12.9	9.7	12.7	22.8	10.1	14.7	51

Source: World Bank, Global Monitoring Database.
Note: The table depicts the global multidimensional poverty headcount ratio and share of population deprived in each indicator, circa 2015–18. The monetary headcount is based on the international poverty line. Estimates are population-weighted averages of survey year estimates for 140 economies for 2015, 138 for 2016, 134 for 2017, and 123 for 2018. Estimates are not comparable with those presented in previous sections due to changes in underlying composition. The multidimensional poverty headcount ratio indicates the share of the population in each region defined as multidimensionally poor. The coverage rule applied to the estimates is identical to that used in the rest of the chapter. Details can be found in online annex 3A.
a. The table conforms with the coverage criteria for global poverty reporting. For reporting year 2017, the global population coverage is 54 percent. In low- and lower-middle-income countries, it is 55 percent. For other reporting years, the coverage figure shown is the same for both populations.

TABLE 3.3

Declines across all dimensions of the multidimensional poverty measure are apparent even when restricting comparison to a consistent set of economies over time

Reporting year	Deprivation rate (% of population)						Multidimensional poverty headcount ratio (%)
	Monetary	Educational attainment	Educational enrollment	Electricity	Sanitation	Drinking water	
2012	5.7	8.5	2.7	4.5	12.5	7.9	7.8
2013	4.9	8.0	2.3	4.0	11.8	7.4	6.8
2014	4.4	7.8	2.4	3.6	12.2	6.4	6.1
2015	4.2	7.3	2.2	3.1	11.1	6.4	5.7
2016	4.2	7.2	2.0	2.8	10.0	5.7	5.7
2017	3.7	7.0	2.1	2.6	10.2	4.3	5.1
2018	3.4	6.9	2.0	2.4	9.3	4.5	4.8
2019	3.5	6.3	2.4	2.2	8.9	4.2	4.6

Source: World Bank, Global Monitoring Database.
Note: The table presents estimates of the multidimensional poverty headcount ratio and share of population deprived in each indicator for Bolivia, Colombia, Costa Rica, the Dominican Republic, Ecuador, Paraguay, and Peru. Estimates are population-weighted averages of survey year estimates and are reported from circa 2012 through circa 2019 for these countries because they have data available for the entire time window. Estimates are not comparable with regional estimates for Latin America and the Caribbean in previous tables that cover 14 economies. The monetary headcount is based on the international poverty line. The multidimensional poverty headcount ratio indicates the share of the population in each region defined as multidimensionally poor. The coverage rule applied to the estimates is identical to that used in the rest of the chapter. Details can be found in online annex 3A.

Pandemic impacts from a multidimensional perspective

Multidimensional impacts indicate long-term consequences

The pandemic has had substantial impacts on poverty and inequality and, as reviewed at the outset of this chapter, on many nonmonetary dimensions of well-being. This section explores the wider range of pandemic impacts and how these losses relate to declines in the more familiar monetary poverty measures. The exercise focuses on two key nonmonetary dimensions: mortality and education. For mortality, every region of the world has suffered elevated death rates during periods of peak COVID-19 transmission. As for education, the closure of schools is a severe challenge to the human capital investments in today's school-age children—a challenge that may have long-lived consequences if the human capital scarring is not remediated.

Although all countries have suffered losses of life, income, and human capital, outcomes of the pandemic have been quite heterogeneous. For example, some countries have suffered high mortality and education losses, but they have been able to limit the impacts of monetary poverty by enacting social protection policies. Other countries have seen limited increases in mortality but have recorded significant monetary poverty or education losses.

Any attempts to compare the well-being impacts of premature mortality, income loss, and learning loss must come with caveats. First, the data available since the outset of the pandemic on these three dimensions are still scarce in many countries. Often, national estimates are derived from research papers that provide estimates in the absence of underlying data. Therefore, the reported impact estimates may capture the order of magnitude of the impact in these three dimensions but may not define precise levels of impact. To mitigate this issue, whenever possible the analysis makes conservative assumptions that often understate the total impact. Second, many important impacts, especially in the health dimension such as quality of life reductions associated with long COVID-19, are not considered. For the purposes of this exercise, COVID-19 affects health only through mortality. Likewise, the analysis considers only the incidence of poverty and thus ignores the depth of poverty. Third, there is considerable uncertainty around the implications of learning loss for future poverty. This uncertainty is due to various reasons, including whether learning loss may be compounded when the affected young cohorts enter the labor market, or whether the losses may instead be alleviated over time with concerted private actions and public policies. The analysis simply extends the given estimated losses into the future, without assuming any mitigation through public or private efforts.

