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Lives, Livelihoods, and Learning

A Global Perspective on the Well-Being Impacts of the COVID-19 Pandemic

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Abstract

This study compares the magnitude of national level losses that the COVID-19 pandemic inflicted across three critical dimensions: loss of life, loss of income, and loss of learning. The well-being consequences of excess mortality are expressed in years of life lost, while those of income losses and school closures are expressed in additional years spent in poverty (as measured by national poverty lines), either currently or in the future. While 2020–21 witnessed a global drop in life expectancy and the largest one-year increase in global poverty in many decades, widespread school closures may cause almost twice as large an increase in future poverty. The estimates of well-being loss for the average global citizen include a loss of almost three weeks of life (19 days), an additional two and half weeks spent in poverty in 2020 and 2021 (17 days), and the possibility of an additional month of life in poverty in the future due to school closures (31 days). Well-being losses are not equitably distributed across countries. The typical high-income country suffered more total years of life lost than additional years in poverty, while the opposite holds for the typical low- or middle-income country. Aggregating total losses requires the valuation of a year of life lost vis-à-vis an additional year spent in poverty. If a year of life lost is valued at five or fewer additional years spent in poverty, low-income countries suffered greater total well-being loss than high-income countries. For a wide range of valuations, the greatest well-being losses fell on upper-middle-income countries and countries in the Latin America region. This set of countries suffered the largest mortality costs as well as large losses in learning and sharp increases in poverty.

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Lives, Livelihoods, and Learning: A Global Perspective on the Well-Being Impacts of the COVID-19 Pandemic[1]

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1. Introduction

The COVID-19 pandemic caused not only dramatic increases in mortality in the two years following the disease's emergence, but also severe declines in income and significant interruptions in student learning. Virtually all countries suffered losses in these dimensions, albeit to varying degrees determined in part by initial country conditions, post-outbreak policy choices, and the behavioral responses to such policies. A potential trade-off between lives and livelihoods was recognized early in the pandemic period as various papers investigated the economic consequences of COVID-19 control policies (Loayza and Pennings 2020; Decerf et al. 2021; Ma et al. 2022, Feindouno et al. 2023). This paper measures, through a unified framework, the global distribution of net impacts induced by the pandemic on both lives and current and future livelihoods.

The analysis focuses on the magnitudes of well-being loss generated by the pandemic in the first two calendar years of its emergence, 2020 and 2021. A total of 122 countries, covering roughly 95% of global population in 2019, are included in this analysis.[3] Well-being loss is assessed across the three dimensions of excess mortality, monetary poverty, and school closures. Such a comparison requires the measurement of costs in a common denominator – in this analysis, this denominator is years of human life. As the pandemic induced a global economic contraction during 2020–2021, the increase in the total number of years of life spent below the monetary poverty line in 2020 and 2021 directly captures this dimension. In contrast, the years of life lost from excess mortality or additional years spent in poverty due to school closures mostly take place in the future even though the cause of these losses arose in the initial outbreak period.[4]

Three insights emerge from this analysis. First, the well-being losses in each dimension are substantive from a global perspective as well as, typically, the national perspective. Second, the impact of learning loss on future poverty is likely to exceed the contemporaneous losses from the increase in monetary poverty during the pandemic – three-quarters of countries are expected to have an increase in (discounted) future poverty years greater than current poverty years and the future poverty impact is almost twice as large in magnitude as the contemporaneous poverty impact. Third, countries at different income levels had radically different profiles of well-being loss. The poverty impacts were greatest for lower income countries while, conversely, mortality impacts were greater among higher income countries. Total well-being losses are generally smallest on average in high-income countries and largest on average for low- and, especially, middle-income countries.[5]

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[3] Included countries have population greater than 2.5 million and data on poverty, mortality, and school closures.

[4] For example, the consequence of the premature death of a 60-year-old individual in 2020 in a given country is that she will lose the 18 years of her residual life expectancy over the period 2020 and beyond (assuming the conditional life expectancy of a 60-year-old individual in that country is 78). Similarly, even though the connection is less deterministic, the consequence of the learning loss a student experiences due to school closures in 2020–21 is that the student may spend additional years in poverty over the next decades because of lower aggregate growth.

[5] This conclusion depends on the normative weight (known as α) assigned to excess mortality vis-à-vis additional years spent in poverty. At sufficiently high values of α the total well-being losses in high-income countries surpass those in low-income countries, as greater excess deaths occurred in those countries.

2. Methodology

A unified analytic framework for cross-dimensional comparison

We adopt a sparse version of lifecycle utility that simplifies levels of annual consumption to two states: monetarily poor or not (see Baland et al. (2021) and Decerf et al. (2021) for more discussion of this utilitarian analytic framework). Given this framework, the pandemic is assumed to reduce an individual's lifecycle utility in three ways:

• Years of Life Lost (*YLL*). The excess mortality estimated over the period 2020–21 will have shortened the life of an individual who otherwise would have lived for a number of additional years.

• Current Poverty Years (*CPY*). The induced economic recession may have pushed a nonpoor individual into monetary poverty for the years 2020 or 2021, or both.

• Future Poverty Years (*FPY*). The school closures over 2020–21 lowered the stock of human capital, at least initially, and may depress future incomes thereby pushing more individuals into poverty. The total period considered for these future poverty spells spans 2020–2100, which covers the full working life of the affected student cohort and then subsequent cohorts that may enter a labor force already impacted by lower aggregate growth. *FPY* represents the discounted sum of additional (future) poverty years over 2020–2100 due to school closures in 2020 and 2021.[6]

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

$$WL = YLL + \frac{CPY + FPY}{\alpha}$$

where α is a normative parameter that captures how many poverty years generate an equivalent well-being loss as one lost year of life. α is generally assumed to have a minimum value of 1 as this presumably represents a lower bound for almost all normative choices of α (i.e. a value of 1 equates the well-being loss of a year in poverty to that of a year of life lost). Our approach remains agnostic to the relative weight afforded to poverty years and years of life lost and will present results for a range of α values.

For the poverty measures, Current Poverty Years (*CPY*) and Future Poverty Years (*FPY*s), we adopt the societal poverty line (SPL) of Jolliffe and Prydz (2021) held fixed at its 2019 level (i.e. an anchored-SPL).[7] The SPL is a relative poverty line whose country-specific value depends on the country's median income. We define poverty with the SPL rather than with an international standard such as the international absolute poverty line of US$2.15/day. This choice reflects that governments likely used *country-specific* preferences and references to arbitrate any implicit trade-offs between the ills of mortality, poverty, and learning loss arising from pandemic-related policies.

[6] We apply a discount factor of 3% when computing *FPY*. This is the value used in Azevedo et al. (2021) and Psacharopoulos et al. (2021) and a standard value in the analysis of health interventions (recommended, for example, by the Panels on Cost-Effectiveness in Health and Medicine (Sanders et al., 2016)).

[7] The societal poverty line for a given country is defined as max($2.15, $1.15 + 0.5 x median income) per capita per day in 2017 PPPs (Jolliffe et al. 2022).

