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COVID-19-induced Human Capital Shocks, Lifetime Labor Productivity, and Inequality

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Abstract

Using a human capital model with stochastic lifetimes, we assess the potential long-term impacts of human capital spending shocks in the early years of the COVID-19 pandemic on survival, lifetime income, and inequality. In the model, health and education spending separately affect survival rates and potential labor productivity, respectively, which allows us to trace how the pandemic's effects may propagate through the economic lifecycle. We calibrate the model using recent National Transfer Account estimates for the Philippines. Simulation results suggest that the COVID-19 pandemic is likely to negatively affect health and labor productivity, thereby potentially worsening income inequality in the long run. These impacts appear to be more pronounced for some birth cohorts.

Keywords: COVID-19, National Transfer Accounts, human capital

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COVID-19-induced Human Capital Shocks, Lifetime Labor Productivity, and Inequality

Michael R.M. Abrigo[1], Connie Bayudan-Dacuycuy[2], and Aniceto C. Orbeta Jr.[3,4]

1. Introduction

The 2019 coronavirus disease (COVID-19) pandemic unmasked many weaknesses and introduced new challenges in the Philippine education and health systems. Enduring issues on resource availability, including manpower, facilities, technologies, and supplies in both education and health sectors, have been made more prominent and stretched further with government-imposed mobility restrictions to control the spread of COVID-19. This has affected household access to critical human capital investments, among others, with large potential long-run implications.

By and large, early pieces of evidence on the impact of the COVID-19 pandemic show that households had cut back on human capital spending on children, at least in the early phase of the pandemic. For example, school attendance among five-year-old children had decreased from 92.2% in 2019 to 78.2% in 2020 (Philippine Statistics Authority [PSA], 2020, 2021), thereby reversing the rising enrollment trend from earlier years. This also suggests that the affected cohorts of children will attend the schooling cycle later compared with earlier cohorts. Further, several studies (e.g., Ulep, et al., 2021; Ulep, 2022) documented consistent declines in help-seeking behavior for health, such as patient consultation and hospitalization, especially among children and the elderly, across disease groups because of the pandemic, which may be indicative of broader impacts of COVID-19 on population health.

Less discussed in the literature is the distributional impact of COVID-19 on human capital investments. While school attendance among primary and secondary school-aged children appears to be similarly affected across income classes, students from more affluent households are better equipped to study under alternative schooling modes (PSA, 2020, 2021; Orbeta, 2022). Such early-life differential in household access to computers and the internet, housing square footage per person, and the availability of better-educated home caregivers are expected to affect the distribution of human capital. It, therefore, has important implications for future survival, productivity, and income inequality.

Assessing the impact of the COVID-19 pandemic shocks on long-term economic outcomes, however, poses several challenges. On the one hand, the global pandemic has affected virtually whole populations and economic systems, making the identification of natural experiments to exploit in impact studies somewhat difficult. On the other hand, the long-term nature of these outcomes requires a substantial period for these effects to be actually measured. When these impacts are manifested, it may be too late to implement corrective policy actions, if needed, or for these policies to take effect.

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To assess how the COVID-19 pandemic may impact yet-to-be-observed long-term outcomes, this study employs a human capital model with uncertain lifetimes useful in highlighting the potential adverse effects of a pandemic on the time paths of health and education spending. It allows us to trace how education and health spending shocks induced by the global pandemic may propagate separately through the economic lifecycle. It also provides a mechanism to calculate a first-order approximation of the potential magnitude of the impacts on life expectancy, productivity, and income inequality. We show that the COVID-19 pandemic is likely to negatively affect health and labor productivity, and increase inequality in the long run.

Our study highlights the scale and scope of COVID-19 pandemic impacts based on two complementary sets of simulations. The first set of scenarios assumed a lifetime exposure of agents to COVID-19 human capital spending levels, while the second assumed only a two-year exposure. Expectedly, the former yielded a very large decline in life expectancy. The latter resulted in estimates more consistent with international evidence. Interestingly, there appears to be some heterogeneity in impacts across age groups. We showcase how seemingly disparate shocks emanating from addressing a particular issue in one sector may spread to other parts of the economy and through time. We also document the importance of government policies in shaping household behavior during crises.

The rest of the study is organized as follows. The next section reviews recent successes and challenges in the Philippine education and health systems. We also summarized government responses to the COVID-19 pandemic in these sectors and how household behavior had changed relative to previous periods, partly in response to these government policies. In Section 3, we then present a human capital model that distinguishes how health and education spending may separately affect productivity. We discuss how we parameterize this model using available data in Section 4. The results of the model calibration are also presented. Next, we used the model to simulate and assess the likely impacts of the COVID-19 human capital spending on survival, lifetime income, and inequality. We summarize the results of these simulation exercises in Section 5. Finally, Section 6 concludes with policy implications drawn from our results.

2. Human capital spending during the early COVID-19 pandemic

Over the last decade, the Philippines has made several important strides in expanding human capital investments through new education and health entitlements. In education, for example, the government adopted the K-to-12 program in 2012, emphasizing the value of kindergarten education while catching up with global standards on the length of the whole basic education cycle, among others. In addition, in 2017, the government introduced universal free public post-secondary and tertiary education. On the health front, the country's social health insurance program has expanded considerably with free coverage provided to vulnerable sectors, including the poor, persons with disabilities, and the elderly. On top of this is the country's flagship anti-poverty conditional cash transfer program, which provides cash grants to poor households in exchange for meeting certain education and health requirements. Indeed, over the last decade, access to education and health services has dramatically increased, especially among the poor, although critical issues remain.

In education, while the Philippines has recorded notable gains in school participation over the past decades, particularly in basic education, the country's education quality lags behind its regional and aspirational peers based on internationally comparable student assessments. Among 79 high- and middle-income countries in the 2018 Programme for International Student Assessment (PISA) conducted by the Organisation for Economic Co-operation and Development, for instance, the Philippines ranked last in Reading and second to last in Mathematics and Science. This may be related to education spending differences across countries (Abrigo, 2021a) and other environmental factors. Further analysis of PISA test scores in the Philippines underscores the importance of household and community support, in addition to school endowments, in explaining variations in student outcomes (Orbeta et al., 2020).

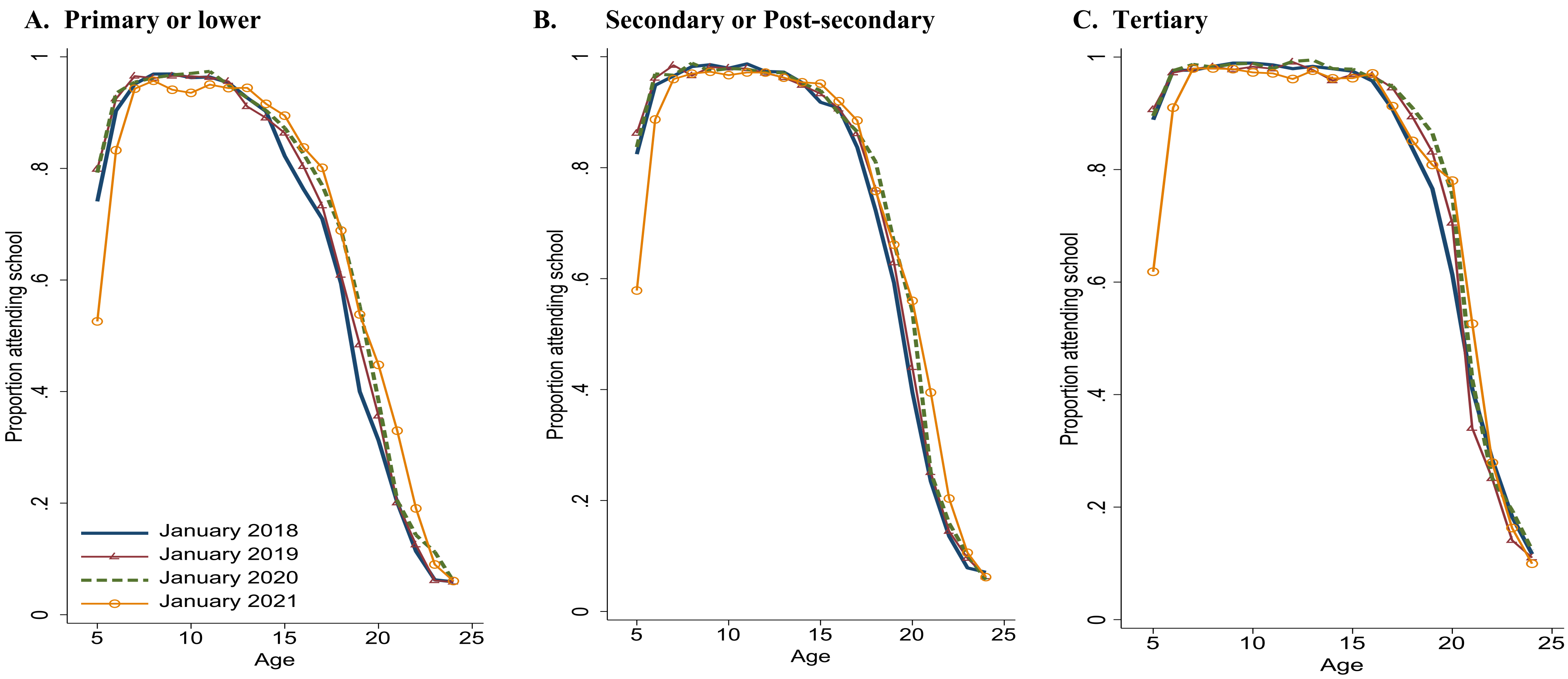
Similarly, in health, although spending per capita has more than doubled over the last two decades, the Philippines continues to fare behind other Southeast Asian countries in per capita health spending and in health outcomes, including infant-, child-, and maternal-mortality rates. In addition, large spatial and socioeconomic disparities in the access and distribution of endowments continue to exist. In 2015, for example, per capita health spending among households in the Bangsamoro Region was about half of those in the National Capital Region (Abrigo, 2021b). In the same year, three of every four cities and municipalities in the country had health personnel-to-population ratios below the 45 physicians, nurses, and midwives per 10,000 population recommended by the World Health Organization (Abrigo and Ortiz, 2019).

Notwithstanding these extant issues, the COVID-19 pandemic threatens whatever gains the Philippines has painstakingly amassed over the years.

