Scars of Pandemics from Lost Schooling and Experience: Aggregate Implications and Gender Differences Through the Lens of COVID-19

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Abstract

Pandemic shocks disrupt human capital accumulation through schooling and work experience. This study quantifies the long-term economic impact of these disruptions in the case of COVID-19, focusing on countries at different levels of development and using returns to education and experience by college status that are globally estimated using 1,084 household surveys across 145 countries. The results show that both lost schooling and experience contribute to significant losses in global learning and output. Developed countries incur *greater* losses than developing countries, because they have more schooling to start with *and* higher returns to experience. We also estimate the returns to education and experience separately for men and women, to explore the differential effects *by gender* of the COVID-19 pandemic. Surprisingly, gender differences are small and short-lived. While the employment shock is larger for women, the lower returns to experience for women relative to men dampen their income losses relative to men. The higher returns to education for women are offset by higher schooling of men, especially in developing countries, resulting in similar human capital losses for men and women. These findings challenge some of the ongoing narratives in policy circles. The methodology employed in this study is easily implementable for future pandemics.

JEL: O11; O12; O15; E24; J11; J16; J17; J31.

Keywords: Pandemics; Human Capital; Returns to Education; Returns to Experience; Gender; Female Relative Income; Labor Markets; Development Accounting; COVID-19.

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Human capital accumulation can occur through learning in school and learning at work (Lagakos et al., 2018b,a; World Bank, 2018; Rossi, 2020; Jedwab et al., 2021c). Macroeconomic events such as downturns affect the accumulation of human capital at work, with potentially persistent consequences. However, *downturns due to pandemics are different*. Pandemic mitigation measures include not just workplace closures but also school closures. As a result, they *disrupt human capital accumulation not just at work but also at school*, with potentially severe long-term consequences beyond those of a typical downturn. More generally, national school closures are rare.

We explore the potential long-term economic scars from pandemic-induced disruptions to human capital accumulation at school and at work through the lens of the COVID-19 pandemic, as both workplaces and schools were shut down around the world. Significant declines in employment occurred as a result of the initial lockdowns, and continued due to behavioral changes. Given that future pandemics are likely to be similarly disruptive, the COVID-19 experience is useful for calibrating the aggregate impact of different pandemic scenarios. In addition, given that the returns to education and experience are known to vary around the World, and given that the COVID-19 shocks to schooling and employment may have affected men and women differently, such an exploration would ideally distinguish between countries at different levels of development, and also study the impact on male and female workers independently.

We quantify aggregate impacts through a development accounting framework that tracks the accumulation of human capital in the population over time. We calibrate the framework using returns to experience and returns to education by college status and gender that are consistently estimated for the World using 1,084 household surveys across 145 countries (1990-2016). Finally, we use the framework to compute the short and long term losses from disruptions to human capital accumulation due to pandemic shocks for countries at different income levels, and for men and women separately.

We initially treat countries as though they were *symmetrically* affected. We find that the long-term impact of a pandemic shock through human capital accumulation can be substantial, and for most scenarios is *higher in richer nations.*

In the most severe scenario, welfare decreases in high-income countries by 4.3 percent in perpetuity, 3.0 percent in middle-income countries and 1.9 percent in low-income countries. Given the discount rate, this is equivalent to a one-time loss of 111

percent, 89 percent and 74 percent of GDP respectively. Even 40 years after a pandemic shock, high-income countries remains 4.2 percent below steady state GDP, compared to 2.6 percent for middle-income countries and 0.8 percent for low-income countries. This is because the effect of human capital lost through disruptions to school and work persists until all the affected students and workers have left the labor force.

There are several reasons for the *asymmetric* impact of a *symmetric* shock on countries of different income levels. One is that returns to education do not vary much across income levels but there is significantly less schooling to begin with in middle and low income economies: the average years of schooling in each group is 13, 8 and 6 years, respectively. The negative effect of the employment shock is also higher in high-income economies, due to the presence of higher returns to experience there.