Following Mahler et al. (2022), we calculate the SPL for each country in 2019 and use this threshold, held fixed in 2019, to calculate poverty in the subsequent years. In this sense, the anchored-SPL is a country-specific absolute poverty line. The societal poverty line is generally close in value to each country's national poverty line and therefore an appropriate benchmark to measure national poverty. An added benefit of the SPL is that it uses a consistent definition across all countries compared to national poverty lines which have varying definitions specific to each country.

Excess mortality and years of life lost

The impact of COVID-19 on mortality has been so severe that global life expectancy declined for the first time since at least 1950 (Heuveline 2022) and the World Health Organization (WHO) estimates that approximately 14.9 million excess deaths occurred between January 1, 2020, and December 31, 2021 (WHO 2022a). Excess mortality estimates are widely viewed as a more complete measure of pandemic mortality impacts than nationally certified COVID-19 deaths due to incomplete national death registers in many countries (Msemburi et al. 2023). Furthermore, and relevant to the inquiry here, excess mortality is due not only to the direct mortality effects of COVID-19 infection but also the net effect of disruptions in the availability of medical care and care-seeking behaviors as well as declines in real income.[8]

To estimate the total years of life lost (*YLL*) due to the excess mortality witnessed over the 2020-21 period we first take the WHO estimates of excess deaths in each country, disaggregated by age, over the period 2020–21 (WHO 2022b). The number of years of life lost from an excess death will depend on a country's residual life expectancy at the age at which the excess death takes place. We use pre-pandemic reported life expectancies, conditional on surviving age, from the 2017 Global Burden of Disease Study (Dicker et al. 2018).[9]

The increase in poverty over 2020-2021

We adopt poverty estimates for 2020 from Mahler et al. (2022), updated using fall 2023 data in the Poverty and Inequality Platform, who employ various data sources and methods to estimate poverty globally in 2020. For 2021, we utilize the poverty nowcasting methodology described by the World Bank (2022). In short, this approach takes the prior year's income or consumption distribution and adjusts this distribution forward using distribution-neutral growth from national account sources.[10] In our case, we use the welfare distribution for 2020 from Mahler et al (2022) and project them forward to 2021 using

[8] While income declines were substantial (World Bank, 2022a), health service disruptions were also widespread and largely due to a combination of declines in spending, intentional service reductions, and fewer individuals seeking care (WHO 2022b). One review found a 37 percent reduction in the use of health care services across 20 economies over the initial pandemic period of January–May 2020 (Moynihan et al. 2021). Another, focused on maternal and child health services in eight Sub-Saharan African countries, reports 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). Disruptions such as these may have increased the young child mortality rates in 2020 and 2021 by as much as 3.5% (Ahmed et al. 2022).

[9] Both the excess death information and the conditional life expectancies are not reported from single years of ages but rather age ranges. We standardize the age ranges across the two sources and then assume that the age at which the excess death occurs takes place in the mid-point of the given range. The reconciled age ranges are the following: 0-24, 25-39, 40-49, 50-59, 60-69, 70-79, and 80+. For practical purposes, we assume the maximum lifespan to be 94, i.e. the conditional life expectancy for an individual 95 years and over is negligible.

[10] See the Mahler, Castaneda Aguilar, Newhouse (2022) for details on the nowcasting methodology used by the World Bank.

the per capita GDP growth rate from the World Bank's World Development Indicators. We calculate poverty in each country for 2021 using these welfare distributions along with the anchored-SPL.

To isolate the impact of the COVID-19 pandemic on poverty, we estimate counterfactual income or consumption distributions for each country in 2020 and 2021. These distributions are projected forward using the 2019 distribution from World Bank's Poverty and Inequality Platform and the per capita GDP growth rates forecasted prior to the pandemic (World Bank, 2020). Poverty for both years is calculated using the same anchored-SPL threshold define above. The counterfactual poverty rates give us a baseline of poverty levels had there been no COVID-19 pandemic and are used to estimate the "excess" poverty due to the pandemic.

The estimate of *CPY* – the additional number of people living in poverty each year – is the difference between the country specific number of poor estimated for 2020 and 2021 and the number of poor using the counterfactual distribution.

Future poverty from learning losses

School closures, one of the primary social distancing policies enacted in many countries to limit COVID-19 transmission, can severely impact the future human capital of current school-age children. Various studies have estimated the aggregate income loss from reduced future earnings (if such learning loss is not remediated). Globally, estimates of the present value of future earning losses would range between US$10 trillion (Azevedo et al. 2021 and Psacharopoulos et al. 2021) and US$21 trillion (Schady et al. 2023), depending on the effectiveness of mitigation measures. More recently, Jedwab et al. (2023) project a welfare loss equivalent to a one-off loss of 63, 55, and 36 percent of the annual income in high-, middle-, and low-income countries, respectively.[11] Overall, this amounts to US$50 trillion.

Our alternative approach adopts a neoclassical growth model with a detailed treatment of human capital (the Long-Term Growth Model (LTGM) with the human capital extension (LTGM-HC)).[12] We apply the LTGM to evaluate the impact of school closures on future income levels *for each country in our sample* due to lowered human capital. The future income losses generated by the LTGM are then used to calculate the *FPY*. We summarize the methodology below.

Cross-country data from UNESCO records the length and intensity of school closures in 2020-2021.[13] We then convert the school closure durations into Learning-Adjusted Years of Schooling (LAYS) lost - a measure that takes into account the national average quality of schooling (Kraay 2018 and Filmer et al. 2020). Next, we calculate the impact of school closures on the average human capital of the workforce from 2020 to 2100 in the LTGM-HC by tracking the human capital of successive population cohorts.[14]

[11] To compare with Jedwab et al (2023), our estimates of future GDP losses would be equivalent to a one-off loss of 28, 45, 54 and 46 percent of the 2020 GDP in high, upper-middle, lower-middle, and low-income countries, respectively.

[12] For more details about the LTGM, see Loayza and Pennings (2022) or visit https://www.worldbank.org/LTGM.

[13] The UNESCO data records for each day of 2020 and 2021 whether schools are fully closed, partially closed, or open.

[14] For example, consider a one-year loss of formal schooling for the 15–19-year-olds in 2020-2021. Adjusting for the (median) quality of education, the cohort losses are 2/3 of one LAYS, leading to an 8% fall in the cohort's future productivity – based on international empirical evidence of an 8% return to raw years of schooling, the LTGM-HC

We then estimate future GDP per capita growth under the pre-pandemic baseline trend and the scenario with school closures from the pandemic. As a neoclassical growth model, GDP in the LTGM is calculated using a standard Cobb-Douglas production function of human and physical capital, labor, and total factor productivity. In the short term, the effect of a fall in human capital growth on GDP growth is given by the labor share ($\beta < 1$). In the long term, induced changes to physical capital accumulation leads to a larger effect of human capital on GDP growth, an effect which is subsequently proportional.[15] Appendix 1 discusses the assumptions taken to calibrate the LTGM to each country, including the length of school closures and the quality of education, as well as further details of the model.