In the early phase of the pandemic, the government cut short the closing education cycle in summer of 2020 and delayed the start of the succeeding cycle to October instead of the usual June for basic education. The education system shifted to remote learning, with face-to-face classes pilot-tested only in November 2021 and progressively expanded beginning in February 2022. Over this period, the K-to-12 curricula were streamlined from the original 14,171 competencies down to 5,689 – called the Most Essential Learning Competencies – to lighten the load of both teachers and students. An additional PhP4.4 billion was earmarked for basic education to support the government's Basic Education Learning and Continuity Plan (Orbeta, 2022).

Despite these important public sector interventions, school participation rates among basic education learners have dropped in the first year of the COVID- 19 pandemic (see Figure 1). The decline had been steepest among the youngest age groups as households delayed children's school entry or even pulled them out of school. Those from lower socioeconomic backgrounds appear to have been affected more severely. By January 2021, only half of the five-year-old children from households with heads having primary education or less were enrolled in school, compared with three in every five children from households with college-educated heads. Interestingly, school participation among the college-aged population continued to expand in the early phase of the pandemic, sustaining previous growth from the introduction of the free tertiary education program.

Figure 1. School attendance by age and highest educational attainment of household head: Philippines, 2018-2021



Source: Authors' calculations based on January rounds of the quarterly Labor Force Surveys.

Among those enrolled in school, remote learning is expected to result in learning disparity across socioeconomic classes (Orbeta, 2022). While more than 40 percent of private-school students used a more interactive online mode, more than 80 percent of public-school pupils used less interactive printed modules. In addition, there appear to be marked differences in the available home support for learning. Orbeta (2022), for example, documented that only three percent of household heads in the poorest household income quintile have a secondary education or better, compared with 28 percent in the richest household income quintile. This is particularly critical when teachers are not available to guide students, like in remote learning. Even in pre-pandemic face-to-face classes, the quality of home support has been documented to be predictive of test scores (Orbeta et al., 2020). Household access to broadband internet and ownership of a computer, television, and cellular phone, which may aid in remote learning, also vary across socioeconomic classes, with home conditions of more impoverished families being less conducive to learning.

Access to health care services was also significantly affected by the COVID-19 pandemic. Consultations in primary health care units and hospitalizations have declined with the onset of the pandemic (Ulep, 2022) and have not returned to their pre-pandemic level since, at least for inpatient care, as shown in Figure 2. The figure presents the trend in the number of hospitalized patients by top major disease groups between 2018 and 2021 based on social health insurance claims (Philippine Health Insurance Corporation, 2022). Children and the elderly appear to be the most affected (see Figure 3), highlighting how the global pandemic has affected the most vulnerable populations.

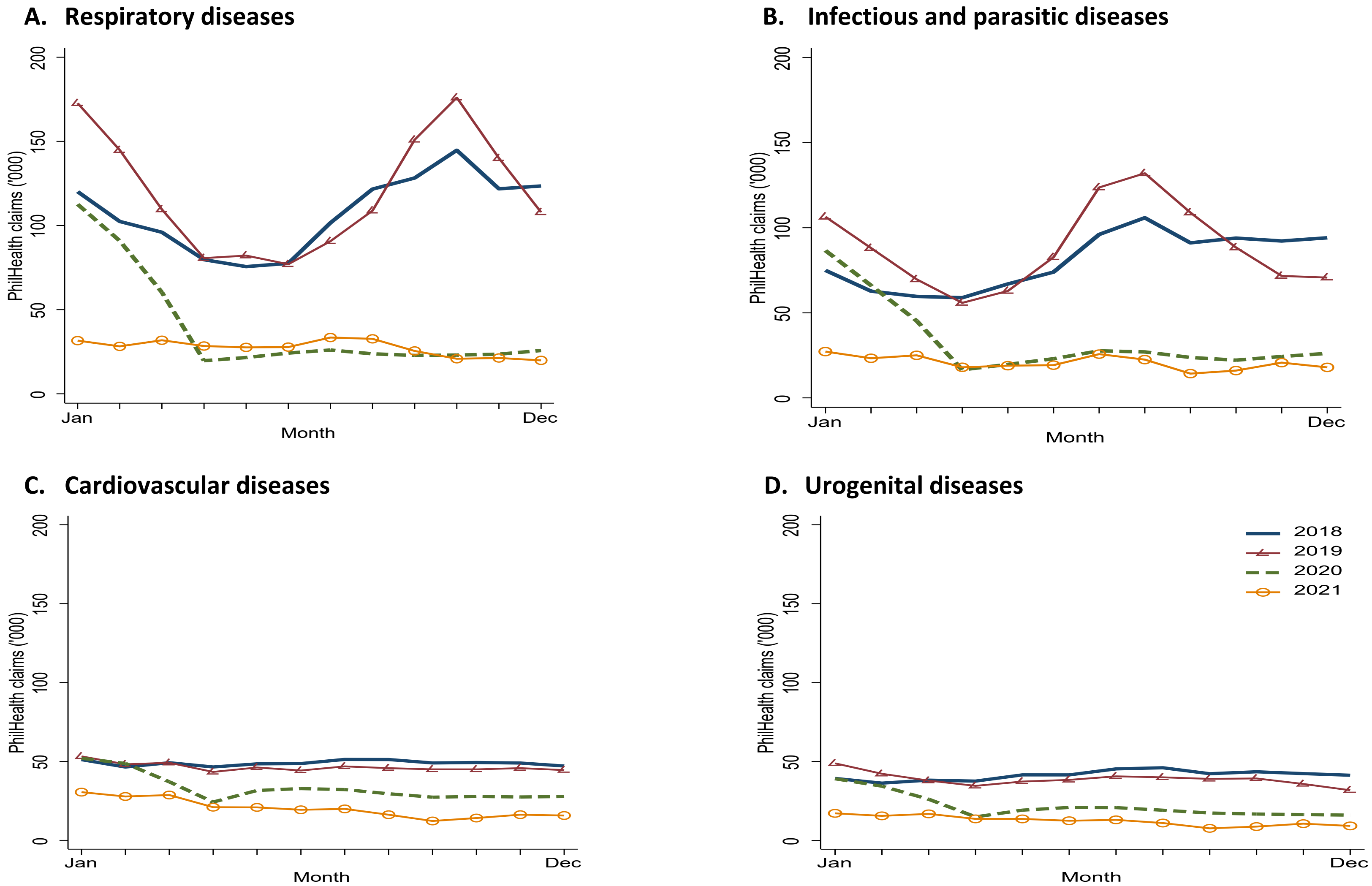
Strict stay-at-home directives, particularly for children and the elderly, and the reallocation of health resources to COVID-19 response in the early months of the pandemic may have contributed to the observed drop in patient consultations and hospitalizations (Ulep, 2022). However, it remains a conundrum why it has not been reversed with more relaxed community quarantine rules or with fewer COVID-19 cases.

Aggregate education and health expenditures have increased during the COVID-19 pandemic. Compared with 2018 levels, total education spending increased by 1.2 percent, while that for health by 10.7 percent. But this increase masks the true level of human capital spending as COVID-19-related expenditures have artificially ramped up expenditures on health and education.

Excluding expenditures related to the COVID-19 response[5] reveals some deterioration in aggregate non-COVID-19 human capital spending by at least PhP118 million (see Figure 4). The decline was higher for health (15.2 percent) compared with education (0.1 percent), which are both primarily due to falling household spending. Between 2018 and 2020, total household consumption of education and health declined by 7.8 percent and 18.2 percent, respectively, if we exclude COVID-19-related expenses. Government spending, on the other hand, increased by 9.4 percent for education, offsetting the fall in household education spending, but decreased by 9.2 percent for health over the same period.

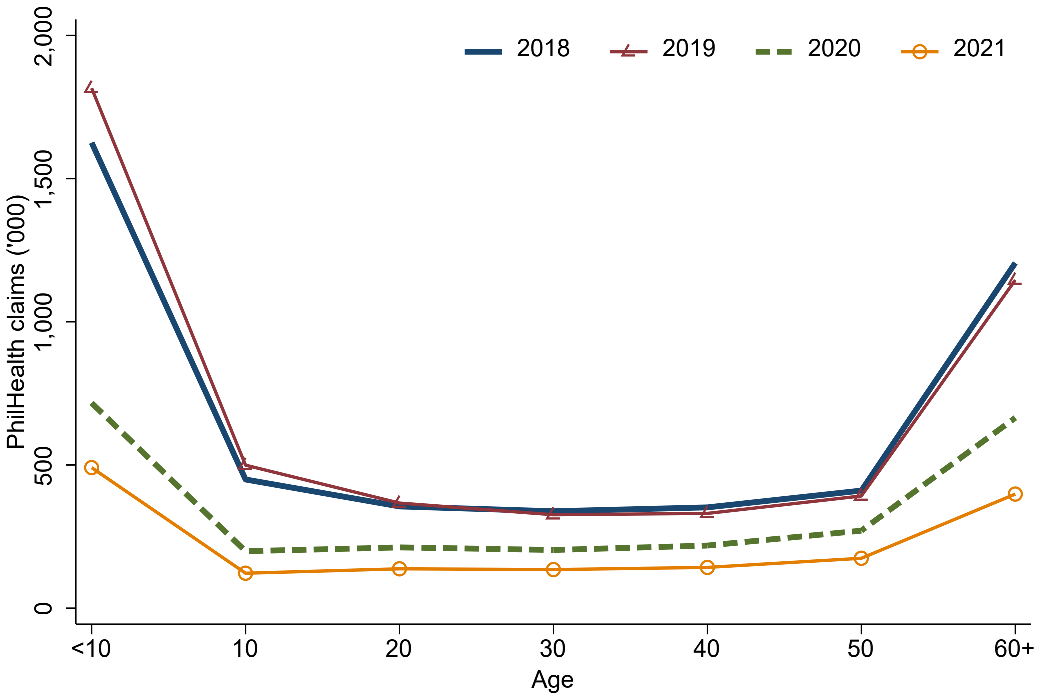
[5] COVID-19-related expenditures were based on government disbursements as recorded by the Department of Budget and Management (2022), and social health insurance records by the Philippine Health Insurance Corporation (2022).