It is possible to aggregate losses across these three dimensions using several different approaches. One approach adopts the framework of the MPM, which already records monetary poverty and education, and combines it with a life expectancy measure, reflecting mortality impacts to generate a poverty-adjusted life expectancy, or PALE (see box 3.1). However, the main analysis in this section adopts a straightforward disaggregated years-of-life framework that

BOX 3.1

Poverty-adjusted life expectancy: An index aggregating poverty and mortality

Mortality and poverty are arguably the two major sources of well-being losses at the global level. Poverty reduces the quality of life, while mortality reduces the quantity of life. However, mortality is often not addressed by most measures of well-being. It must be treated in a unique way because of its exclusive nature: one cannot be dead and simultaneously deprived in other dimensions. As shown by Baland, Cassan, and Decerf (2022), a lifecycle perspective provides the justification for aggregating mortality and poverty through the poverty-adjusted life expectancy (PALE) indicator. When considering multidimensional poverty, PALE is defined as

$$\text{PALE} = LE\,(1 - \theta * MPM),$$

where LE is life expectancy at birth; MPM is the multidimensional poverty headcount ratio (numerous definitions of poverty can be used, but this example adopts the MPM); and the normative parameter θ (between 0 and 1) captures the fraction of period utility lost when multidimensionally poor. At one extreme, when $\theta = 0$—that is, when spending one year in multidimensional poverty is considered the same as spending that year out of multidimensional poverty—PALE corresponds to life expectancy at birth. At the other extreme, when $\theta = 1$—that is,

(continued)

BOX 3.1

Poverty-adjusted life expectancy: An index aggregating poverty and mortality *(continued)*

when spending one year in multidimensional poverty is considered the same as losing one year from premature death—PALE can be interpreted as the number of years that a newborn expects to live free from multidimensional poverty *if she were confronted throughout her lifetime with the mortality and MPM poverty observed during the birth year*. For this latter extreme, PALE thus corresponds to the poverty-free life expectancy index initially proposed by Riumallo-Herl, Canning, and Salomon (2018).

Henceforth, it is assumed that $\theta = 1$, a conservative assumption that ascribes a rather small relative weight to mortality. Analyzing the data in this manner is not to normatively equate a year lived in poverty with a year of life lost. Both are distinct and significant forms of deprivation. Rather, it provides a lower bound on the relative weight of premature mortality, which is rooted in the assumption that, if given the choice, people would choose an additional year of life in multidimensional poverty to the loss of a year of life to early mortality. Indeed, $1/\theta$ can alternatively be interpreted as the number of additional years one would be willing to spend in multidimensional poverty to gain one year of life.

PALE provides a lens through which one can analyze some of the main well-being losses of the COVID-19 pandemic. Indeed, excess mortality is captured through its impact on life expectancy, while income losses and school closures are captured through their impact on the MPM. An approach based on the MPM provides the same global standard of deprivation cutoffs and dimensional weights for all countries when aggregating dimensions.

Conducting this analysis requires simulating the changes to the MPM because very few countries already provide postoutbreak MPM data. For each country in the data, the impact of the pandemic on PALE is defined as the difference between a baseline prepandemic value and a pandemic value. The baseline value is computed from the most recent MPM data available for the country, along with the more recent estimate of prepandemic life expectancy at birth. The pandemic value is then simulated off this baseline value on the basis of several assumptions described in online annex 3B.

The baseline value of PALE is plotted against gross domestic product (GDP) per capita in figure B3.1.1. Countries with larger GDP per capita have larger PALE values for two reasons. First, they have higher life expectancy at birth. Second, and more important, they have much less multidimensional poverty. The austere deprivation standards embedded in the MPM frequently bind in a lower-income country, but almost no one is multidimensionally poor in high-income countries.

For two reasons, the absolute reduction of PALE in low- and lower-middle-income countries (LICs and LMICs) over the pandemic period is larger than that in upper-middle or high-income countries (UMICs or HICs), despite starting from a lower baseline PALE estimate. First, the extreme poverty shock is, as expected, larger in LICs and LMICs than in UMICs and HICs. Second, and more important, school closures have a much larger impact on the MPM rate in LICs and LMICs than in UMICs and HICs. This could appear to be surprising because school closures were not shorter in UMICs and HICs than in LICs and LMICs. However, the education shock alone is not sufficient for households to be considered multidimensionally poor when they have no other deprivations. Because of the austere deprivation cutoffs used by the MPM, the vast majority of households in HICs and UMICs face no deprivation and thus would not be rendered multidimensionally poor by school closures alone. By contrast, the large impact of the education shock on the MPM in LICs and LMICs reflects the fact that many households living in these countries already face deprivations in other dimensions; therefore, many of them are pushed into multidimensional poverty when they become also deprived in school enrollment.