The LTGM-simulated paths for GDP per capita growth under both the pre-pandemic baseline (without school closures) and school closure scenario are then applied in a distributionally neutral fashion to the pre-pandemic (2019) national income distributions and with the fixed 2019 poverty lines. The additional number of poor individuals in each year in 2020-2100 is derived as the difference between the numbers of poor individuals obtained for the school closure scenario and the baseline. Finally, these forecasted poverty estimates for years 2020-2100 are discounted to the present using the discount factor of 3%. These estimates of future poverty due to learning loss may be conservative as they assume that the future income of all students is affected proportionately even though in reality disadvantaged individuals may have suffered heavier learning losses (Agostinelli et al., 2022; Bundervoet, Davalos, and Garcia, 2022; Moscoviz and Evans, 2022). Of course, this projected future increase in poverty may be averted through remedial public and private actions.

3. Results

Well-being loss by dimension.

Figure 1 presents in a flexible manner the bivariate relationship between well-being loss in each of the three dimensions at the national level and 2019 per-capita national income (at the start of the pandemic). Table 1 then summarizes these estimates of well-being loss by country-income groups. Several patterns emerge, beginning with the observation that well-being losses accrued over 2020-2021 are substantial in all three dimensions. Overall, the estimates imply that an average person in the world (population weighted) lost almost 3 weeks of life (19 days), spent an additional two and half weeks in poverty in the years 2020 and 2021 (17 days), and faces the possibility of an additional month of future life in poverty due to school closures (31 days).

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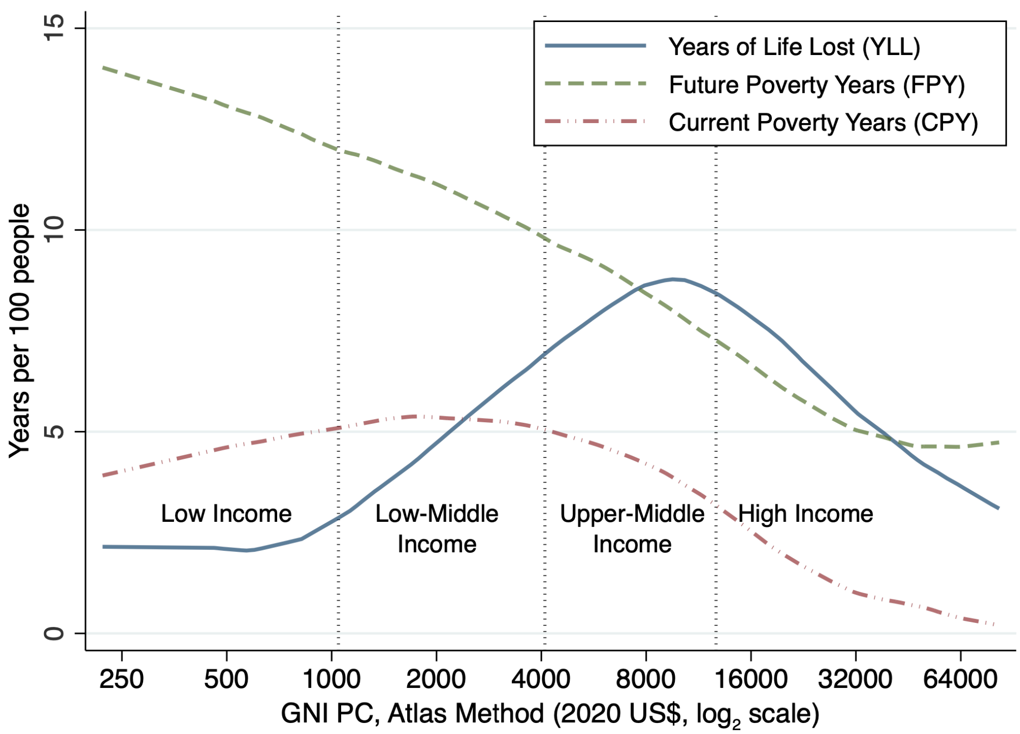
applies a 12% return to learning-adjusted years of schooling. The oldest cohort members enter the workforce immediately, leading to an instant reduction in human capital of the workforce. Human capital growth continues to be depressed until 2035, when the youngest cohort at school age during the pandemic enters the labor force.

[15] For natural-resource rich countries, we use the Natural Resource Extension of the LTGM, which decomposes the economy into resource and non-resource sectors. This allows us to account for heterogeneous β across sectors.

Figure 1. Welfare costs of the COVID-19 pandemic in 2020 and 2021, by national per capita income



Note: The curves for Years of Life Lost (*YLL*), Future Poverty Years (*FPY*), and Current Poverty Years (*CPY*) (in years per 100 people) are smoothed based on fitted values from separate locally weighted polynomial regressions. In each regression, the natural logarithm of GNI PC (2020 US$, Atlas Method) is the independent variable, while *YLL*, *FPY*, or *CPY* is the dependent variable. A bandwidth of 0.75 is used in all regressions.

In terms of well-being loss variation across national incomes, *YLL* tends to increase with national per capita income up to a point in the upper-middle income designation and then declines. *YLL* increasing with national income at the lower income range partly reflects the relatively younger populations in low- and lower-middle-income countries who are less at risk from severe COVID-19 infection. This is not the case for various upper-middle-income countries with particularly large *YLL* estimates as they combined a relatively older population with a relative lack of health system capacity to fully protect that population from COVID-19 risks as well as possibly delayed access to the initial COVID-19 vaccines.

The contemporaneous poverty shock, *CPY*, is relatively high for low- and lower-middle-income countries, then declines and even approaches 0 for the wealthiest countries. The fact that *CPY* declines with income is not a purely mechanical result as these poverty changes are based on country-specific poverty lines rather than a fixed international standard. Instead, this result at least partially reflects the greater ability of high-income countries to implement social policies to shield their populations from the income losses brought on by social distancing measures and any slowdown in economic activity.

Regarding *FPY*, low-income countries, whose school systems are typically of lower quality, experienced severe learning losses due to extended school closures. Their relatively young populations further imply that a large fraction of the total population was affected by these learning losses. The estimate of *FPY* declines monotonically with national income.

Table 1: Estimates of Years of Lives Lost (*YLL*), discounted Future Poverty Years (*FPY*), and Current Poverty Years (*CPY*) per 100 people by country income groups

	Not weighted by population			**Weighted by population**		
	Excess mortality	**School closures**	**Current poverty**	**Excess mortality**	**School closures**	**Current poverty**
	***YLL* per 100**	***FPY* per 100**	***CPY* per 100**	***YLL* per 100**	***FPY* per 100**	***CPY* per 100**
LICs	2.1	13.5	4.4	2.3	15.5	5.3
LMICs	3.4	10.4	6.3	5.8	8.7	9.4
UMICs	11.2	9.4	3.9	4.4	6.8	1.6
HICs	4.6	4.9	1.0	6.4	7.4	-1.2
World	5.3	9.0	3.7	5.1	8.4	4.7

Note: Income groups are classified according to World Bank FY23 income classification. Acronyms: LIC – low income country; LMIC – lower middle income country; UMIC – upper middle income country; HIC – high income country. FPY represents the sum of additional (future) poverty years over 2020–2100 due to school closures in 2020 and 2021, discounted at 3%.