Figure 2. Social health insurance claims by top major diseases: Philippines, 2018-2021



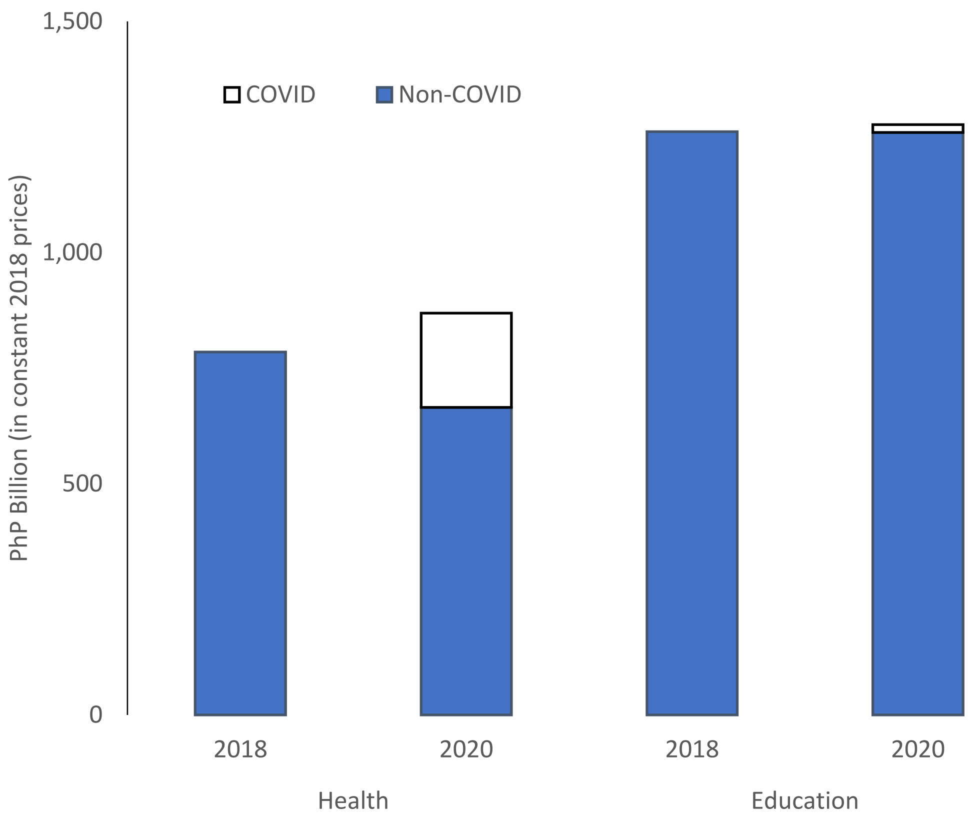
Source: Authors' calculations based on PHIC data.

Figure 3. Social health insurance claims by age group: Philippines, 2018-2021



Source: Authors' calculations based on PHIC data.

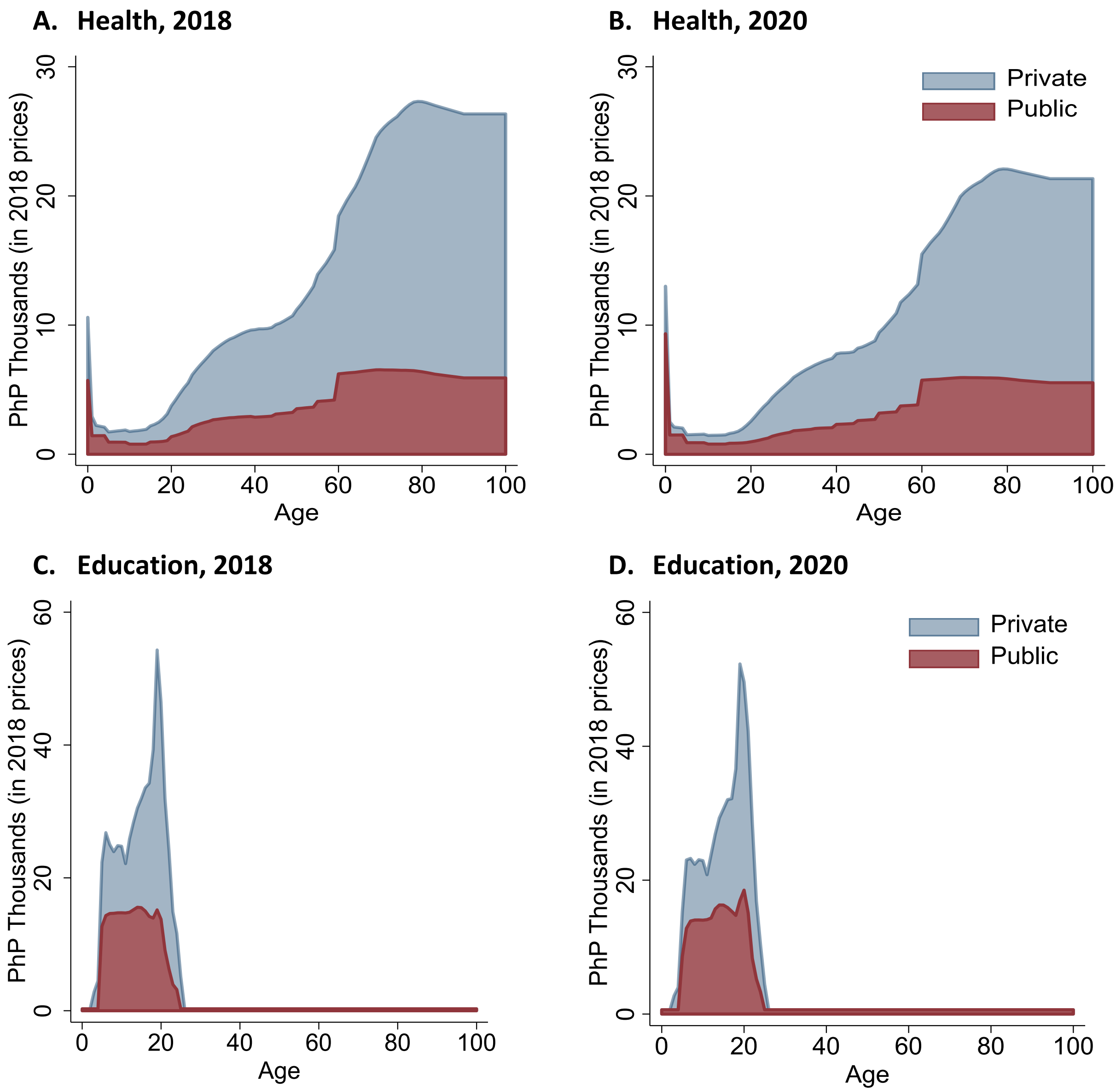
Figure 4. Aggregate human capital spending (in PhP billions): Philippines, 2018 and 2020



Source: Authors' calculations based on PHIC, DBM and PSA data.

Figure 5 shows non-COVID-19 education and health consumption per capita by age between 2018 and 2020. These estimates capture differences in utilization patterns and relevant costs, as well as the many factors that affect these, across age groups between these two periods. The figure highlights the importance of the public sector in smoothing consumption during crises. While non-COVID-19 health spending has declined across age groups, expansion of government health spending, particularly of social health insurance, among infants had more than offset the decline in household health spending for this age group over this period. Similarly, while household education spending by age had declined between 2018 and 2020, increased government spending, especially for secondary, post-secondary, and tertiary education, narrowed overall spending cuts across age groups and even expanded those for the population in their early twenties.

Figure 5. Human capital spending per capita by age: Philippines, 2018 and 2020



Source: Authors' calculations.

3. A simple model of human capital, survival, and productivity

The documented changes in age patterns of human capital spending are expected to have important implications on future economic outcomes. However, assessing the long-term impacts of the COVID-19 pandemic poses several important challenges. First, COVID-19 has affected large swathes of populations within and across economies, with degrees of severity likely affected by both observable and latent factors. This makes identifying natural experiments to exploit for impact assessments particularly difficult. Second, we are interested in long-term outcomes, which are yet to be observed in the real world. While the COVID-19 pandemic affected virtually the whole world and is expected to have important implications on individuals and the aggregate economy alike, measurement of long-term outcomes, by its nature, requires a significant time period to pass.

In this section, we discuss a simple economic model based on the current understanding of processes surrounding human capital acquisition to assess the potential long-term impacts of the COVID-19 pandemic on survival and labor productivity. As a heuristic device, the human capital model we present below lacks many intricacies of the real world. However, it allows us to clarify the potential pathways through which human capital shocks affect the entire economic lifecycle and to estimate the first-order approximation of its magnitude through simulation exercises.

Consider an economy lived by individuals, indexed by $i = 1,2 \ldots, N$. Given some initial endowment and schedule of prices, each individual chooses a lifetime age-specific bundle of goods and services based on some well-behaved utility function that each individual maximizes. Without loss of generality, we group goods and services under three main headings, namely, health, education, and others. We are agnostic about the form of the utility function, how agents interact with each other, or the process through which utility-maximizing bundles of goods and services are derived. We are interested, however, in how their health and education consumption relates to their survival and lifetime labor income.

Following Grossman (1972), we distinguish between health and education as inputs to human capital, which, in turn, affects individual productivity. In particular, we assume that health spending affects productivity only by influencing individual age-specific survival probabilities, while education spending improves efficiency in producing goods and services. That is, health consumption allows individuals to become productive, while education makes them productive per se.

Current consumption of health and education goods and services are transformed into health and knowledge stocks, respectively, through distinct production functions. These stocks accumulate across the years, although a portion of these depreciates through time at some exogenous age-specific rate. These stocks then determine whether an individual survives or the level of its productivity at each age. We discuss these mechanisms in more detail below.

We specify age-specific health stock $H_{i,h}(a)$, as

$$H_{i,h}(a) = \alpha_h \cdot c_{i,h}(a)^{\phi_h} + [1 - \rho_h(a)] \cdot H_{i,h}(a-1); \qquad (1)$$
$$0 \leq \rho_h(a) \leq 1; \ \alpha_h, \phi_h, c_{i,h}(a) \geq 0,$$

where $c_{i,h}$ is individual health consumption at age $a = 1,2, \dots, T$, and α_h and ϕ_h are total factor productivity and production elasticity, respectively, which governs how $c_{i,h}(a)$ is converted into units of health stocks. We do not impose any functional form assumption on the age-specific depreciation rate $\rho_h(a)$ other than these should be bounded between 0 and 1. We assume that the initial health stock, i.e., the birth stock, $\lambda_h \geq 0$, and health stock depreciation rates are common among individuals and are set by nature.