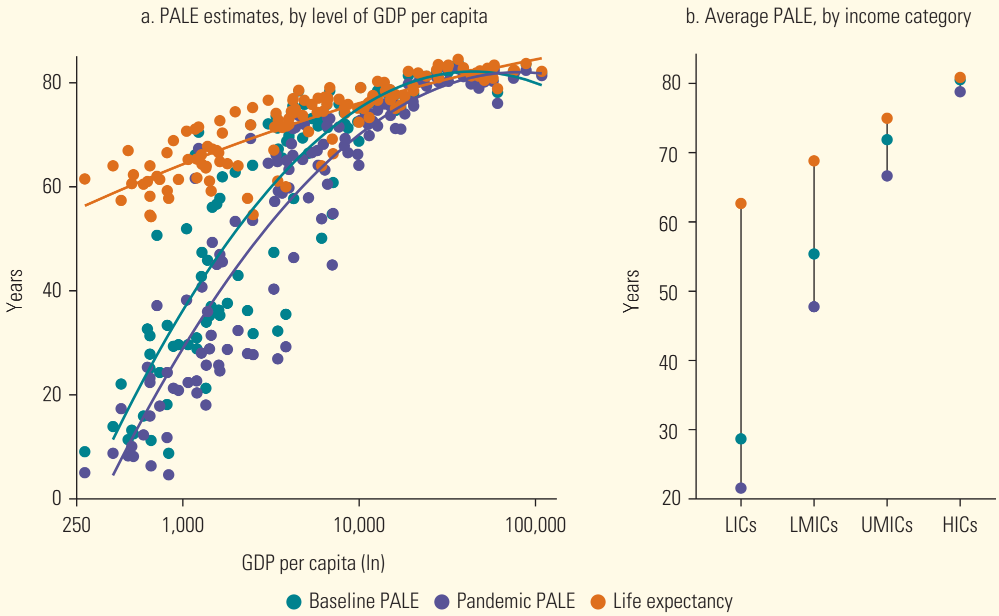
(continued)

BOX 3.1

Poverty-adjusted life expectancy: An index aggregating poverty and mortality *(continued)*

FIGURE B3.1.1

Lower-income economies have experienced larger reductions in poverty-adjusted life expectancy



Sources: Original estimates based on multidimensional poverty measure data from World Bank, Global Monitoring Database; mortality data from Heuveline 2022.

Note: Panel a shows the number of years, in each economy, of life expectancy, baseline poverty-adjusted life expectancy (PALE) using prepandemic data, and pandemic PALE using assumptions in online annex 3B. Economies are sorted by GDP per capita on the horizontal axis using a logarithmic scale. The relationship between each measure and log GDP per capita is shown using a quadratic line of best fit. Panel b shows the same metrics aggregated by income category using a simple average (not weighted by population). GDP per capita is for 2019 expressed in 2015 constant US dollars. GDP = gross domestic product; HICs = high-income countries; LICs = low-income countries; LMICs = lower-middle-income countries; ln = logarithm; UMICs = upper-middle-income countries.

Finally, the results suggest that the main drivers of the decline in PALE vary across country income groups. Figure B3.1.2 depicts the fraction of the total reduction in PALE that can be attributed to each dimension, as determined by a Shapley decomposition (see online annex 3B). The rise in mortality risk had the largest impact on PALE in higher-income countries, whereas the restrictions in access to education have the greatest influence on the declines in PALE in lower-income countries. This figure further highlights that the rise in monetary poverty was the least influential of the three factors modeled in determining the sharp declines in PALE.

There are many possible approaches to the aggregation of pandemic impacts across disparate dimensions, and all require interpretation of some normative framework. PALE is one such example grounded in the World Bank's MPM that suggests the largest impacts are experienced by the poorest economies, driven primarily by widespread school closures as well as by elevated mortality and increases in poverty.

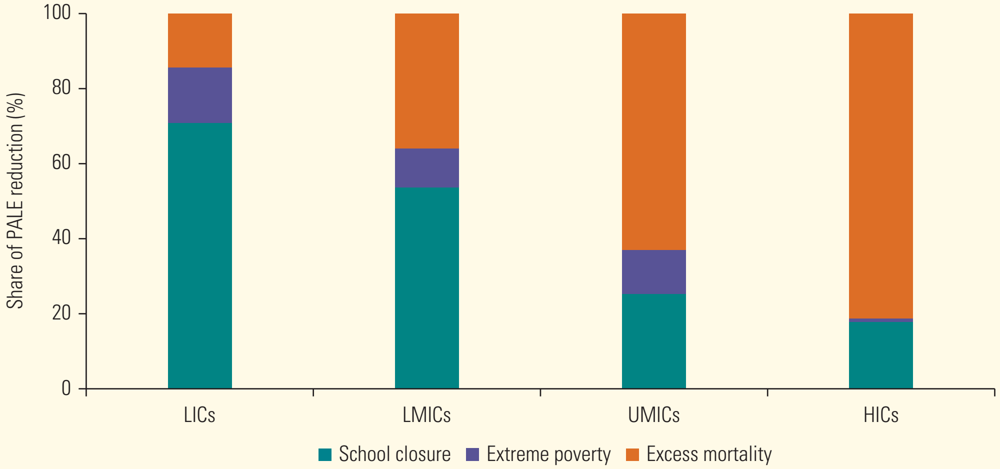
(continued)