From a global perspective, the wellbeing loss from school closures dominates the loss from *CPY* with the *FPY* estimate being about twice as large as *CPY*. This is also largely true within country income cateogries. The wellbeing loss from the *YLL* estimate also exceeds that from the *CPY* estimate for any calibration of the relative value of life relative to poverty that exceeds one (i.e. $\alpha \geq 1$) at the global level. This is not the case for lower- and lower-middle-income countries where higher valuations of α are necessary for the wellbeing loss from *YLL* to exceed that from *CPY*.

Finally, while the global averages do not appreciably change if we weight the cross-national average estimates by population, the relative size of each dimensional loss can shift within income categories when impacts are population weighted. In high-income countries, the US and other larger countries actually experienced declines in contemporaneous poverty, and hence a negative *CPY*, due to effective social protection policies. This lowers the high-income *CPY* estimate once weighted by population. China experienced very low excess mortality over 2020-2021 in part because of its restrictive zero-COVID-19 policy (only experiencing an increase in excess deaths in the second half of 2022, outside our sample, when some of these restrictions were relaxed), thereby appreciably lowering the *YLL* among upper-middle-income countries once weighted for population. India experienced one of the largest increases in current poverty and thus a population weighted lower-middle-income country estimate of *CPY* that is almost 50% higher relative to the unweighted estimate (World Bank, 2022).

Relative loss within countries.

We next contrast the relative sizes of the three types of well-being losses at the country level. The results are again presented by country-income groups in Table 2, which examines the proportion of countries where (a) the *YLL* estimate exceeds the *CPY* estimate, (b) the *YLL* exceeds the sum of *CPY* and *FPY*, and (c) the *FPY* estimate exceeds *CPY*. Regardless of national income level, it is clear that the long-term effect of school closures may have larger poverty consequences than the immediate poverty impacts due to social distancing (first column). For 78% of all countries, and no less than 68% in any income category, the *FPY* estimate is greater than *CPY*. This underscores the importance to mitigate learning losses associated with school closures in nearly every country.

Second, the relative importance of excess mortality in total well-being loss tends to increase with national income (second and third columns). This is true when either comparing excess mortality to current poverty or when comparing excess mortality to the sum of current and future poverty. Only 35 percent of low-income countries have a larger *YLL* than *CPY*, while 42 percent of high-income countries have a larger *YLL* than the sum of *CPY* and *FPY*. High-income countries were more successful at mitigating the possible poverty impact of the pandemic rather than its mortality impact. This is not the case for lower income countries with fewer available resources.

Table 2: Within-country comparison of *YLL*, *CPY* and *FPY*: proportion of countries, by country income group, where one dimension exceeds others

	Future vs Current poverty	Life Years lost vs additional poverty years	
	FPY>CPY	***YLL>CPY***	***YLL>CPY+FPY***
LICs	0.83	0.35	0.09
LMICs	0.73	0.30	0.12
UMICs	0.68	0.64	0.39
HICs	0.87	0.68	0.42
World	0.78	0.51	0.27

Note: The table reports unweighted proportions of countries where the inequality holds.

While Table 2 explores “how frequently” *YLL* estimates are larger than *CPY* (or *CPY+FPY*), Figure 2 quantifies the degree to which poverty impacts exceed or fall short of mortality costs. The figure plots for each country the ratio *CPY*/*YLL* (blue circles) as well as the ratio (*CPY+FPY*)/*YLL* (red crosses). These two ratios thus provide the number of additional poverty years estimated in the country for each year of life lost. These two ratios can be interpreted as a “break-even” α values, which is the value of the normative parameter α for which one would conclude that the well-being loss coming from the country’s years of life loss is exactly equal to the well-being loss coming from its additional poverty years. These break-even values can help the reader assess which channel leads to the larger wellbeing loss. If the reader’s preferred α value is larger than the break-even value, then the well-being loss from YLL is larger than the wellbeing loss from CPY (or from CPY+FPY).

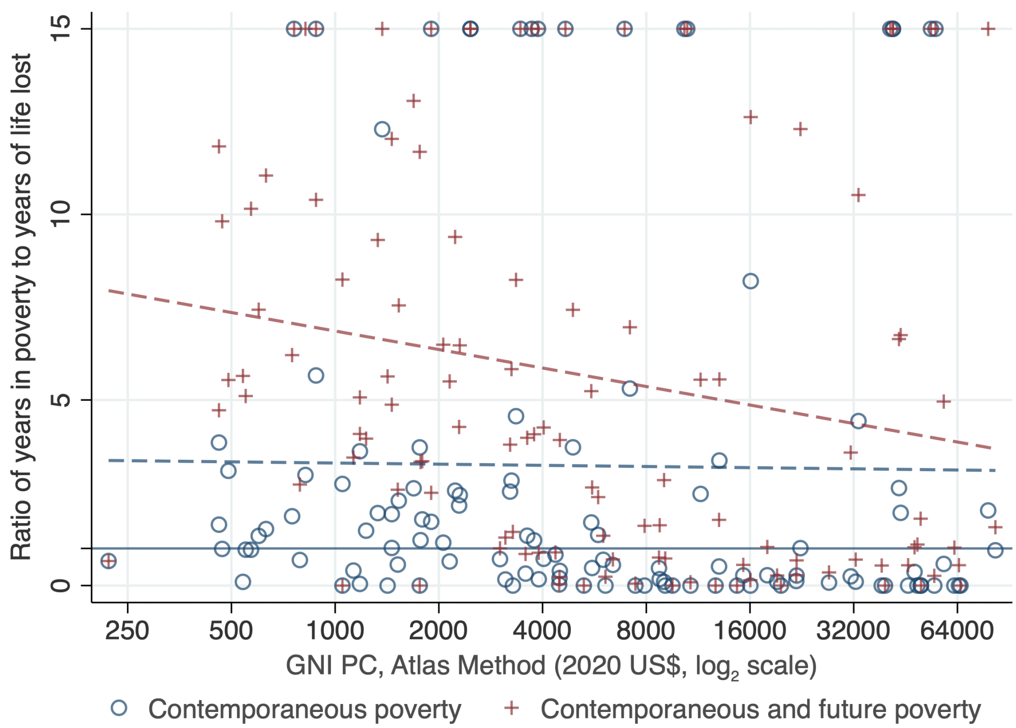
When considering the ratio *CPY*/*YLL*, the blue regression line suggests that the average break-even α value is fairly constant across the range of national income at an approximate value of three. The interpretation for this value is that *CPY* and *YLL* have on average generated equal well-being losses when assuming that three years lived in poverty generate the same ill-being as one year of life lost. If the preferred α value is larger than three, then the reader may conclude the well-being loss from YLL is on average larger than the wellbeing loss from CPY. [16]

The negative slope for the regression line that compares *YLL* with *CPY* and *FPY*, focusing on the red scatter plot, underscores that the relative burden of excess mortality increases with national income per capita. The higher GDP per capita the lower the break-even value for α. The fitted line suggests that one needs to consider approximately seven years lived in poverty (*CPY* + *FPY*) as the same well-being loss as one *YLL* to equalize well-being losses from the two sources in the average low-income country. In contrast, only four *CPY* equate with one *YLL* for the same conclusion in the average high-income country.