An individual's survival depends on his/her health stock at any period being above some threshold, $\underline{h} \geq 0$, named the death stock. For a progressively rising $\rho_h(a)$, especially at old age, replenishing the health stock becomes increasingly expensive. When incomes do not grow at least as fast, then death is inevitable.

The proportion of the population surviving up to some age t, given by $\pi(t)$, may be defined based on observed age-specific hazard rates $\theta(a)$ up to age t as follows

$$\pi(t) = \prod_{a=0}^{t} [1 - \theta(a)] \, ; \qquad (2)$$
$$\theta(a) = P\big[H_h(a) < \underline{h} \, | H_h(0), H_h(1), \dots, H_h(a-1) \geq \underline{h}\big].$$

The individual evolution of the knowledge stock, $H_{i,k}(a)$, is similarly defined as that of health stock with some slight modification. Unlike in health stock production, we introduce a stochastic component to the total factor productivity of knowledge stock production, which captures individual differences in how agents transform education consumption into productive knowledge stock units:

$$H_{i,k}(a) = [\alpha_k \cdot \psi_i] \cdot c_{i,k}(a)^{\phi_k} + [1 - k(a)] \cdot H_{i,k}(a-1);$$
$$0 \leq \rho_k(a) \leq 1; \ \alpha_k, \phi_k, c_{i,k}(a) \geq 0; \qquad (3)$$
$$\psi_i = \frac{\exp(z_i)}{E[\exp(z_i)]},$$

where $c_{i,k}(a)$ is age-specific education consumption, and the rest of the parameters are similarly defined as in (1) but with subscript k, representing knowledge. The individual-specific age-invariant stochastic component of total factor productivity, ψ_i, is strictly non-negative and has population mean equal to unity. Without loss of generality, we assume that the birth knowledge stock, λ_k, to be zero.

The knowledge stock represents some productivity potential that is actualized only when an individual is employed in the economy. Let $L_i(a)$ be an indicator function equal to one when individual i is employed at age a, with $E[L_i(a)] = p(a)$ being exogenously set. Normalizing wages at 1 per unit of knowledge stock, the age-specific annual labor income of an individual, $l_i(a)$, is given by

$$l_i(a) = \begin{cases} H_{i,k}(a) \cdot L_i(a) & , H_{i,h}(t) \geq \underline{h} \; for \; all \; t \leq a \\ 0 & , H_{i,h}(t) < \underline{h} \; for \; some \; t \leq a \end{cases} \quad (4)$$

It must be recognized that the above model is rather simplistic and devoid of many important real-life nuances. For example, we assume that survival depends only on health consumption. In reality, however, individual health status depends on many other factors, including consumption of non-health goods and services, genetics, and living conditions, among others (Marmot and Smith, 1997; Fuchs, 2004). Further, we assume that knowledge stock depends only on education consumption. However, productivity-enhancing knowledge may also be derived from experiences, particularly while working (Mincer, 1974; Lemieux, 2006). Finally, there may be alternative motivations to consume health or education goods other than investments to improve the chances of survival or to raise future labor income, such as for leisure. These are beyond the scope of our model.

That being said, the above specifications provide a first-order approximation of the mechanisms surrounding survival and productivity that is in line with mainstream human capital theory. This allows us to disentangle and trace the potential pathways through which human capital shocks induced by the COVID-19 pandemic may affect long-term outcomes.

4. Calibration of human capital model to baseline outcomes

We estimate the parameters in the health and knowledge stock laws of motion expressed as equations (1) and (3) in the previous sub-section using a series of simulated method of moments (c.f. McFadden, 1989) based on moment conditions that may be derived from equations (2) and (4). We sequentially estimate the model parameters starting with the health stock law of motion, which feeds into the parameter estimation for the knowledge stock law of motion.

Let π^D and π^M be the vector of survival rates from data and calculated from the model, respectively. We exogenously set α_h, ϕ_h, and $\underline{h}$ equal to one, which, together with information on $c_{i,h}(a)$, allows us to pin down the vector $\{\rho_h(a)\}$. Conditional on the observed $c_{i,h}(a)$ and parameters $\{\alpha_h, \phi_h, \underline{h}\}$, we performed a standard numerical search for $\{\rho_h(a)\} \in [0,1]$ to match the model moments π^M with the observed moments π^D as closely as possible by minimizing

$$Q_h = (\pi^D - \pi^M)' W_h (\pi^D - \pi^M), \quad (5)$$

where W_h is a conformable weight matrix, which we set as an identity matrix following Meghir and Pistaferri (2004). This allows hypothesis testing that is robust to within-individual correlations and across time. Calculation of the covariance matrix of the estimated parameters is similar in form to the classical generalized method of moments (McFadden, 1989).

Given $c_{i,h}(a)$, the estimates for $\{\rho_h(a)\}$, our maintained assumption on $\{\alpha_h, \phi_h, \underline{h}\}$ and the derived $H_{i,h}(a)$, we can then estimate the parameter vector $\{\alpha_k, \phi_k, \rho_k(a)\}$ conditional on $c_{i,k}(a)$. Similar to the estimation procedure above, let l^D and l^M be the vector of observed and simulated per capita labor income stacked over age. Performing a similar minimization procedure as above allows us to match the schedule of lifetime per capita labor income in the model with that observed in the data. In addition, however, we also want to mimic the observed income inequality in our simple model of the economy. In order to do this, we introduce another parameter η, such that $z_i = \eta \cdot v_i$ where $v_i \sim N(0,1)$.

Let G^D and G^M be the observed Gini coefficient from official national estimates and the calculated Gini coefficient based on lifetime labor income of individuals in the model. Numerical search for $\{\alpha_k, \phi_k, \rho_k(a), \eta\}$ is then performed to match the stacked vectors $\omega^D = \{\,l^D, G^D\}$ and $\omega^M = \{l^M, G^M\}$ by minimizing

$$Q_k = (\omega^D - \omega^M)' W_k (\omega^D - \omega^M), \qquad (6)$$

with the weight matrix W_k also set as a conformable identity matrix.

We calibrate the model to new estimates of National Transfer Accounts (NTA) for 2018 Philippines. NTA is a national accounting system that measures different resource flows across and within generations or age groups in an economy that is consistent with the United Nations (UN) System of National Accounts. NTA provides estimates of age-specific per capita education consumption, health consumption, and labor income, among others, that are required in our model. Details of NTA estimation are provided in the UN (2013) manual, with recent historical estimates for the Philippines presented in Abrigo, et al. (2020). In addition to Philippine NTA data, we also used 2015-2020 life table estimates by the United Nations (2019) and the 2018 Gini coefficient estimated by PSA (2019a).

We adopt a synthetic cohort approach in our estimation. We assume that the age-specific consumption and income observed in the Philippine NTA represent the value of consumption and income an individual expects if he/she is to live a whole lifetime in 2018. We simulated 10,000 individuals with maximum lifespans of 100 years, representing more than one million agent-year observations. We randomly assign to each individual a lifetime schedule of human capital consumption based on the joint distribution of age-specific health and education consumption derived from the NTA-adjusted 2018 Philippine Family Income and Expenditure Survey (PSA, 2019b). Employment status is also assigned randomly based on age-specific employment-to-population ratios calculated from the October 2018 Labor Force Survey (PSA, 2019c). Using these simulated observations, we minimize the objective functions in (5) and (6) to identify baseline parameter values of our human capital model.

Table 1 presents parameter estimates of our human capital model. For the health law of motion, we constrained the parameters of the health stock production function to allow the identification of lifetime depreciation rates. It is straightforward to show that any affine transformation of health consumption does not change the statistical ordering of individual mortality. We did not impose any parameter constraints on the education law of motion other than that the birth knowledge stock is nil for everyone.

The estimates in Table 1 capture some key features of human capital dynamics. First, health stock depreciates faster with age, which is in line with previous estimates (e.g., Grossman, 1972; Halliday, et al., 2019). Before age 30, health stock depreciates at less than one percent per year. However, this progressively rises. By age 90, the annual rate of health stock depreciation is above 10 percent. Second, knowledge stock depreciation is relatively small in magnitude and remains flat throughout the lifetime, unlike that for health. Consequently, knowledge stock may steadily accumulate throughout an agent's lifetime with minimal loss from depreciation. Third, the output elasticity of knowledge production cannot be statistically distinguished from unity. This suggests that knowledge stock increases at about the same rate as individual education investments.

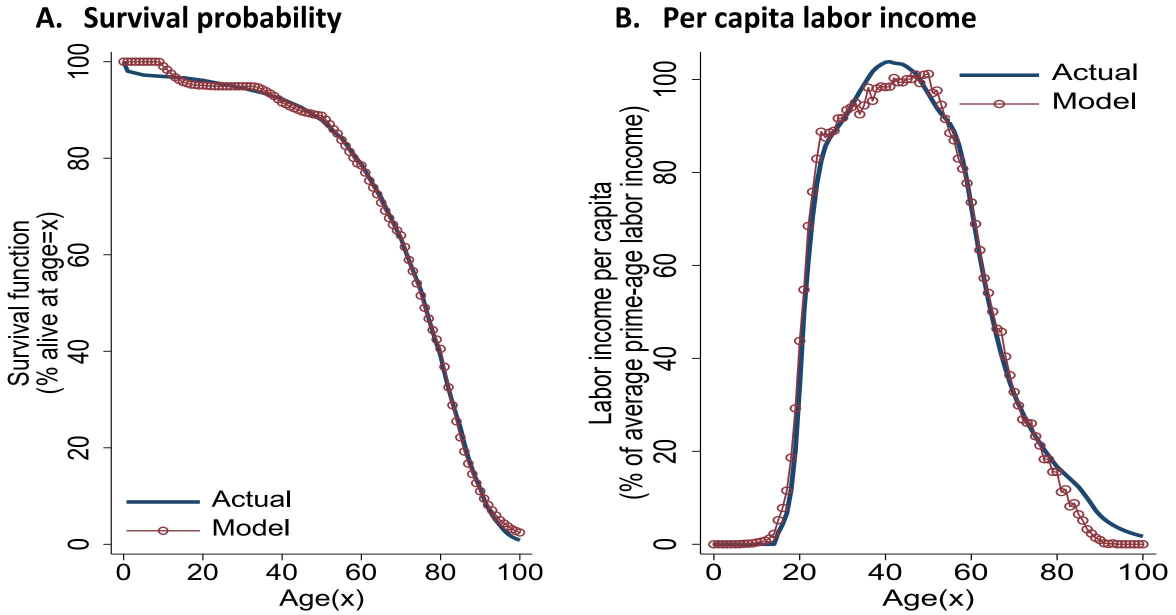
Table 1. Simulated method of moments model estimates