The disruption to schooling is also likely a greater influence on long-term outcomes than the disruption to experience – as the interruption to work affects mostly low-skilled workers, whereas the interruptions to schooling are more widespread, and as the returns to education are several times larger than the returns to experience.

Then, we use our framework to pinpoint carefully *which pandemic scenario most accurately reflects the COVID-19 shock*. We achieve this through a thorough analysis of several variables that vary across income levels and that affect the shock's severity – such as data on school closures, access to and effectiveness of distance learning, and evidence on the extent of disruption to employment to different types of workers.

While high-income countries are more vulnerable to a symmetrical shock due to the relative importance of human capital, the impact of COVID-19 on the high- and middle-income countries is similar. The reason is that middle-income countries are hit much harder both in terms of employment loss and the severity of school closures. This contrasts with the policy literature on COVID-induced schooling disruptions that argues that the impact disproportionately falls on low income economies.[1]

More precisely, the welfare impact is equivalent to 2.5 percent of steady state income in perpetuity in high-income economies, compared to 2.2 percent in middle-income economies and 1.5 percent in low-income economies.[2] Even after ten years, when the

[1]For example, Brookings (2020a) states that the "students in low-income countries and those in sub-Saharan Africa will be the most negatively affected. [...] The learning gap between rich and poor will likely grow during the pandemic, not just between high- and low-income countries [...]."

[2]This is equivalent to a one-off hit of 63, 55 and 36 percent of income respectively. Alternatively, this is

direct impact of the shock has worn off, the welfare impact is 1.2 percent in high-income countries, compared to 1.2 percent in middle-income countries and 0.7 percent in low-income countries.[3] Finally, at the beginning, the employment shock accounts for 84, 70 and 75 percent of the welfare cost going forward (73 percent for the World). There is still, however, some enduring cost from lost experience, particularly in high-income countries. After 10 years, the losses from experience account for 52, 21 and 27 percent of the enduring cost of lost human capital (27 percent for the World).

Lastly, the policy literature suggests COVID-19 had a disproportionate impact on female workers.[4] To explore this issue, we repeat our quantitative exercise separately for men and women. We accomplish this through several steps.

First, we find lower returns to experience for women, especially in richer nations. While this may be surprising given the lower rates of discrimination in richer nations, returns to experience are lower in poorer nations, which constrains how different in absolute terms returns for men and women can be. In contrast, returns to education are slightly higher for women, possibly because education is a stronger signal of intrinsic productivity for employers when experience is more discounted due to discrimination.

Second, we use these returns along with data on the schooling and experience distributions for men and women to compute the impact of the shock on the income of men and women separately. The impact is relatively symmetric past the first few years of the pandemic. The reason is that, while the employment/experience shock hurts women more than men, the schooling shock has the opposite effect, at least in the high and low-income economies. In the high-income economy, more women are college educated, which is less affected by the schooling shock than primary and secondary education. In the low-income economy, women are less affected by the schooling shock because they have less schooling. More broadly, the differences in returns to schooling and experience between men and women are too small to have a significant influence.

Our study makes several contributions to the literature, for example on the macroeconomic impact of pandemics (e.g., Barro et al., 2020; Coibion et al., 2020;

equivalent to $\$15,478$, $\$3,478$ and $\$419$. Overall, this amounts to 59 percent of global GDP ($\$50.3$ trillion).

[3]This is equivalent to a one-off hit of 29, 29 and 17 percent of income respectively. Alternatively, this is equivalent to $\$15,478$, $\$3,478$ and $\$419$. Overall, this amounts to 29 percent of global GDP ($\$24.4$ trillion).

[4]For example, the United Nations (2020), the World Bank (2020a) and Brookings (2020b) have highlighted how COVID-19 will permanently, not just temporarily, hurt women more than men.