BOX 3.1

Poverty-adjusted life expectancy: An index aggregating poverty and mortality *(continued)*

FIGURE B3.1.2

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



Sources: Original estimates based on multidimensional poverty measure data from World Bank, Global Monitoring Database; mortality data from Heuveline 2022.

Note: The figure shows the share of reduction in poverty-adjusted life expectancy (PALE) in each income category attributable to excess mortality, additional extreme poverty, and school closure, using an average Shapley decomposition. PALE reduction is a simple average of economies in each income category and is not weighted by population. PALE reduction represents the peak value of each shock occurring between 2020 and 2021. HICs = high-income countries; LICs = low-income countries; LMICs = lower-middle-income countries; UMICs = upper-middle-income countries.

allows a policy maker to consider a range of values when assessing the relative importance of the declines in each of these three dimensions.

In the flexible disaggregated years-of-life framework used for the analysis in the remainder of this section, loss estimates in each of the three dimensions—mortality, income, and learning—are measured using the same unit: years of human life. Premature mortality is captured through an estimated number of years of life lost for each individual, depending on the age at death, and these individual-level figures are then aggregated across a population. The immediate monetary impacts lead to additional years of life spent in monetary poverty due to the increase in poverty incidence. Learning losses can also generate additional years of life spent in monetary poverty; however, in contrast to the immediate impacts on poverty, these additional years are realized in the future, stemming from lower productivity and lower long-run growth.

The conceptual foundation for this analysis and the main assumptions sustaining its estimates are presented in box 3.2 (with further explication and estimation details explained in online annex 3C). The goal of the analysis is to compare, at the country level, the magnitudes of the well-being losses generated by the pandemic through its impacts occurring *over the period 2020–21* on excess mortality, monetary poverty, and school closures. Because these impacts materialize over different dimensions of well-being, such a comparison requires the analyst to express these impacts in comparable units—years of life. The years of life spent below the monetary poverty line as a result of the pandemic-induced economic contraction during 2020–21

BOX 3.2

Lifecycle foundations for multidimensional comparisons in terms of years of life

Comparing the size of well-being losses on the basis of three dimensions (excess mortality, monetary poverty, and school closures) requires expressing them in the same units. The analysis considers an extension of the framework of Decerf et al. (2021), which is grounded in a simplified version of lifecycle utility, with period consumption levels reduced to only two states: being poor monetarily or not. The pandemic is assumed to reduce an individual's lifecycle utility in three ways:

- *Mortality.* The excess mortality estimated over the period 2020–21 may have prematurely cost the life of an individual who otherwise would have lived for a certain number of additional years.
- *Current poverty.* The economic recession may have pushed a nonpoor individual into monetary poverty in either 2020 or 2021, or both.
- *Future poverty (school closures).* The school closures over 2020–21 may depress future incomes in such a way that the individual is pushed into poverty for several years (over the period 2020–50, corresponding to the working life of the affected student cohort), whereas this person would not have been poor in the absence of the pandemic.

Under these assumptions, the total well-being losses (*WL*) over the whole population deriving from the mortality, poverty, and learning detriments observed up to December 2021 are proportional to a weighted sum of years of life either prematurely lost to excess mortality or spent in poverty. In more formal terms,

$$WL = CPY + \alpha\, YLL + FPY,$$

where *CPY* is the number of additional (current) poverty years spent in 2020 and 2021; *YLL* is the number of years of life lost due to excess mortality in 2020 and 2021; *FPY* is the number of additional (future) poverty years due to school closures in 2020 and 2021, whose scarring effects will materialize over the period 2020–50; and α is a normative parameter that expresses the relative weight of mortality in relation to poverty. The parameter α captures how many poverty years generate an equivalent well-being loss as one lost year of life.

The number of current poverty years (*CPY*) begins with the observation that one additional year spent in poverty constitutes one poverty year. The additional years in poverty are obtained following the information in chapter 1 based on the societal poverty line anchored to its 2019 value. The increase in the fraction of poor is the difference between the nowcasted poverty headcount and the counterfactual poverty headcount based on prepandemic growth rates. *CPY* is the sum of the additional number of people who were poor in 2020 and 2021.