Parameter		Health			Education		
		Est.	S.E.		Est.	S.E	
Total factor productivity	α	1.000	0.000	e	0.408	0.010	***
Production elasticity	φ	1.000	0.000	e	0.955	0.035	***
Birth (initial) stock	λ	1.000	0.000	e	0.000	0.000	e
Death stock	$\underline{h}$	1.000	0.000	e	…	…	na
Productivity shock SD	η	…	…	na	0.570	0.009	***
Depreciation rate	ρ_{10}	0.008	<0.001	***	0.086	0.170	
	ρ_{20}	0.006	<0.001	***	<0.001	0.004	
	ρ_{30}	0.010	<0.001	***	<0.001	0.001	
	ρ_{40}	0.028	<0.001	***	<0.001	0.001	
	ρ_{50}	0.025	<0.001	***	<0.001	0.001	
	ρ_{60}	0.043	<0.001	***	0.014	<0.001	***
	ρ_{70}	0.061	<0.001	***	0.026	0.001	***
	ρ_{80}	0.082	<0.001	***	<0.001	0.001	
	ρ_{90}	0.122	<0.001	***	<0.001	0.017	
Q		0.014			0.070		
pseudo-R^2		0.999			0.993		
N		10,000			10,000		

Notes: N – number of observations; e – exogenous; na – not applicable; *** indicate statistical significance at the 1% alpha level. The pseudo-R^2 measure is calculated as the squared Pearson correlation between the model estimate and the data.
Source: Authors' calculations.

Figure 6 compares the data and model estimates of the age schedules of survival probabilities (Panel A) and per capita labor income (Panel B). The figures show substantial overlap between the data and the model estimates, although some important deviations exist. In Panel A, for example, model estimates of survival probabilities below age 10 overstate actual propensities relative to those observed in the data. In Panel B, the model understates per capita labor income among middle-age and elderly populations. While the differences could be somewhat trivial, these suggest that the model potentially excludes some important real-life human capital dynamics across the economic lifecycle.

Figure 6. Baseline survival probability and per capita labor income by ages



Source: Authors' calculations. Survival probability is calculated from UN (2019) World Population Prospects Philippine life table.

Using parameter estimates in Table 1, calibrated based on age-specific target moments shown in Figure 6, we then calculated the following indicators: (1) life expectancy at birth, le_0, (2) average undiscounted lifetime labor income, $\bar{l}$, and (3) Gini coefficient, $G(l_i)$. We then compared these with baseline data (Table 2). Except for the Gini coefficient, we did not specifically target these moments, thus can be used to benchmark the performance of our model. The difference between model estimates and the data is within one percent despite deviations in estimates of lifecycle profiles in Figure 6.

Table 2. Baseline outcomes: Data v. model estimates

	Actual	Model		
		Est.	90% confidence band	
Life expectancy at birth (in years)	71.4	71.5	71.5	71.6
Lifetime labor income (in PALY years)	45.9	46.3	45.5	48.7
Gini coefficient	0.43	0.43	0.42	0.43

Notes: PALY – average labor income of prime-age adults, aged 30-49 years.
Source: Authors' calculations.

5. Simulated impacts on survival, productivity, and inequality

Based on the estimated baseline parameters, we then performed policy simulations to assess how the COVID-19 pandemic shocks on human capital spending are likely to affect important long-term economic outcomes. More specifically, we look at how age-specific survival rates, average lifetime labor income, and inequality are likely to be affected by changes in the average levels and covariation in health and education consumption over the economic lifecycle.

We provide three alternative scenarios in our policy simulations. In addition to using the observed distribution of per capita human capital spending in 2020, we separately assess the potential impact of changes in education and health spending on our selected outcomes. This allows us to identify the relative importance of shocks on each of these human capital pathways**.**

In these alternative scenarios, we use the human capital spending patterns in the first year of the COVID-19 pandemic netted out for health and education spending that is related to COVID-19 prevention and treatment. This is done to make the spending comparable to the 2018 expenditures. We assumed that COVID-19-related spending have no spillover effects on non-COVID-19 outcomes since these expenditures are used specifically for direct COVID-19 pandemic response. The only way COVID-19 spending may affect non-COVID-19 outcomes in our model is when these expenditures crowd-out other human capital spending unrelated to COVID-19 prevention and treatment. These early pandemic distributions of human capital spending are based on new Philippine NTA estimates for 2020.

We focus on the impact of the above alternative scenarios on life expectancy at birth, and on the distribution of lifetime labor income. We compare the values of le_0, $\bar{l}$ and $G(l_i)$ at baseline and in the alternative scenarios to assess the impact of the distributional change in human capital spending during the early COVID-19 pandemic on these long-term outcomes.

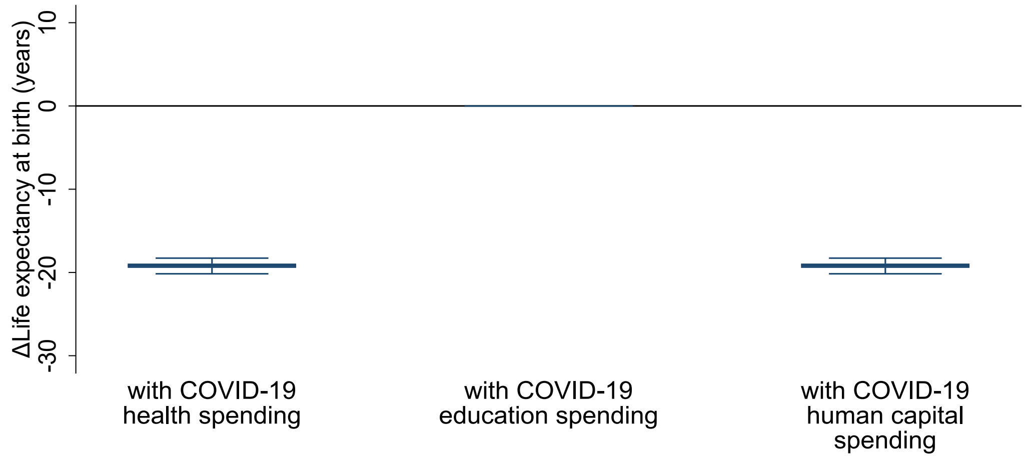
5.1 Lifetime exposure to COVID-19 human capital spending

In Figure 7, we present estimates of life expectancy at birth, average lifetime labor income, and Gini coefficient for three alternative scenarios vis-à-vis baseline estimates. The distribution of the simulated outcomes is based on 1,000 Monte Carlo draws from the parameter distribution in Table 1. The alternative scenarios are based on NTA estimates of health and education expenditures, excluding those related to COVID-19 response, by age in 2020**.** Simulations in this exercise are done assuming that agents starting at age zero have a lifetime exposure to COVID-19. The results may be interpreted as the expected impact if the simulated population is to consume health and education goods based on the alternative lifetime spending schedules, and thus may be treated as upper limits of the potential impact of COVID-19 human capital spending exposure.

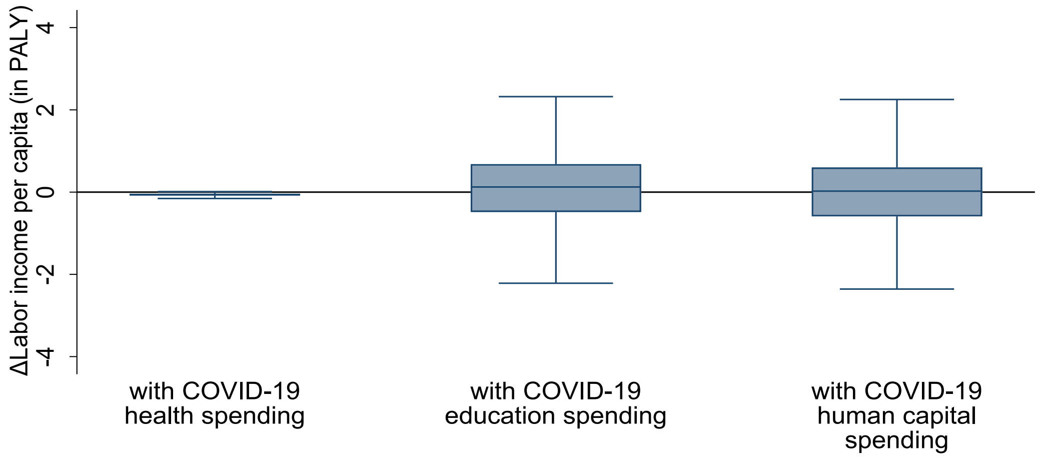
The results of the policy experiment show that the simultaneous changes in health and education expenditure age profiles will lead to a deterioration in life expectancy (Panel A), no impact on average lifetime labor income (Panel B), and an increase in income inequality (Panel C) relative to the 2018 baseline. The effect on survival is substantial, with life expectancy at birth calculated to decline by as much as 19.2 years. The simulated impact on average lifetime labor income relative to baseline is both economically and statistically not significant. On the other hand, lifetime labor income inequality is estimated to increase by about 7 percent, to 0.46 Gini coefficient compared with the baseline 0.43.

Figure 7. COVID-19 human capital spending and simulated impact on long-term outcomes

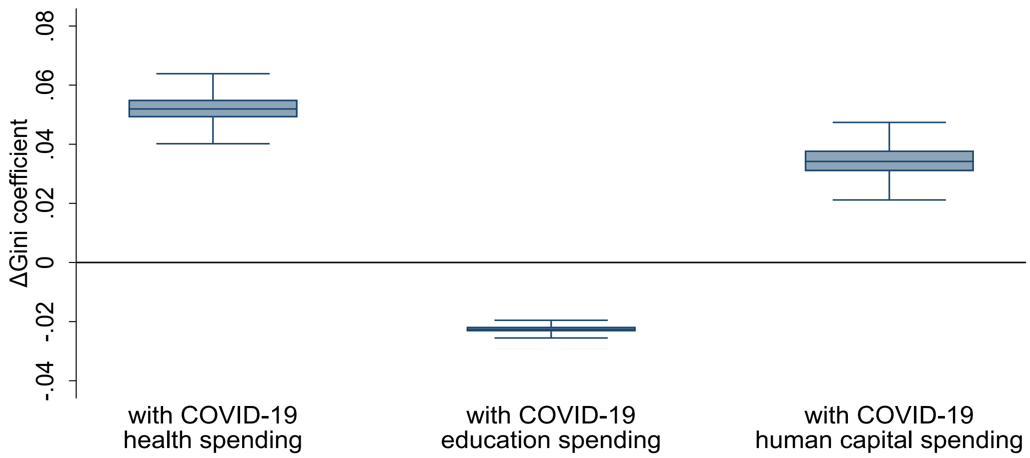
A. Life expectancy at birth



B. Average lifetime labor income



C. Lifetime labor income inequality



Note: Estimates are based on 10 thousand simulated lifetimes subjected to one thousand random draws from the parameter distribution in Table 1. Following standard box and whiskers plot convention, the lines on the box represent the 25th, 50th and 75th percentiles of simulated outcomes. The whiskers represent the upper and lower adjacent values of the distribution.
Source: Authors' calculations.