Fernandez-Villaverde and Jones, 2020; Guerrieri et al., 2020; Jorda et al., 2020; Ng, 2021).[5]

While other studies on the global learning losses due to COVID-19 have appeared independently of this study – e.g., Azevedo et al. (2020), Hanushek and Woessmann (2020) and Psacharopoulos et al. (2021) estimate the impact of disruptions to schooling –, we are to our knowledge the first to thoroughly quantify the human capital effects of COVID-19 by income level: (i) considering *both* education and employment/experience losses; (ii) relying on returns to education and experience that were consistently estimated for the world using 1,084 household surveys across 145 countries;[6] (iii) performing a thorough analysis of the education and experience shocks using evidence on school closures, access to and effectiveness of distance learning, and on disruptions to employment for different types of workers;[7] (iv) examining the output dynamics associated with the shocks; and (v) studying how they vary by gender. Lastly, Hanushek and Woessmann (2020) study OECD economies only and Fuchs-Schündeln et al. (2020) and Jang and Yum (2022) focus on the distributional effects of school closures.

We then also contribute to a sparse literature on the relationship between experience and economic development (Manuelli and Seshadri, 2014; Lagakos et al., 2018b,a; Islam et al., 2019; Jedwab et al., 2021c), as well as a large literature on the link between schooling and development (Klenow and Rodriguez-Clare, 1997; Hall and Jones, 1999; Bils and Klenow, 2000; Hendricks, 2002; Caselli, 2005; Hanushek and Woessmann, 2012; Schoellman, 2012; Caselli and Ciccone, 2013, 2019; Jones, 2014, 2019; Hanushek et al., 2017; Hendricks and Schoellman, 2018, 2022; Flabbi and Gatti, 2018). While the macroeconomics literature has looked at the potential long-term impact of economic downturns or economic transitions or the impact of structural transformation through

[5]See Jedwab et al. (2020) and Beach et al. (2020) for recent surveys of the literature on past pandemics.

[6]In contrast, the three studies assume similar returns to education across countries. In Azevedo et al. (2020) returns to education do not vary across education levels. Hanushek and Woessmann (2020) then consider measures of the returns to learning (test scores), which are typically only available for high-income countries. Lastly, we discuss how sensitive our results are to implementing important robustness checks when estimating the returns, for example related to cohort effects and self-employment.

[7]Psacharopoulos et al. (2021) have a uniform assumption across countries about access to and effectiveness of distance learning. Azevedo et al. (2020) only use data on access, not effectiveness. Our results on COVID-19's effects (first circulated in September 2020) were developed independently of the estimates provided by Psacharopoulos et al. (2021) (May 2020), Azevedo et al. (2020) (June) and Hanushek and Woessmann (2020) (September). While these studies have done a superb job in studying learning losses from COVID-19, their objective was to rapidly share their results with policy-makers. Being two years into the pandemic, we use novel information on the various dimensions listed in the text.

human capital,[8] the long-term impact of disruptions to human capital accumulation due to pandemics has, to our knowledge, not been studied in this literature.[9]

In addition, we contribute to the literature on gender inequality and economic development,[10] as well as the literature on macroeconomics and gender. The latter literature focuses on understanding the cause of increased female labor force participation over time, or the differences in labor market outcomes by gender over the business cycle.[11] Alon et al. (2020), Alon et al. (2021) and Albanesi and Kim (2021) find that, in the United States, the COVID-19 shock had a disproportionately severe impact on female employment compared to male employment. In contrast, Goldin (2021) argues that the main difference in the impact on employment is by education group, not by gender. We take into account gender differences in schooling, as well as in the returns to human capital, finding that the short run impact is greater on women, but that the long run impact is similar to men, for countries at different levels of development.

Furthermore, we focus on understanding the global and long-lasting effects pandemics might have on income for men and women through disruptions to human capital accumulation – and thus on *female relative income*.[12] As a step towards this goal, we estimate the returns to education and experience separately for women and men. Nonetheless, the impact of the COVID-19 pandemic on men and women turns out not to be very different. We note that, to our knowledge, these returns have not been globally estimated using a consistent methodology before, so these stylized facts were not previously available in the literature. Finally, we implement a series of robustness

[8] Studies on downturns include Ljungqvist and Sargent (1998), Davis and Von Wachter (2011) and Kahn (2010). Studies on economic transitions include Dauth et al. (2019) and Jedwab et al. (2021c). Studies on structural change include Schoellman and Hobijn (2017), Islam et al. (2019) and Buera et al. (2020).