The number of years of life lost (*YLL*) derives from estimates of the number of excess deaths in a country over the period 2020–21 (Wang et al. 2022). The number of years of life lost due to a COVID-19–related death corresponds to a country's residual life expectancy at the age at which the excess death takes place. Because data on the age distribution of excess deaths are not available in most countries, the analysis assumes that the age distribution of excess deaths from all causes corresponds to the age distribution of excess deaths arising from COVID-19. This assumption likely underestimates the number of years lost because COVID-19 mortality mostly affects older persons.

The number of future poverty years (*FPY*) is based on a simulation of the future earning losses caused by learning losses due to school closures observed up to November 2021, using projected declines in national income from a long-term growth model (Loayza et al. 2022; Loayza and Pennings, forthcoming). School closures can lead to widespread learning losses that, in turn, reduce the stock of human capital—a key factor in long-term economic growth—and thus lower national income in the future. The counterfactual growth projections of learning losses are applied to distribution-neutral poverty forecasts, and then the difference between the fraction of poor on

(continued)

BOX 3.2

Lifecycle foundations for multidimensional comparisons in terms of years of life *(continued)*

a baseline growth path (without learning loss) and on a learning loss scenario path is determined. The change in the number of future poverty years is the sum of the additional number of poor individuals over all the years in the period 2020–50.

Estimates of a country's learning loss are derived from data on the duration of its school closure, the quality of its schooling system, and findings from World Bank (2022a) that estimate, on average, a one-to-one correspondence between the duration of school closure and the extent of learning loss. Because of the complexity of long-term growth simulations, the analysis focuses on 61 economies that represent a range of regions and national income levels. Decerf et al. (forthcoming) provide more details on this approach.

Beyond the length of school closures, the size of the economic growth impacts in each country in the long-term growth model simulations depend on several parameters. The first is the quality of education: other things being equal, a year of school closure has less effect on human capital formation and economic growth in countries with poor-quality schools. On average, one year of schooling closure becomes two-thirds of learning-adjusted years of schooling lost (estimates of prepandemic school quality are taken from Kraay 2018). The second parameter is the size of the affected school-age cohorts in school in 2020–21 relative to the size of the working-age population in the future. By 2050, this ratio is about one-third, although it varies across countries and accumulates at different rates over time. As for the third parameter, the effects on growth depend on the return to years of learning-adjusted schooling, which are assumed to be 12 percent (and so the return to a year of raw schooling is 8 percent). In a typical country, the effect on the gross domestic product per capita in the *very* long run is the product of four numbers—school closure length × education quality adjustment × returns to quality-adjusted attainment × relative size of affected cohort—though by 2050 it is only 70 percent as large because of partial adjustment of the physical capital stock.

These estimates of *FPY* are conservative for two reasons. First, the analysis assumes that the future income of all students is affected to the same degree, even though disadvantaged individuals may have suffered heavier learning losses (Bundervoet, Davalos, and Garcia 2022). This finding suggests that future income of the poor and near-poor should be more than proportionally affected, pointing toward larger future impacts on poverty. Second, some alternative projections of the economic consequences of school closures typically yield larger losses in part because of the inclusion of losses in work experience, which are not addressed here (Samaniego et al. 2022).

directly capture this dimension. By contrast, the years of life associated with excess mortality and school closures capture the subsequent *consequences* of the impact of the pandemic on these dimensions. These consequences occur mainly in the future. For example, the consequence of the premature pandemic-induced death of a 60-year-old individual in 2020 is that she will lose the 15 years of her residual life expectancy over the period 2020–35. Similarly, even though the connection is less deterministic, the consequence of the learning loss a student experiences because of school closures in 2020–21 is that the student may spend additional years in poverty over the next decades. The objective of this analysis is not to investigate the impacts of the pandemic over different time horizons, but merely to compare the impacts (on three dimensions) that occurred over the period 2020–21 by expressing them in comparable units, even though some detriments may not appear until the future.[2]

Because the analysis presents the estimated impact on each dimension either through a number of years of life lost or through a number of additional years lived under the poverty line, this approach remains agnostic to the relative weight afforded to poverty years and years of life lost. It therefore allows policy makers to set their own weights and determine which dimension of loss is most consequential for well-being.