These indicate that a continuous lifetime exposure to human capital spending at the level during the early COVID-19 pandemic is likely to lead to a deterioration in life expectancy and in income inequality. This has serious implications for the country's attainment of several national and international goals. At the international level, the country's progress to attain the Sustainable Development Goal (SDG) of ensuring healthy lives and promoting well-being for all ages (SDG 3) and reducing inequality (SDG 10) may be stalled or reversed.

At the national level, issues on inclusive growth had hounded the country even when the economy had experienced substantial economic growth. COVID-19 has ushered more considerable setbacks to attaining inclusive growth due to the heterogeneous endowments of people to address the challenges in human capital accumulation during sustained shocks. Plausibly, those with inferior endowments will miss opportunities to invest in health and in education. Missing these opportunities may have adverse ripple effects on time-dependent human capital and development outcomes. For example, it takes a school year to attain specific education milestones. Those who were unable to attend school or were able to participate but did not receive ideal instructions and guidance will lag relative to their cohorts. A similar situation is expected in health outcomes, with more adverse implications for the sick who failed to secure medical and professional help.

Increasing inequality also has implications for the attainment of the Filipinos' aspirations articulated in the Ambisyon Natin 2040, at the heart of which is social mobility. As summarized by Krueger's (2012) "Great Gatsby Curve" and supported by succeeding influential studies (e.g., Chetty et al., 2014), inequality is inversely related to social mobility. While the evidence is highly concentrated in industrialized Western economies, the inequality-mobility paradigm arguably also holds in developing societies like the Philippines. Children from well-endowed households are expected to fare better in later life due to the abundant resources, tools, and social connections available to them.

The reduction in life expectancy needs a more nuanced interpretation. A decline in life expectancy may have an ambiguous effect on income per capita through a positive accounting effect with population decline and a negative effect through foregone human capital potentials. However, which effect dominates depends on the phase an economy is in its demographic tranisition (Cervellati and Sunde, 2011).

In the case of the Philippines, where early-life mortality rate has declined and fertility rate has been declining, a reduction in life expectancy, particularly as a result of increased adult mortality rates, is likely to depress income per capita for at least two reasons. First, the early death of prime-age adults will slow down the growth of the relatively more productive working-age population relative to the growth in elderly and children population. Second, these early deaths are setbacks to productive human capital investments since returns to these investments will not be maximized. These compounding effects suggests that the country may fail to fully realize economic potentials brought about by demographic change, i.e., the so-called demographic dividends.

Separating the effects of changes in health and in education expenditures provide some insights into the drivers of the overall impact of the COVID-19 human capital expenditure shocks.

The drop in per capita health expenditures in the early COVID-19 pandemic relative to the 2018 baseline is expected to lead to a decline in life expectancy at birth, no change in average lifetime labor income, and a rise in income inequality. The impact on life expectancy may not be unexpected, given the significant drop in health expenditures in 2020. Inspection of the simulated observations shows that those who die earlier relative to their baseline outcomes not only have lower health expenditures by age, but also have lower education expenditures due to the positive covariation between health and education spending. Consequently, these less endowed simulated observations have lower lifetime labor income prospects. Their dying earlier leads to an increase in lifetime labor income inequality, but not enough to change the overall average for the simulated population.

The shock on per capita education expenditure by age, on the other hand, appears to have no effect on life expectancy and average lifetime labor income and a slightly negative effect on income inequality. Again, this may not be unexpected given that the change in education expenditures by age is not as drastic as those for health expenditures, including among young learners. As shown in Figure 5, per capita education spending increased slightly for those in their early twenties.

5.2 Some qualifications

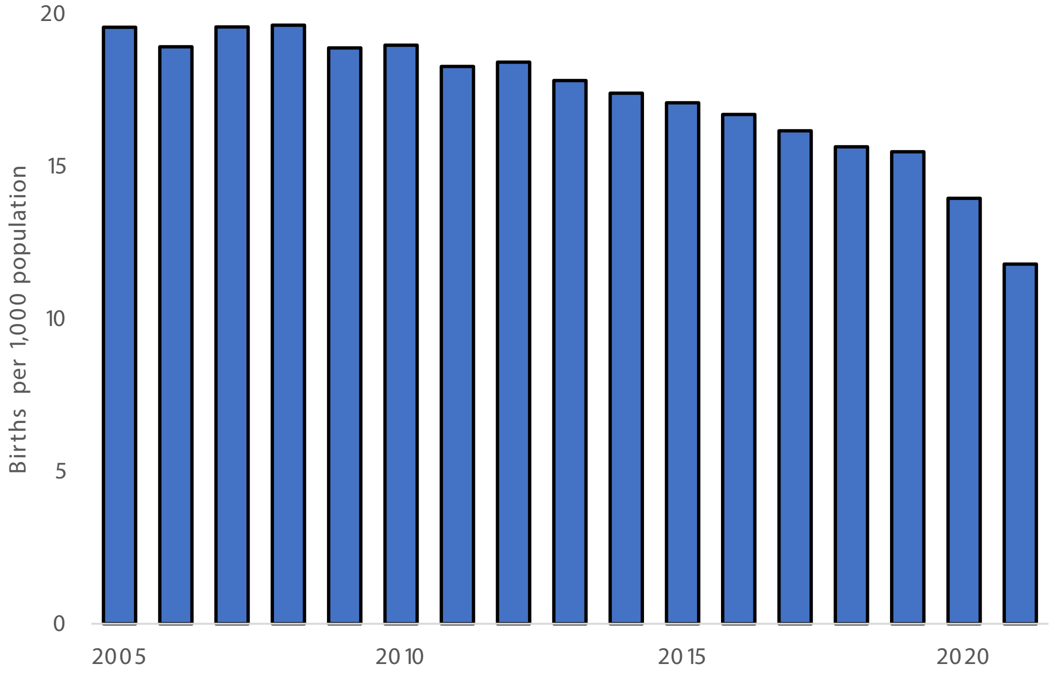
The human capital model we employed in our simulation exercise allows us to conceptually disentangle the different pathways of how human capital shocks induced by the COVID-19 pandemic may propagate through the economic lifecycle. However, it cannot be overemphasized that the simple model we used lacks many of the real world's intricacies and refinement. That being said, we believe that the simulated impacts we present in the previous subsection may be grossly incorrect for several reasons.

A decline by almost 20 years, or more than a quarter of the baseline life expectancy of 71.5 years, spells a major catastrophe that should have decimated a large portion of the population, which we did not observe in the real world. While there has been an increase in excess deaths due to COVID-19 (Ulep, 2022), this is nowhere near what our model predicts. And there could be a number of reasons for this departure.

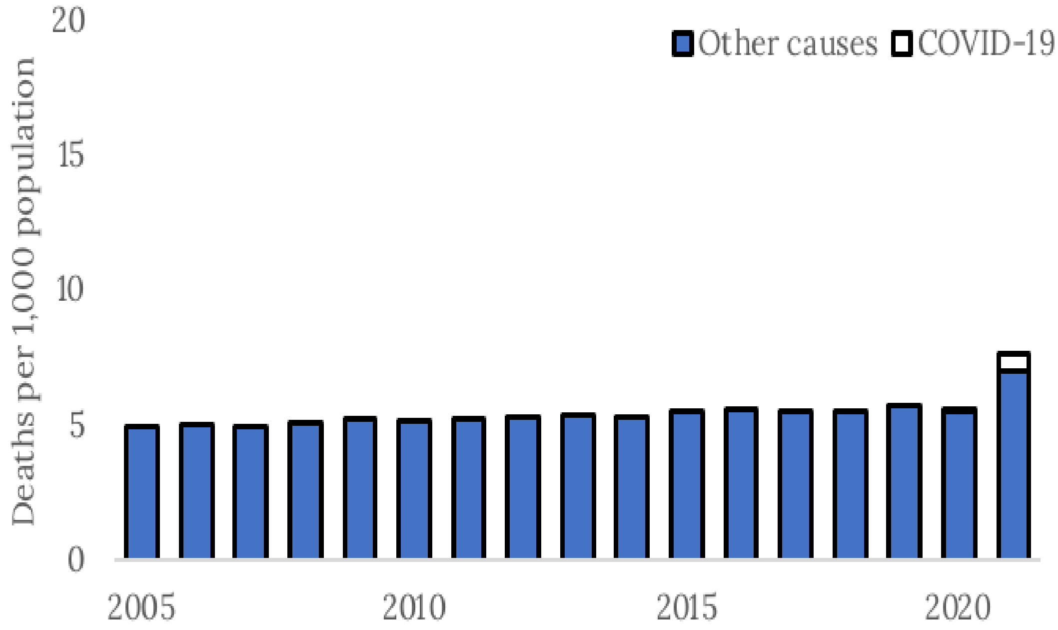
First, we only modelled survival and not fertility. As shown in other studies (e.g., Dehejia and Lleras-Muney, 2004; Sobotka, et al., 2011), fertility is countercyclical with economic activity as a result of changing opportunity costs of childbearing and of fertility behavior during uncertain times, like in pandemics or in economic downturns. That is, we have not considered averted deaths from infants not being born in the first place. This has some empirical support in the Philippines, as we have seen a non-trivial decline in the absolute number of reported live births in 2020 that cannot be accounted for by the long-run declining trend in crude birth rates (Figure 8, Panel A).

Figure 8. Vital rates: Philippines, 2005-2021

A. Crude birth rate



B. Crude death rate



Source: PSA, various years.