Note that many upper-middle and high-income countries are below the solid line that corresponds to a ratio of one. Any country whose ratio is below one experienced greater aggregate years of life lost than years in poverty and, as a result, experienced larger well-being losses from excess mortality than from poverty (as long as being dead is considered worse than being poor, i.e., $\alpha \geq 1$).

Figure 2. The mortality versus poverty trade-off as a function of per capita GDP – "break even value" that equates wellbeing loss from mortality with wellbeing loss from poverty

[16] Note that, for clarity, we top-code ratios to 15 for countries in which *YLL* from excess mortality is dwarfed by years of poverty (either *CPY* or *CPY+FPY*). We also bottom code this ratio to 0 for countries where years of poverty (*CPY*) are negative. This data truncation does not qualitatively affect the regression lines shown in the figure. In particular, top coding this ratio at a value higher than 15 does not substantively affect the slope estimates.



Note: Contemporaneous poverty ratio calculated as *CPY*/*YLL*, contemporaneous and future poverty ratio calculated as (*CPY*+*FPY*)/*YLL*. The blue and red dashed lines trace the trends predicted by linear regressions of each ratio against the logarithm base 2 of GNI PC with slopes of -0.03 and -0.5 respectively. The black (solid) corresponds to a ratio of 1. Ratios are capped at 15, and ratios with negative numerators and denominators were excluded. Ratios with a negative denominator and a positive numerator were set to 15. Ratios with a positive denominator but a negative numerator were set to 0.

Aggregation of well-being losses.

The analysis has so far investigated well-being loss in three separate dimensions. Any aggregation of these measures into a summary measure of loss not only depends on the number of years of life lost or spent in poverty, but also on the value selected for the normative parameter α (the number of poverty years that are equivalent to one life year lost).

Instead of positing an arbitrary value for this parameter, we will explore a range of plausible values. We have already posited a minimum α value of 1. For reasonable values greater than 1, one approach derives a calibrated value of the α parameter from a specified utility function, as in Baland et al (2023). This method, discussed in more detail in Appendix 2, generates country-specific values of α. The mean value of α over all countries in our sample is 4.02, which we round to 4 and take as one potential benchmark for α, however there is significant variation for α with generally larger values of α among higher-income countries.[17] The country specific α's range from approximately 1 to 10.

[17] One reason for these larger values is that poor individuals in higher-income countries have higher mean incomes than poor individuals in lower-income countries.

Turning now to the comparison of total well-being losses from all three dimensions, Table 3 presents total loss for a range of α values, including the value of 4 derived from the exercise above. The first three columns adopt a value for α that is common to all countries (1, 4, and 10). The last column considers the calibrated country-specific α presented in Appendix 2. Analysis of this sort enables a determination of whether the larger excess mortality in high-income than in low-income countries creates a greater toll for well-being than the larger poverty impacts (*CPY* and *FPY*) in low-income countries.

Table 3: Average total well-being loss by income group in life-year equivalent terms (not weighed by population)

	α = 1 (*YLL* per 100)	**α = 4 (*YLL* per 100)**	**α = 10 (*YLL* per 100)**	**country-specific α (*YLL* per 100)**
LICs	19.9	6.5	3.9	14.8
LMICs	20.1	7.6	5.0	11.0
UMICs	24.5	14.5	12.5	15.4
HICs	10.4	6.0	5.2	5.6
World	18.0	8.5	6.6	11.0

Note: Total well-being loss is measured as YLL+(CPY+FPY)/α. Country-specific **α** values are detailed in Appendix 2.

Regardless of the value assumed for α in Table 3, the typical upper-middle-income country experiences the largest total well-being losses – not unexpected as the average upper-middle-income country experiences among the greatest well-being losses from all three sources (Table 1). Even when considering country-specific values for α, which weigh poverty impacts less in upper-middle-income countries than in low-income countries, the total well-being losses in upper-middle-income countries are on average slightly larger than those in low-income countries. Furthermore, one would need to consider a global value for α of at least equal to 5 for high-income countries to experience larger total well-being losses than low-income countries. If we adopt country-specific α, then high-income countries suffered the smallest total well-being losses than other country income group.

Finally, we conduct the same analysis by regions of the world rather by country-income groups in Appendix Table 1. The results suggest wide variation across regions. Countries in Latin American and the Caribbean suffered particularly high well-being losses, greater than those found in all other regions ($\forall\alpha, 1 \leq \alpha \leq 10$). The average country in that region experienced large well-being losses from both *YLL* and *FPY*. These countries typically have a substantial share of older population cohorts combined with relatively limited resources to treat or prevent COVID-19 infection. Additionally, these countries also implemented longer school closures and could not uniformly enact sufficient social protection policies to shield their population from immediate income losses. The average country in the Eastern Europe and Central Asia region also experienced very high excess mortality losses. This is again the result of relatively elderly populations that could not be fully protected from COVID-19 risk. If we consider $\alpha > 11$, then this region experienced the largest total well-being loss in 2020 and 2021.

4. Conclusion

All countries suffered losses of life, income, and human capital due to COVID-19, although the impacts in each dimension varied substantially across countries. While some countries bore high mortality and education losses, they were able to limit the increases of monetary poverty through ambitious social protection policies. Other countries witnessed comparatively modest increases in mortality but recorded significant monetary poverty increases or education losses, while others suffered to a relatively high degree in all three dimensions.

For most countries, and across all levels of income, the immiserating effects of school closures over the pandemic period will exceed the rise in poverty experienced at the start of the pandemic (unless soon mitigated). For the poorest countries, the combined poverty costs of learning deficits and short-run income loss exceed the mortality costs except under a high valuation of the trade-off parameter α. For higher income countries, the mortality costs often exceed the income costs even at relatively low values of α.

When combining all dimensions, upper-middle-income countries suffered the greatest aggregate loss as these countries bore some of the highest mortality impacts as well as experienced significant income and learning losses. The relative detriment for these countries is clear regardless of the choice of α. Looking across regions, it is countries in Latin America and Eastern Europe and Central Asia that bore the greatest loss again due to some of the highest mortality impacts combined, in the case of Latin America, with steep income and learning losses.

Of course, an exercise of this nature must come with caveats. Many important aspects of well-being are not considered, such as income losses for households well above the poverty line or the quality-of-life reductions for individuals suffering from “long COVID”. Likewise, the analysis considers only the incidence of poverty and not the depth of poverty. Importantly, there is unavoidable uncertainty around the implications of learning loss for future poverty, including whether the documented losses may instead be alleviated over time through a combination of private actions and public policies and the degree to which there are intergenerational implications of learning loss (Neidhofer et al., 2021; Jang and Yum, forthcoming).

We used “years of life” as common denominator to express well-being losses coming from mortality and reduced income (current and future). An alternative common denominator would be “currency units”, using the Value of Statistical Life approach (VSL) to express excess mortality in currency units. Neither years of life nor currency units provide an unambiguously better lens than the other. The currency units approach faces limitations including that many people find offensive the mere idea of placing a “price” on a human life. Further, the VSL typically attributes smaller monetary values to human life in lower income countries than in higher income countries (Kniesner and Viscusi, 2019), while our approach attributes the same value to a year of life lost in all countries.