The approach here also enables policy makers to consider the total well-being loss that the pandemic generated from March 2020 to December 2021. The well-being loss is also a country-specific measure. When dealing with the pandemic, governments typically do not calibrate their responses as a function of a global standard such as the MPM. Instead, they make trade-offs between the dimensions (mortality, poverty, and education) in accordance with country-specific standards. For this reason, the analysis moves beyond the MPM and the international poverty line and adopts a country-specific absolute poverty line—the societal poverty line. The societal poverty line, anchored to its 2019 level, is closer in value to each country's national poverty line.

As for education detriments, the learning loss from school closures, if not addressed, will result in future losses in well-being when learning losses translate into reduced earnings during the working life of the affected student cohorts. Thus the weight that a government attributes to school closures depends on the size of the cumulated future earning losses, which, in turn, depend on the characteristics of a country's school system, the amount of schooling postponed over the pandemic period, and various characteristics of the economy today and in the future.

Summary of results

A comparison of the increase in years of poverty directly due to pandemic-related economic contraction and years of life lost can be obtained for 159 economies because more computationally intensive long-term growth projections are not needed for this comparison. Middle-income countries experience a higher current poverty shock than high-income ones, as shown in chapter 1, for at least two reasons: differences in the scope of social protection policies adopted in response to the pandemic outbreak and differences in initial poverty levels. HICs likely enacted stronger social protection measures in response to the pandemic, and they typically have a smaller proportion of their population near their societal poverty line. Poverty levels actually fell in some HICs, most likely the result of their social protection measures, which explains why the additional current poverty years are much smaller in HICs (see the third column of table 3.4). Middle-income countries also experienced a higher mortality shock. Interestingly, HICs did not suffer a more severe mortality shock than LICs, in spite of their older populations, who are more at risk for severe disease. Unequal vaccine rollouts and flatter COVID-19 age mortality curves in LICs are likely among the drivers of this pattern (Demombynes et al. 2021).

TABLE 3.4

Years lost to premature mortality exceed increase in years lived in poverty in about half of economies

Country income group	Coverage (number of economies)	Excess mortality (YLL, lost years per 100 persons)	Increase in current poverty years (CPY, years per 100 persons)	Fraction of economies for which CPY < YLL
Low-income	31	3.1	5.2	0.26
Lower-middle-income	33	4.6	5.4	0.42
Upper-middle-income	41	5.5	4.9	0.54
High-income	54	3.0	0.6	0.72
All economies	**159**	**4.0**	**3.6**	**0.52**

Sources: Original calculations based on poverty data from World Bank, Global Monitoring Database; excess mortality estimates from Wang et al. 2022; mortality estimates from Heuveline 2022.
Note: The table compares average excess mortality and increase in current poverty during 2020–21 by country income group for 159 economies. Average values for economies in the sample group are not weighted for population.

Fifty-two percent of countries experienced a greater number of years of life lost than an increase in years in poverty due to the current period shock, as shown in table 3.4. For these countries, if it is assumed that individuals would rather spend one year in poverty than lose this year of life to premature mortality, then this suggests that well-being losses from excess mortality may, in fact, dominate the well-being losses from additional poverty. Surprisingly, according to the estimates, 26 percent of LICs and 42 percent of LMICs suffer more lost years of life than an increase in poverty years. This finding applies to the majority of UMICs and HICs as well. These estimates stand in partial contrast with expectations early in the pandemic period that additional poverty would be a larger source of well-being losses than mortality, at least for 2020 (Decerf et al. 2021; Ferreira et al. 2021).

The analysis that combines information on life years lost and current poverty change with future poverty impacts associated with learning losses focuses on 61 economies. These simulations suggest that the reduction in the year-to-year economic growth due to school closure-related learning losses is small, leading typically to a reduction of 1–3 percent of gross domestic product (GDP) per capita in 2050. These results are largely consistent with those of other studies that project the economic consequences of learning loss (Psacharopoulos et al. 2021; Samaniego et al. 2022). However, this relatively small reduction still leads to a substantial number of future poverty years because the learning losses in 2020 and 2021 will carry a legacy over several decades. The long-term growth model exercise estimates an average cumulative GDP loss over the period 2020–50 of 53 percent of the 2020 GDP per capita.[3] The growth rates produced by the long-term growth model simulations produce a range of future poverty years across countries because of variations in the duration of school closures, the quality of learning in that country, and characteristics of the national economies. For example, resource-rich countries depend less on human capital for growth and thus their future growth is less affected by learning losses.