Second, real people may be more resilient than agents in our model. Relatedly, third, health, in general, and survival, in particular, do not only depend on the consumption of health goods and services. While medical care-seeking practices may be constrained in the early COVID-19 pandemic, people may substitute health consultations, for example, with more careful health-related choices in the short term. We could expect a delay in health effects, especially with mortality, with impacts more likely observable with prolonged exposure to the global economic and health shock. Indeed, in the second year of the pandemic, the Philippines recorded its highest crude death rate (CDR) since World War II (Figure 8, Panel B) that, again, cannot be explained by the long-run trend in its CDR.

Fourth, our simulation is based on a rather extreme case of lifetime exposure to the human capital expenditure shock in 2020. It has only been two years since the start of the COVID-19 pandemic, and the global economy, including the Philippines, is showing some signs of recovery from the 2020 economic slump (World Bank, 2022; International Monetary Fund, 2022; Asian Development Bank, 2022). The shock on human capital spending is likely to be also transitory. While there may still be risks of COVID-19 breakouts from the ever-evolving coronavirus, large-scale inoculation of early generation vaccines and consistent public health guidance provide some protection for the population and the economy (e.g., Dorn, et al., 2022; Deb, et al., 2022).

We also believe that our estimated impacts due to changes in education expenditures during the early COVID-19 pandemic may be incorrect for similar reasons as the last two above. In particular, we explicitly assumed that productivity-enhancing knowledge only comes from the consumption of education goods when it has been well documented in the literature (e.g., Mincer, 1974; Lemieux, 2006) that experience plays an important role in human capital development. In addition, we did not consider qualitative variations in the effectiveness of different education expenditures, such as those for paper-based modules and those for online learning (e.g., Bird et al., 2022; Angrist et al., 2021). A dollar (or peso) is equivalent to any other in our simple model. We also did not factor in the potential long-term scarring effects from schooling delays or gaps (e.g., Samaniego et al., 2022). Finally, we have included in our policy experiments a pre-existing trend in higher education expansion. While we did not have a readily acceptable mechanism to isolate this particular extraneous shock, it nonetheless impacts our analyses by artificially assigning this expansion as due to the COVID-19 pandemic.

With these limitations at hand, we believe our estimated impact on life expectancy may be grossly overstated, although it provides us an upper bound to the potential impact of the COVID-19 shock for a particularly extreme case. Similarly, the estimated distribution of lifetime labor income may also be overstated for the reasons stated above and therefore provides a reasonable bound to our simulation-based estimates. That is, we believe that the true impact of the COVID-19 pandemic on average lifetime labor income may be at best zero, while that for income inequality is non-negative.

5.3 Limited two-year exposure to COVID-19 human capital spending

Given the issues enumerated above, we performed another set of simulation exercises based on a more realistic assumption of agents being exposed to only two years of COVID-19 human capital spending. In these simulations, we provide estimates by cohort at their specific ages in 2020 to highlight the likely heterogeneous lifetime impact of limited exposure to the pandemic across age groups.

We note the following key takeaways. First, life expectancy is expected to decline across almost all cohorts (Figure 9), although the drop from the pre-COVID-19 level is substantially lower compared with lifetime exposure to COVID-19 human capital spending levels. Among the cohorts, younger generations appear to be more adversely affected with up to a year of life expectancy lost, consistent with results from other studies (e.g., Heuveline, 2022; Andrastay and Goldman, 2020). Interestingly, infants born during the early phase of the pandemic are expected to have longer life expectancy as a result of increased health spending per capita during their early developmental years. Second, lifetime labor income is expected to decline among the young aged below 20, and to increase among younger prime-age cohorts (Figure 10). This appears to be driven mainly by changes in education spending rather than by health spending. Third, the change in education and health spending have diverging effects on income inequality (Figure 11). Inspection of the data indicates that per capita education spending was sustained, and even increased for older cohorts of school-aged population during the early years of the pandemic, which is expected to have negative to no impact on inequality across population cohorts. The decline in health spending per capita, on the other hand, is expected to increase income inequality among the young and younger prime-age adults.

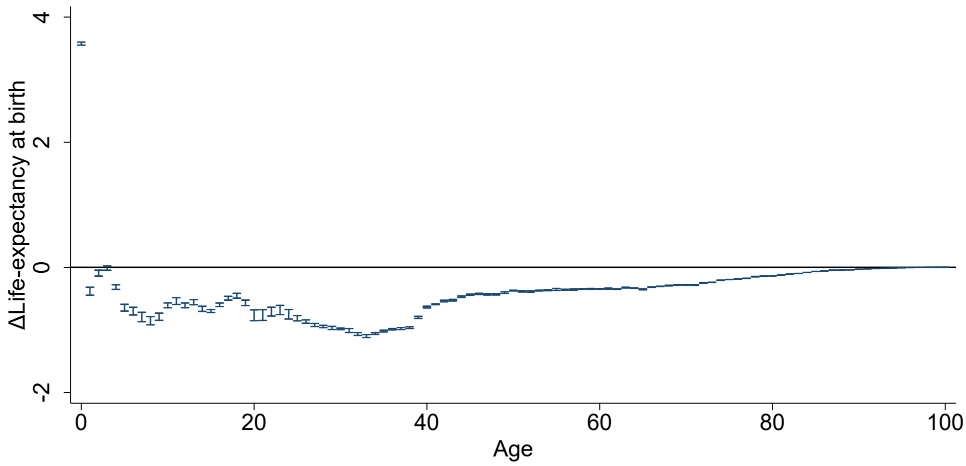
These results highlight the interplay between education and health spending as distinct human capital investments. While education may be the vehicle that can lead to favorable economic outcomes, health is the fuel for attaining these results. During a pandemic, health spending is critical in maintaining favorable outcomes in life expectancy and lifetime income inequality. Unfortunately, the decline in health spending during the early phase of the COVID-19 panemdic is likely to result in adverse long-term outcomes. This highlights the need to assess the health programs and other initiatives implemented for the young population during the pandemic. Understanding what responses worked and could have worked better is crucial in designing responses to future global health crises. While the sustained education spending during the early pandemic phase is expected to yield favorable future economic outcomes, strategic education investments are still needed to improve the productivity of younger cohorts.

6. Concluding remarks

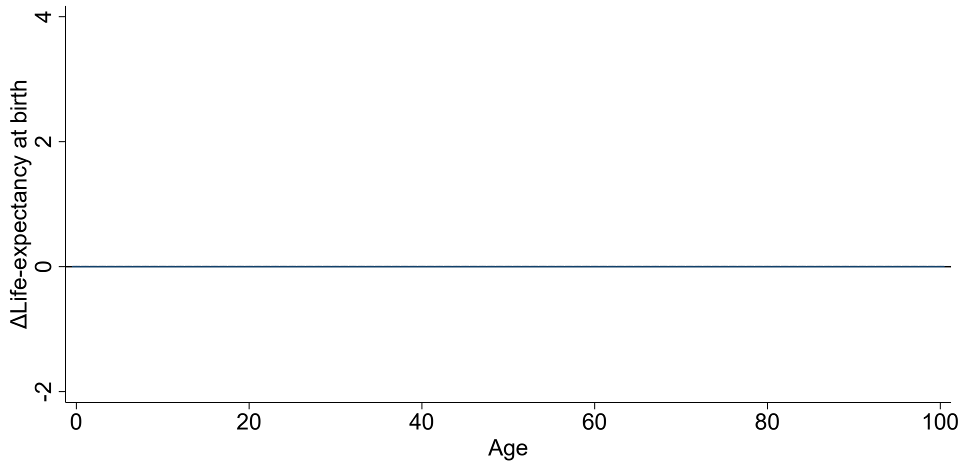
The COVID-19 pandemic highlighted existing weaknesses and introduced new challenges to the Philippines' education and health systems. These threaten the country's recent successes in expanding human capital spending to enhance development outcomes. Worries about long-term economic scarring from delays in schooling and in help-seeking induced by the COVID-19 pandemic are of particular importance due to its persistence and likely severity. An equally important but less discussed issue is how the pandemic may exacerbate existing inequalities and how this may endure through generations.