[9] Human capital could be accumulated at work *passively* or *actively*. There is a long tradition of modeling growth through learning-by-doing, see Arrow (1962), Uzawa (1965), Lucas (1988) and Jovanovic and Nyarko (1996). An alternative would be to assume that human capital requires investment and that agents are compensated for hours worked, as in Ben-Porath (1967) and Rosen (1972). In such a framework it might be that, since active learning is front-loaded, initial wages are actually higher than measured (assuming reported hours include hours spent studying at work) so the returns to experience might be biased upwards in richer nations if there is more learning there. See Jedwab et al. (2021c) for a discussion of why this bias is unlikely to be significant. See Ma et al. (2021) for contradictory evidence.

[10] See Cuberes and Teignier (2014) for a survey of the literature. Other studies include: Galor and Weil (1996); Lagerlof (2003); Greenwood et al. (2005); Doepke and Tertilt (2009, 2018); Hyland et al. (2020).

[11] See Acemoglu et al. (2004), Fernandez et al. (2004), Olivetti (2006), Attanasio et al. (2008), Ngai and Petrongolo (2017), Erosa et al. (2017), Attanasio et al. (2018) and Albanesi and Sahin (2018).

[12] There are studies on the impact of relative income on the bargaining power and socio-economic outcomes of women (Duflo, 2003; Qian, 2008; Jensen, 2012; Majlesi, 2016). See Duflo (2012) for a survey.

checks, including accounting for cohort effects, the impact of having children, selection into the workforce, and measurement error due to self-employment varying by gender.

More generally, our findings challenge some of the ongoing narratives in policy circles, which highlights the methodological contributions of this study.

In our framework the only determinant of income is human capital. Gollin (2002) shows that labor shares vary from 0.65 to 0.80 around the world. To the extent that other resources do contribute to output, one might want to lessen the impact of pandemic shocks accordingly. On the other hand, idle machinery does not produce goods, and to the extent that output disruptions affect the production of capital goods these resources would also diminish in quantity as a by-product of the shocks to human capital. As a result, it is not clear that such an adjustment is necessary, nor is it likely to be significant.

Section 1. describes our development accounting framework. Section 2. explains the calibration, and Section 3. explains how we model the pandemic shock. Section 4. describes the impact of pandemic shocks on different countries under different scenarios that affect countries symmetrically, and Section 5. discusses scenarios that might be relevant for specific groups of countries over the COVID-19 pandemic specifically. Section 6. provides estimates of the return to schooling and experience for men and women, and applies our framework to study the differences in the impact of the COVID-19 shock across male and female workers. Section 8. concludes.

1. Development Accounting Framework

For our analysis, we require an accounting framework that tracks the accumulation of human capital and aggregates its returns across individuals. We build on the framework in Jedwab et al. (2021c), as it allows us to match a variety of statistics required for our exercise, including the distribution of schooling and the rate at which human capital of different forms is accumulated over the life cycle. First, we describe how our framework works in the steady state: this scenario will serve both as the initial condition before the pandemic shock, and as a counterfactual. Then, we introduce the shock.

1.1. Economic Environment

Time is discrete. There is a measure of agents m_t which changes over time. Each year t, $b_t = b_0 g_b^t$ agents are born with age $a = 0$, where g_b is the growth factor in birth rates over time. Agents of age a die with probability $\delta(a)$, and proceed to age $a+1$ with probability $1 - \delta(a)$. We assume there is some $\bar{a}$ such that $\delta(a) = 1$ for $a \geq \bar{a}$.

An agent i is born with schooling $s_{it} = 0$. With probability $\pi_s(0)$, agents begin schooling at age $\underline{a}$. An agent i currently in school with schooling s_{it} proceeds to the next level of schooling $s_{it}+1$ with probability $\pi_s(s_{it})$, otherwise they leave school.