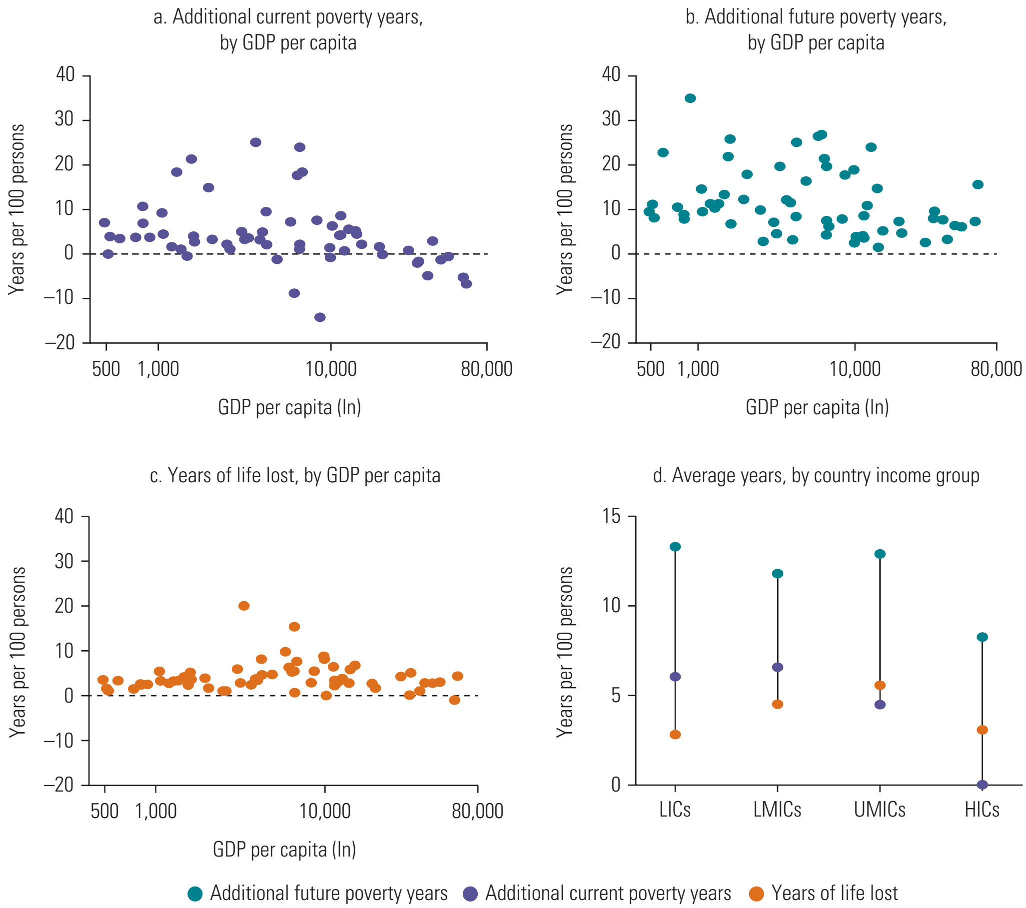
For the 61 economies in the simulations, all three sources of well-being losses are quite substantial. The average citizen of these countries (unweighted by population) will experience 15 lost days per person due to premature mortality, an additional 15 days of current poverty per person, and 42 additional future poverty days per person.[4] Figure 3.4 plots the three well-being loss measures in number of years per 100 persons for each economy. This figure captures the variation in the impacts of the three sources, and it suggests that countries experienced the pandemic period up to the end of 2021 very differently, in part because of the national policies they adopted.

Table 3.5 summarizes the magnitude of loss for each dimension by country income group. The summary indicates that, for a wide range of countries and a wide range of valuation of relative loss, the cumulative losses from premature mortality and learning deficits often exceed the immediate impacts of an increase in monetary poverty. According to the simulations, 80 percent of countries will experience greater total years of future poverty due to learning loss than current poverty years: 83 percent of LICs, 75 percent of LMICs, 72 percent of UMICs, and 93 percent of HICs. But interpretations of these findings should be made with care. Even though the future increase in total years in poverty due to the learning loss may be greater than the immediate increase due to the current poverty shock, the future increase is spread over a 30-year period, whereas the immediate increase spans only a two-year period. Therefore, the income losses in 2020–21 may still represent a shock deeper in severity than the future increase in poverty, even if the current increase in poverty appears lower in this exercise.

The fraction of countries that have more years of life lost to premature mortality than years spent in current poverty is 51 percent. Most of the countries in this category are HICs (80 percent) and UMICs (56 percent), whereas LICs account for 17 percent and LMICs for 44 percent. In many countries, both mortality and school closures may yield larger well-being losses than current poverty, even with conservative relative valuations of premature mortality.

FIGURE 3.4

The pandemic's impact on well-being through additional current and future poverty and excess mortality varies substantially across economies



Sources: Original estimates based on poverty data from World Bank, Global Monitoring Database; excess mortality data from Wang et al. 2022; mortality data from Heuveline 2022.