Figure 9. COVID-19 human capital spending and life expectancy at birth by cohort

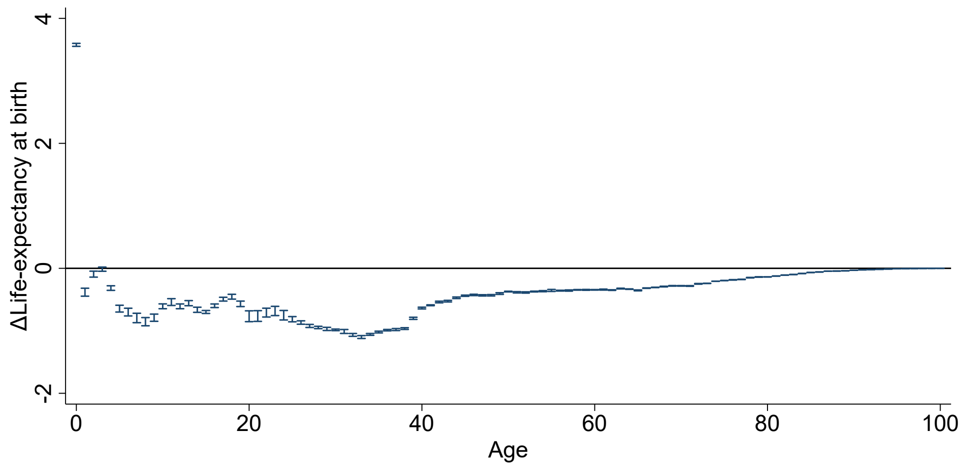
A. With COVID-19 health spending



B. With COVID-19 education spending



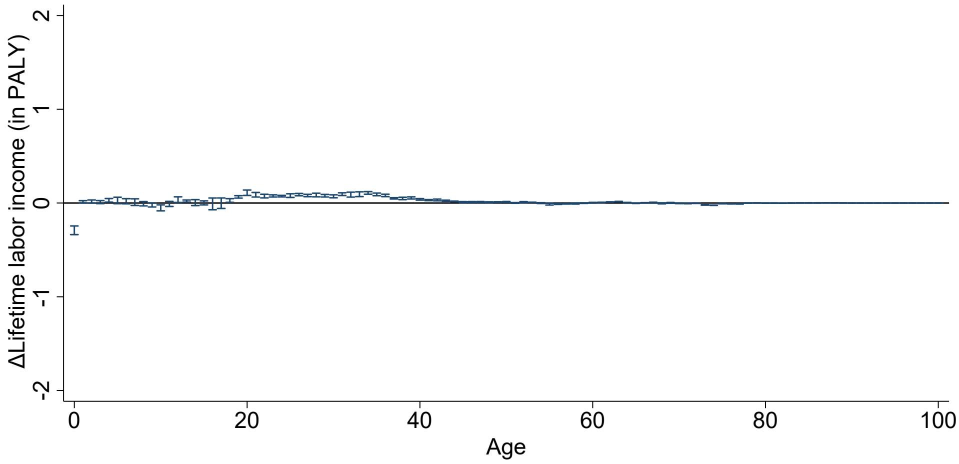
C. With COVID-19 human capital spending



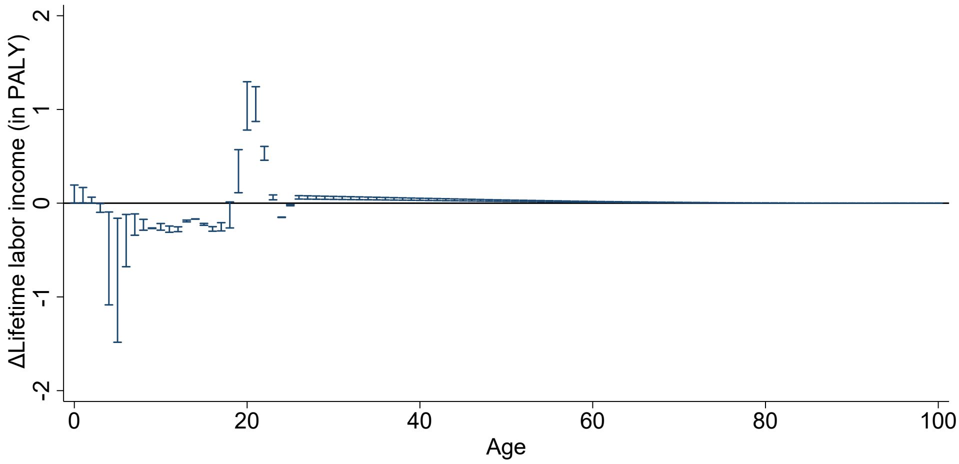
Note: Ninety percent confidence interval shown are based on 10,000 simulated lifetimes subjected to one thousand random draws from the parameter distribution in Table 1. Source: Authors' calculations.

Figure 10. COVID-19 human capital spending and average lifetime labor income by cohort

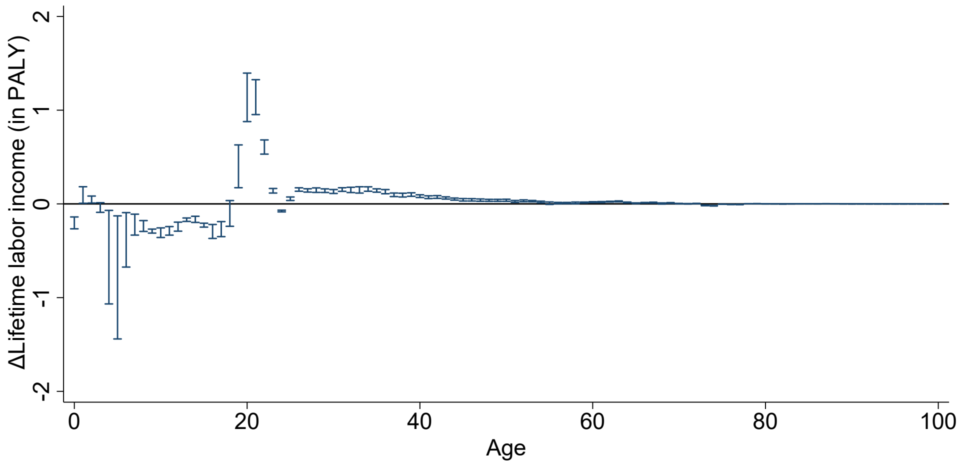
A. With COVID-19 health spending



B. With COVID-19 education spending



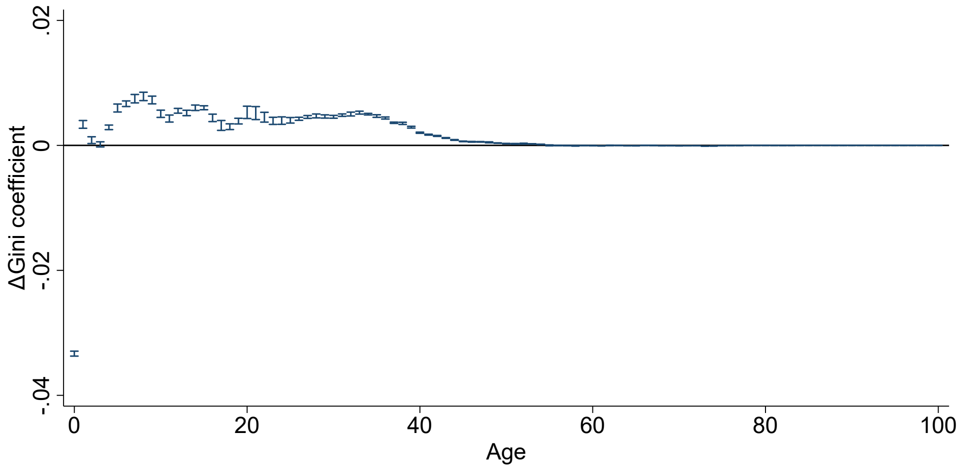
C. With COVID-19 human capital spending



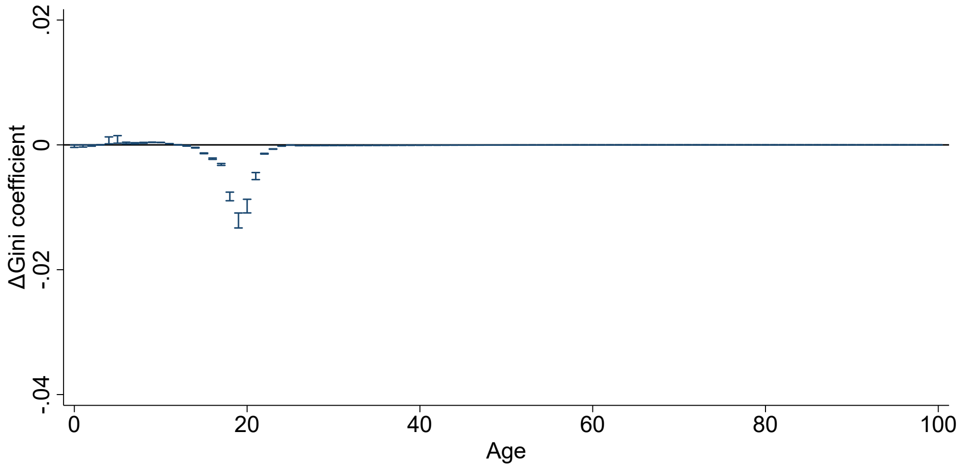
Note: Ninety percent confidence interval shown are based on 10,000 simulated lifetimes subjected to one thousand random draws from the parameter distribution in Table 1. Source: Authors' calculations.

Figure 11. COVID-19 human capital spending and lifetime labor income inequality by cohort

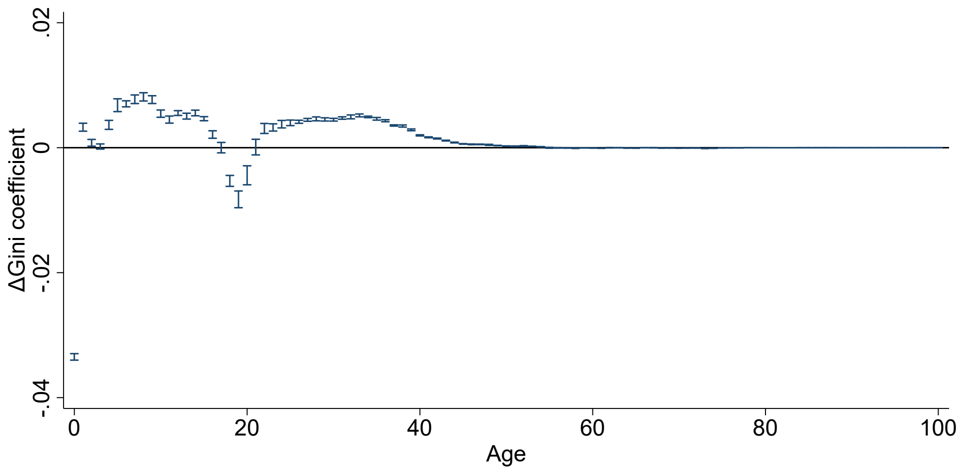
A. With COVID-19 health spending



B. With COVID-19 education spending



C. With COVID-19 human capital spending



Note: Ninety percent confidence interval shown are based on 10,000 simulated lifetimes subjected to one thousand random draws from the parameter distribution in Table 1. Source: Authors' calculations.

In this study, we parameterized a simple human capital model to disentangle how the COVID-19 pandemic may propagate through the economic lifecycle through human capital spending shocks. This allowed us to provide a first-order approximation of the likely impact of the COVID-19 pandemic on several long-term outcomes. The qualitative results are neither unexpected nor controversial. While we believe that the estimates we presented are overstated compared to actual outcomes, these nonetheless provide us reasonable bounds of the true impacts of the global economic and health shock. To wit, the COVID-19 pandemic is likely to negatively impact health and productivity and raise inequality in the longer term.

The study highlights the multifaceted and broad reach of the COVID-19 pandemic. We documented sharp declines in school attendance and in help-seeking during the early phase of the pandemic, which has also been documented elsewhere (e.g., Ulep, 2022; Orbeta, 2022). In addition, we showed that while increased government education spending was able to partially offset declines in household spending, diversion of public funds to COVID-19 response had significantly reduced spending in other health programs. Children, the elderly, and the poor appear to be affected more severely.

The study opens opportunities to introduce or strengthen policies and programs to alleviate, if not fully address the potentially detrimental effects of COVID-19 on health, productivity, and inequality. The literature is replete with policy advice (e.g., Reyes, 2022) and is not repeated here for brevity. It must be underscored, however, that government and public policies play many important roles in shaping household behavior and, thereby, their experience of the pandemic and the ensuing recovery period.

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