Any adopted national disease control policy implicitly involved trade-offs between lives and current and future livelihoods. Regardless of the exact magnitude of loss in each dimension, the losses estimated here suggest that optimal polices would have been best attuned to national conditions – global policy recommendations would clearly not have reflected differences in mortality risk or the importance of schooling in aggregate growth as both are partially a function of population age structure. If national policy makers at the start of 2020 were somehow made aware of an analysis of this nature, it is interesting to speculate whether the same courses of action would be chosen. For some countries, especially low-income ones, perhaps greater efforts would have been made to limit school closures and otherwise ensure continuity of learning. For other countries, especially those that suffered the greatest mortality shocks, perhaps even more attention would have been paid to the design of efficient protective disease control policies as well as greater advocacy for more equitable early global access to vaccines.

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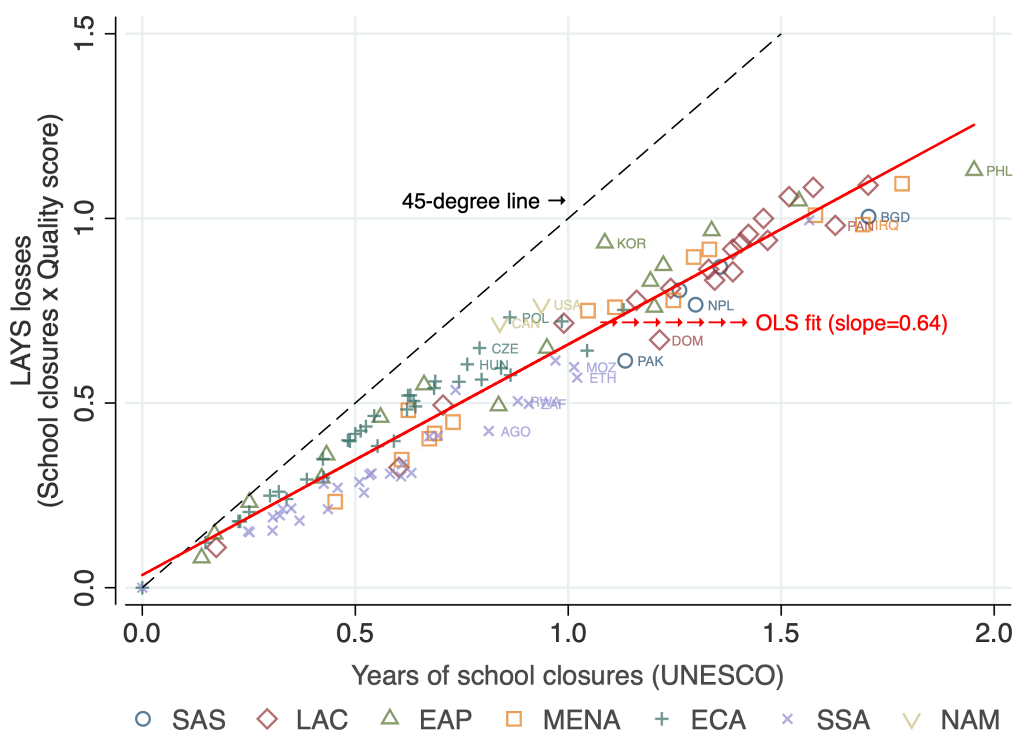
Online Appendix 1: Methodology for Calculating the Effect of School Closures on Future Growth

This appendix provides details on the methodology applied to simulate future growth scenarios with and without school closures in 122 countries used to compute the Future Poverty Years (*FPY*) measure. To do so we apply the World Bank Long Term Growth Model (LTGM) (Loayza and Pennings 2022), the LTGM-Natural Resource extension (LTGM-NR, Mendes et al. 2022) and the LTGM–Human Capital Extension (LTGM-HC) (Mendes and Pennings 2023).[1] This appendix builds on Mendes and Pennings (2023), which describes the methodology in greater detail, and the intermediate results in terms of growth rate. Appendix section 1.1 briefly describes the LTGM-HC and the methodology to estimate economic losses from school closures. Appendix section 1.2 provides a summary of the assumptions underlying the growth simulations for each country.

1.1 Calculating the effect of school closures on economic activity

The LTGM-HC converts school closures in 2020-21 into human capital (losses) for today's children when they join the workforce 1 to 14 years later and traces out the consequences for future GDPPC growth (the methodology for turning the growth path into a poverty rate is described separately in the main text). There are two channels through which school closures affect growth. First, there is a *direct* effect as lower future human capital means a less productive workforce, and so less output can be produced. Second, the LTGM-HC allows for an *indirect* effect as an initial fall in GDP (driven by slower human capital growth) slows down the future accumulation of physical capital, exacerbating the initial shock. The methodology to calibrate the LTGM-HC to *each country individually* is broken down into four steps discussed below.

Appendix Figure 1 School closures and learning losses during COVID-19



Note: LAYS is Learning-Adjusted Years of Schooling. Source: HCI; UNESCO.

[1] For more information on the LTGM, visit the LTGM website: https://www.worldbank.org/LGTM.

Step 1. School closure data. For each country, we collect data from UNESCO on estimated years of COVID-19 school closures during the 24 month period from 1 March 2020 to 28 February 2022.[2] More specifically, we compute the number of school years lost as the ratio of days of school closed and the length of the academic year.[3] We assume that children did not learn when schools were closed and that a month of school closures leads to a month of lost learning based on the review in Schady et al. (2023). The data is displayed along the X-axis in Figure 1. The median length of school closures is 0.7 years (8.5 months) ranging from zero (Belarus, Tajikistan, Burundi) to nearly two years (the Philippines).

Step 2. **Convert schooling losses to human capital losses by population cohort.** At this stage, we use the LTGM-HC to convert the UNESCO schooling losses into relative *productivity* losses of young cohorts at school age (5-19 years). As raw years of schooling is an incomplete measure of learning outcomes and productivity gains, we follow the HCI and adjust it by education quality, as below:

$$\Delta LAYS_c = Q_c \text{ x } \Delta S_c$$

where $LAYS_c$ denotes learning-adjusted years of schooling of cohort c, S_c denotes schooling rates, and Q_c is the quality adjustment. The quality score ranges from 0 to 1 based on the ratio of the country's harmonized test scores to a benchmark value of top performance (taken from the HCI).[4] $\Delta LAYS_c$ is plotted Y-axis Figure 1 and is roughly 2/3 as large as the length of school closures. The relationship between LAYS and productivity also follows that in the HCI:

$$\tilde{h}_c = H_c e^{\phi(LAYS_c - 14)}$$

where $\tilde{h}_c$ measures human capital in units of productivity relative to a benchmark of complete education and health $(h^{\star})$ and H_c is the health component of human capital, kept constant as the focus of the *FPY* is on education. From now on, we work with the more common definition of $h_c = \tilde{h}_c \times h^{\star}$, where human capital is productivity relative to zero schooling and health (this normalization does not affect the results). The parameter ϕ denotes the returns to quality-adjusted education: the percentage increase in human capital for one extra LAYS. We set $\phi = 12\%$, which roughly matches the 8% return on raw years of schooling (before adjusting for quality), standard in the literature (see Patrinos and Angrist, 2018). Fourteen years of schooling is the benchmark LAYS of full quantity and quality of education. Also, note that a one-year loss of raw schooling leads to $\phi Q_c\%$ fall in the productivity of cohort c.