Agents not in school work with probability $\pi_e(a_{it})$ where a_{it} is age. The probability $\pi_e(\cdot)$ will be less than one to capture the possibility of unemployment and non-participation. If they work, they generate earnings and accumulate experience. $\pi_e(\cdot)$ depends on age because youth unemployment differs from average unemployment, and because agents typically do not enter the workforce until a certain age a_w.

Earnings w_{it} of a working agent i at date t satisfy $\ln w_{it} = h_{it}$ where h_{it} is their human capital measured in units of the return it generates. Let $r_s(\cdot)$ be the return to education, and let $r_e(\cdot)$ be the return to experience. While in school,

$$h_{it} = h_{i,t-1} + r_s(s_{it}) \tag{1}$$

where $r_s(s_{it})$ is the return to schooling level s_{it}. When not in school,

$$h_{it} = \begin{cases} h_{i,t-1} + r_e(s_{it}, p_{it}) & \text{with probability } \pi_e(a_{it}) \\ h_{i,t-1} & \text{otherwise} \end{cases} \tag{2}$$

where $r_e(s_{it}, p_{it})$ is the return to experience, which may depend on schooling s_{it} and on potential experience $p_{it} \equiv a_{it} - \max\{a_w, s_{it}\}$.

Finally, GDP per person $pcGDP_t$ equals total earnings divided by the population:

$$pcGDP_t = \frac{\int e^{h_{it}} dm_t}{\int dm_t}.$$

We model human capital as earnings potential. Returns are based on earnings data.[13]

1.2. Steady State

Regardless of m_0, it is straightforward to show that the distribution of schooling and experience in this environment will converge to a stationary distribution m_t^* after $\bar{a}$ periods, where $m_{t+1}^* = g_b m_t$ and the distribution of schooling s and human capital h are constant over time (i.e. the share of the population with a given level of education or experience is the same). The age structure of the model would then be a stationary distribution where the population of each age group rises over time by the factor g_b.

[13] It could be that r_s and r_e reflect different amounts of human capital. Alternatively, it could be that agents earn the same quantity of raw human capital in different countries but it is rewarded differently. Either interpretation of equations (1) and (2) is consistent with our quantitative exercises.

Alternatively, if we define $\mu_t \equiv \frac{m_t}{\int dm_t}$, there exists a unique μ^* such that $\lim_{t\to\infty} \mu_t = \mu^*$, $\int d\mu_t = 1$ and $pcGDP_t = \int e^{h_{it}} d\mu^*$ after at most $\bar{a}$ periods regardless of μ_0. This is because each generation born after date zero has a deterministic composition of s and p, given by the probabilities $\pi_s(\cdot)$ and $\pi_e(\cdot)$ and the composition of the previous generation.[14]

For our experiments, we will assume that the model begins in stationary state μ^*. Then, we subject the model to the pandemic shock. The economy eventually returns to μ^* , once all agents affected by the shock have left the market.

2. Calibration

We calibrate the framework to match certain statistics in a pre-pandemic steady state. We do so for three groups of countries: high-income, middle-income and low-income economies (HIC, MIC and LIC, respectively). The reason for doing so are as follows. It is of interest to identify the impact of the shock on countries at different income levels. However, it is best to do this for groups of countries (rather than for individual countries) as averaging avoids the undue influence of outliers and measurement error.

2.1. Calibrating the Steady State

Calibration requires selecting values for the return functions for schooling and experience $r_s(\cdot)$ and $r_e(\cdot)$. We also need values for g_b and $\delta(\cdot)$, as well as the age at which schooling begins $\underline{a}$, and the probabilities for schooling $\pi_s(\cdot)$ and work $\pi_e(\cdot)$.