Note: The figure shows the number of years per 100 persons, in each economy, of additional current poverty (panel a), additional future poverty due to school closures (panel b), and life lost due to excess mortality (panel c). Economies are sorted by GDP per capita on the horizontal axis using a logarithmic scale. Panel d shows the same metrics aggregated by income category using a simple average (not weighted by population). Each measure is calculated as the peak value occurring between 2020 and 2021, and the poverty line used is the societal poverty line anchored to its 2019 level. GDP per capita is for 2019 expressed in 2015 constant US dollars. GDP = gross domestic product; HICs = high-income countries; LICs = low-income countries; LMICs = lower-middle-income countries; ln = logarithm; UMICs = upper-middle-income countries.

These documented pandemic impacts across the dimensions of premature mortality, monetary poverty, and learning loss underscore the importance of monitoring well-being in a broader fashion than monitoring monetary poverty alone. The relative magnitude of losses across these dimensions and how these magnitudes vary by country highlight the potential trade-offs that policies aimed at addressing the impacts of the pandemic face. Remediating the recent learning losses is likely a key need for many countries, perhaps as important as the need to protect the poor and vulnerable from the income losses of this recent period. One important way to address these losses is through fiscal policy. Part 2 of this report turns to the role fiscal policy can play in promoting an inclusive and effective recovery.

TABLE 3.5

Years lost to premature mortality and the increase in years of future poverty exceed the increase in years of current poverty in most economies

Country income group	Excess mortality (YLL, years per 100 persons)	Current poverty (CPY, years per 100 persons)	Future poverty (FPY, years per 100 persons)	Fraction of economies for which largest additional well-being loss may not be due to current poverty		
				YLL > CPY	FPY > CPY	YLL > CPY and/or FPY > CPY
Low-income	2.8	6.1	13.3	0.17	0.83	0.83
Lower-middle-income	4.5	6.6	11.8	0.44	0.75	0.75
Upper-middle-income	5.6	4.5	12.9	0.56	0.72	0.78
High-income	3.1	0.0	8.3	0.80	0.93	1.00
All economies	**4.1**	**4.2**	**11.5**	**0.51**	**0.80**	**0.84**

Sources: Original calculations based on poverty data from the World Bank's Global Monitoring Database; excess mortality estimates from Wang et al. 2022; mortality estimates from Heuveline 2022.
Note: The table compares well-being losses due to excess mortality, current poverty, and future poverty (school closures) during the COVID-19 pandemic (2020–21), by country income group. Current poverty captures the increase in years spent in societal poverty over the period 2020–21. Future poverty captures the impact that the school closures over the period 2020–21 are estimated to have on years spent in societal poverty over 2020–50. In both cases, the societal poverty threshold is fixed at its 2019 value. Average values for "all economies" are not weighted for population. CPY is number of additional (current) poverty years spent in 2020 and 2021; FPY is number of additional (future) poverty years due to school closures in 2020 and 2021; YLL is number of years of life lost due to excess mortality in 2020 and 2021.

Notes

1. The Global Monitoring Database (GMD) is the World Bank's repository of multitopic income and expenditure household surveys used to monitor global poverty and shared prosperity. The household survey data are typically collected by national statistical offices in each country, and then compiled, processed, and harmonized. The process is coordinated by the Data for Goals (D4G) team and supported by the six regional statistics teams in the Poverty and Equity Global Practice. The Development Data Group contributes historical data (before the 1990s) and recent survey data from the Luxembourg Income Study (LIS) Database. Selected variables have been harmonized to the extent possible so that levels and trends in poverty and other key sociodemographic attributes can be reasonably compared across and within countries over time. The GMD's harmonized microdata are used in the global poverty measures reported in the World Bank's Poverty and Inequality Platform, the World Bank's multidimensional poverty measure, and the Global Database of Shared Prosperity. As of June 2022, the GMD contained more than 2,000 household surveys conducted in 170 economies. For a few economies, the welfare aggregate of the GMD spans up to 40 years, from 1971 to 2021, whereas for most other economies coverage is significantly less.
2. This exercise compares current monetary loss with future losses due to current nonmonetary impacts on learning and mortality. Although the conclusion of chapter 1 suggests that the direct poverty implications of the pandemic period will extend beyond 2021, this exercise looks just at the immediate effects on poverty in relation to the long-run effects of learning loss and premature mortality. It ignores the possibly longer-lived consequences of the immediate poverty increase on future poverty levels.
3. See table 3C.1 in online annex 3C for a list of economies included in this analysis.
4. When weighted by population, the average citizen of these countries will experience an additional 19 days of current poverty, 11 lost days due to premature mortality, and 37 additional future poverty days. These global numbers are heavily driven by the simulations for China and India, in which China has almost no reported excess mortality and India has a very large estimated increase in current poverty.

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