Step 3. **Convert human capital losses by cohort into workforce human capital losses.** The LTGM-HC keeps track of human capital by population cohorts to compute the evolution of the average human capital of the workforce from 2020 to 2050:

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[2] For more details, visit the UNESCO's dashboard on the global monitoring of school closures caused by the COVID-19 pandemic: https://covid19.uis.unesco.org/global-monitoring-school-closures-covid19/.

[3] UNESCO codes days into "Fully Closed" and "Partially Closed" with the latter getting a weight of 0.5. As such:

$$Yrs\ of\ school\ closures_i = (\sum DaysFullyClosed_{i,t,} + 0.5 \sum DaysPartiallyClosed_{i,t,})/LengthAcademiYear(days)_i$$

The length of academic year varies across countries and is calculated as the sum of days "Fully Closed", "Partially Closed" and "Fully Open" (academic breaks are excluded).

[4] After adjusting for quality, an extra year of schooling in a top-performing country is equivalent to two years of schooling in a mid-range country with $Q_c = 0.5$. For example, Ghana and Singapore have quality scores of 0.48 and 0.92, respectively, so a typical student in Ghana learns in one year the same as a Singaporean learns in roughly six months.

$$h_t = \sum_c \lambda_t^c h_t^c$$

where λ_t^c is the share of the 5-year cohort c in the total workforce in period t. The exact distribution of λ_t^c over time and across cohorts will depend on the country's demographics, but $\lambda_t^c = 0$ for all cohorts of children (0-19) or retirees (65+).

We can now derive the effect of a one-year loss of raw schooling (not one year of LAYS) of cohort c on the growth rate of the human capital of the workforce in year t. For simplicity, assume that the average human capital of the workforce equals that of the affected cohort ($h_t \approx h_{c,t}$):[5]

$$\frac{\partial h_t / h_t}{\partial S_c} \approx \frac{\lambda_t^c}{5} \frac{\partial h_t^c / h_t}{\partial S_c} = \omega_t^c \phi Q_c$$

where $\omega_t^c \equiv \lambda_t^c / 5$ is approximately the working-age population share of a 1-year age cohort (a fifth of the 5-year cohort c). The expression above is useful to describe the dynamic effects of school closures due to COVID-19. Consider a one-year loss of raw schooling of the 15–19-year-old cohort in 2020-2021. Adjusting for quality, the cohort losses the equivalent of Q_{c_0} years of learning, leading to a $\phi Q \times 100\%$ fall in the cohort's future productivity. The oldest members of this cohort enter the workforce immediately, leading to an immediate reduction in human capital growth. The percentage *annual* fall is approximately $\phi Q_c \lambda_t^c / 5 (\equiv \omega_t^c \phi Q_c)$, as the $\lambda_t^c \phi Q_c$ fall for the whole cohort is spread over the 5-year period when this cohort joins the workforce.[6] The last of the affected cohorts, ages 5-9 at the start of the pandemic in 2020, will finish joining the labor force in 2035, and so human capital growth of the workforce will continue to be depressed over 2021-35. In our actual results this is calculated numerically as the difference between human capital growth in two scenarios:

- **Baseline** "pre-COVID-19" trend without school closures in 2020-2021, which assumes constant LAYS for all young cohorts from 2020 to 2100.
- **Scenario** "post-COVID-19" with school closures, which assumes that cohorts at school in 2020-2021 (5-9, 10-14, and 15-19-year-olds) lost ΔS years of raw schooling due to COVID-19 (ΔS taken from UNESCO in Step 1).

Step 4. **Calculate the effect of workforce human capital losses on GDP per capita growth.** Our analysis uses the LTGM and LTGM-NR to convert the path for human capital growth generated by the LTGM-HC into paths for future GDP and GDPPC growth under both baseline and scenario. This requires a number of assumptions about other growth drivers, which are described below.

In the standard LTGM, GDP is calculated from a standard Cobb-Douglas production function (the non-resource sector in the LTGM-NR is the same)

$$GDP_t = A_t (h_t L_t)^{\beta} K_t^{1-\beta}$$

[5] Abstracting from that difference simplifies considerably the analytical expressions at only a small loss of accuracy.
[6] An alternative way to see this is that $\omega_t^c = \lambda_t^c / 5$ as the fraction of the workforce that is treated in the first year.

where β is the labor share, K_t is the stock of physical capital, and $h_t L_t$ is effective labor, decomposed into h_t human capital of the workforce, and L_t, the labor force (number of workers). A_t is total factor productivity (TFP).

In the short term, the effect of a one-percent fall in human capital growth on GDP growth is simply β. So the effect of a one-year loss of raw schooling of cohort c on *annual* GDP growth is (again, assuming $h_t \approx h_{c,t}$ for simplicity):

$$\text{Short-run Effect: } \frac{\partial GDP_t/GDP_t}{\partial S_c} = \beta \omega_t^c \phi Q_c$$

In the long run, the effect is larger due to induced capital accumulation. One can see this by rewriting the production function with a fixed "steady-state" capital-to-GDP ratio $GDP_t = A_t^{1/\beta}(K_{ss}/Y_{ss})^{(1-\beta)/\beta} h_t L_t$. In this case, there is a one-to-one effect of human capital growth on GDP growth (a relationship also used in the HCI):

$$\text{Long-run Effect: } \frac{\partial GDP_t/GDP_t}{\partial S_c} = \omega_t^c \phi Q_c > \text{Short-run Effect}$$

It is important to point out that capital adjustment is very slow, and GDP takes many decades to converge. The effect of school closures in our period of study lies in between the short and long-term effects.

1.2 Assumptions of Growth Fundamentals (calibration of the LTGM)

The growth simulations serve two purposes: first they determine future baseline poverty rates, which affect how sensitive poverty is to changes in distribution-neutral GDP growth.[7] Second, they produce a more accurate measure of the economic effects of change in schooling than the analytical expressions above. This latter aspect is especially important in resource rich economies, where part of GDP—the resource sector—will be insensitive to changes in human capital as it uses almost no labor.

To simulate future long-term growth scenarios for each country, we need to feed the LTGM and LTGM-NR with initial conditions and assumptions on growth fundamentals. This section discusses the most important assumptions: the labor share, initial capital-to-GDP ratio, demographics, investment rates, TFP, and HCI components. Assumptions in LTGM and the non-resource sector of the LTGM-NR are:

- **Labor share.** These values are taken from Penn World Table 10 (PWT10) for 2019 (most recent data).
- **Initial capital-to-GDP ratio.** The initial capital-to-GDP ratio is calculated using the 2019 ratio of rnna/rgdpna from PWT 10. We use alternative data sources if the PWT10 measure is outside a reasonable range. More specifically, if the capital-to-GDP ratio from PWT 10 is above 3.5, we use PWT 9. If PWT 9 is also above 3.5, we use the World Bank's Macro-Fiscal Model (MFMOD) database, which reports lower capital-to-GDP ratios for almost all countries in the sample.

[7] For example, if baseline growth is sufficiently fast to eliminate poverty in a country, then slightly lower GDP growth due to COVID-19 may have virtually no effect on poverty rates, as there are almost no people close to the poverty line.

- **Demographics.** We use the UN's World Population Prospects forecasts for total population growth and the working-age population from 2021 to 2100. The labor force participation rate is set constant at the 2019 value, which is taken from the World Bank's WDI.[8]
- **Investment.** For each country, we set the path for investment equal to the IMF's World Economic Outlook (October 2022) from 2021 to 2027. We then assume that investment converges linearly to the 1980-2019 value over the period 2028-2050, and is constant after that.
- **TFP growth.** In the medium term, 2021-2027, we set TFP growth so that GDP growth in the LTGM matches the WEO projections. From 2028 to 2050, we assume a convergence to a country-specific target based on the empirical evidence that countries with a high share of agriculture in GDP tend to have higher TFP growth in the future (based on the potential for structural transformation).[9]
- **Human Capital Index.** The data for the HCI of young cohorts (5-19 year-olds in 2020-2021 and future cohorts) are taken from the World Bank's Human Capital Project (link), which measures the expected LAYS a child born today is expected to attain by her 18th birthday (including S_c and Q_c). The data for the years of schooling of older generations is from the Barro-Lee Educational Attainment Database (link) or Cohen-Leker 2014.

LTGM-NR: For countries with substantial resource sectors, defined as commodity exports at least 5% of GDP or 1/3 of total exports over 2008-12, we apply the Natural Resource Extension of the LTGM (LTGM-NR), which allows us to account for (i) a reduced sensitivity of aggregate GDP growth to human capital and (ii) how future discoveries and the depletion of reserves affects long-run growth (see Loayza et al. 2022). Key assumptions for the resource sector of the LTGM-NR are:

- **Initial reserves** which are taken from the BP-Energy Dataset for oil, gas and coal; and from the U.S. Geological Survey Database (USGS) for mining industries.
- **Typical discoveries** over 2021-2100 match the historical average over the past ten years (also from BP-Energy and USGS).

[8] Although this assumption might be pessimistic for some countries (particularly in the MENA region), it is unlikely to be an important determinant of the gap between the baseline and scenario growth paths.

[9] More specifically, we set the target for each country based on the following rule of thumb: $gTFP^{target} = 0.2\% + 5 \times Agric\_share$ where $Agric\_share$ denotes the most recent share of agriculture in total Gross Value Added reported by the National Accounts Data from the UN's Statistical Division (UNSD). The relationship is based on a cross-country regression of long-term TFP growth rates on the agricultural share. More specifically, we estimated an OLS regression of country-level TFP growth over 1995-2019 on the share of agriculture in GVA in 1995, on a cross-section of 94 countries. This regression suggests a strong causal relationship between the agricultural share and future TFP growth. A country with an extra 10 percentage points of GVA in agriculture is predicted to have TFP growth 0.5 ppts faster over the next 25 years. The extensive literature on structural transformation supports this prediction. Finally, extreme values are trimmed at the 10th and 90th percentile of the distribution so that future TFP growth roughly ranges between 0 and 1.5%.

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Online Appendix 2: Methodology for calculating a country-specific α

Following Baland et al (2023) Appendix C, we assume that with a CES utility function the parameter α for country c can take the following expression:

$$\alpha_c = \frac{\left(y_c^{non-poor}\right)^{1-\varepsilon} - \left(y^{subs}\right)^{1-\varepsilon}}{\left(y_c^{non-poor}\right)^{1-\varepsilon} - \left(y_c^{poor}\right)^{1-\varepsilon}}$$

where y_c^{poor} and $y_c^{non-poor}$ are respectively the typical incomes of poor and non-poor individuals in country c, y^{subs} is the "subsistence" income, defined as the income level that yields the same welfare level as non-existence (i.e. death), and parameter ε is the inverse of the inter-temporal elasticity of substitution. As one benchmark, we plot in Appendix Figure 2 the calibrated values for parameter α when taking y_c^{poor} and $y_c^{non-poor}$ to be mean income among the poor and non-poor for each country in the data, y^{subs} equal to \$1.075 per person per day, which is half the extreme poverty line, and $\varepsilon = 1.5$, which corresponds to an inter-temporal elasticity of substitution equal to 0.66.[10] The calibrated α increases with per capital national income from a value close to 1 in the poorest countries, to values slightly above 10 in the richest countries. The mean values for calibrated α in LICs, LMICs, UMICs and HICs countries in our sample are respectively equal to 1.5, 2.5, 3.7 and 7.2. Thus, the weight given to poverty years relative to years of life lost is smaller in richer countries. Among other things, this smaller weight given to poverty years reflects the fact that we assume higher poverty lines in richer countries (societal poverty line), so the utility loss when falling into poverty is comparatively smaller to the utility loss of non-existence. In Appendix Figure 2, the fact that the calibrated α_c increases with mean income reinforces the point that well-being losses from poverty are relatively large in relation to those from mortality in low-income countries while the opposite holds in high income countries. Indeed, the break-even values for α (shown in Figure 2) tend to be larger than the calibrated values (shown in Appendix Figure 2) in low-income countries, while the reverse holds in richer countries.

[10] Taking medians instead of means to capture typical incomes among the poor and non-poor hardly affects the calibrated values for α. For y^{subs} =1.075, all but three countries in our sample have $y_c^{poor} \geq y^{subs}$. This number falls to 0 when taking y^{subs} =1 and increases to 7 when taking y^{subs} =1.25, which in both cases only marginally changes calibrated α's. Havranek et al. (2015) show that estimates of the inter-temporal elasticity of substitution (ESI) are heterogeneous. Our value of 0.66 is the average of 0.5, 0.6 and 0.9, the mean estimates they report (Table A1) respectively for the UK, the US and Japan, the three countries for which the largest set of EIS estimates are available. The impact of EIS on α is more substantial. The mean calibrated α in our sample of country for EIS values 0.5, 0.66 and 0.9 are respectively 9.5, 4 and 2.5.

Appendix Figure 2. Country specific α

Note: Solid lines depict the average calibrated α for each country income group, while the dashed line represents the average for the entire sample. Mean income per capita is as of 2019 in 2017 PPP.

Appendix Table 1: Estimate by World Bank regions (not weighed by population)

	Years per 100			*CPY* years per 100		
	Excess mortality	School closures	Current poverty	Total well-being loss: (*CPY*+*FPY*)/α+*YLL*		
	YLL	*FPY*	*CPY*	α = 1	α = 4	α = 10
East Asia & the Pacific	0.0	6.5	5.2	11.6	2.9	1.2
Europe & Central Asia	9.8	3.1	0.2	13.1	10.6	10.1
Latin America & the Caribbean	8.2	15.1	6.6	29.9	13.7	10.4
Middle East & North Africa	4.1	8.0	6.3	18.4	7.7	5.5
North America	7.5	13.2	-1.1	19.6	10.5	8.7
South Asia	2.7	10.5	5.6	18.8	6.7	4.3
Sub-Saharan Africa	1.7	13.5	4.2	19.5	6.2	3.5
World	5.3	9.0	3.7	18.0	8.5	6.6