We obtain the population growth rates g_b and the mortality functions $\delta(\cdot)$ from United Nations (2019). We use the medium variant forecasts over the $2020-2050$ period, assuming that $\bar{a} = 100$. Thus, $\delta(a) = 1$ for $a \geq 100$.[15]

We assume schooling starts at age $\underline{a} = 6$. Agents enter the work force after age $a_w = 18$ unless they are still in school. We then set the schooling transition probabilities $\pi_s(\cdot)$ so

[14] We do not introduce a growth trend as it is easier to identify and discuss deviations from steady states than deviations from trends. Note that we later assume that, for purposes of measuring welfare effects, agent utility over consumption stream $\{c_t\}_{t=0}^{\infty}$ is

$$U\left(\{c_t\}_{t=0}^{\infty}\right) = \sum_{t=0}^{\infty}\left(\frac{1}{1+r}\right)^t \ln c_t,\, r > 0.$$

Suppose $c_t = \tilde{c}_t e^{gt}$ where g is the growth rate and $\tilde{c}_t$ is stationary. Then

$$U\left(\{c_t\}_{t=0}^{\infty}\right) = \frac{g}{r^2}(r+1) + \sum_{t=0}^{\infty}\left(\frac{1}{1+r}\right)^t \ln \tilde{c}_t.$$

All that matters are the deviations from trend $\tilde{c}_t$.

[15] Of course some people do exceed 100 years of life, but this is a very small proportion of the population in all countries. See Web Data Appx. A.1 for these distributions and for details of their calculation.

as to exactly match the schooling distribution for the relevant country group, based on data from the I2D2 database, the World Bank database of more 1,000 household surveys that we use to estimate the returns to education and experience (see below).

We make the following assumptions regarding the probability of working $\pi_e(\cdot)$. We assume that agents may start work once they complete schooling, or reach 18 years of age, whichever is later. At that point, a share l_p of agents participate in the labor force. Those that participate face youth unemployment with probability u_y each year until they are 24. Above 24 they face unemployment each period with probability u, until they retire at age $R = 65$. We assume unemployment and participation are equal across schooling and age groups. We measure l_p, u and u_y for each group using data from World Bank (2020b). Data are based on population-weighted means.

Now we turn to the selection of the returns to schooling and experience. We model $r_s(\cdot)$ and $r_e(\cdot)$ as step functions so as to capture salient features of the data with few parameters, in order to be able to estimate them consistently. Specifically, we assume that schooling returns $r_s(\cdot)$ have two values $\underline{r}_s$ and $\bar{r}_s$ such that:

$$r_s(s) = \begin{cases} \underline{r}_s & \text{if } s \leq 13 \\ \bar{r}_s & \text{if } s > 13 \end{cases},$$

where $s > 13$ supposes that the agent has completed college.

Experience returns $r_e(s,p)$ have three values:

$$r_e(s,p) = \begin{cases} \underline{r}_e & \text{if } s \leq 13 \text{ and } p \leq 25 \\ \bar{r}_e & \text{if } s > 13 \text{ and } p \leq 25 \\ 0 & \text{if } p > 25. \end{cases},$$

The assumption that $r_e(s,p) = 0$ after a certain point reflects the finding in the literature that the returns to experience decrease over time (Lagakos et al., 2018b; Jedwab et al., 2021c). If $\underline{r}_e < \bar{r}_e$, then the returns embody a college premium.

2.2. Returns Parameters

We follow the methodology of Lagakos et al. (2018b) and Jedwab et al. (2021c) to estimate the returns to education and experience by college status: $\bar{r}_s$, $\underline{r}_s$, $\bar{r}_e$ and $\underline{r}_e$.

Sources. The data source is the *International Income Distribution Database* (I2D2) of the World Bank. The database consists of a large number of household and labor force surveys and census samples. The data was initially compiled by the World Bank's *World*

Development Report (WDR) unit between 2005 and 2011. The database has since been expanded.[16] Only select members of the WDR team or research team or individuals in charge of harmonizing the data can access the database. However, a significant number of the surveys can be accessed online or after entering an agreement with the countries' respective statistical office.[17] Finally, the surveys are nationally representative and large enough for our purpose.[18] Jedwab et al. (2021c) also verify that the database generates global patterns that are consistent with patterns observed when using other global databases such as the *World Development Indicators* database of the World Bank.[19]

Sample Size. I2D2 includes about 1,500 survey/census samples. However, wages are only reported for two thirds of them. We restrict our analysis to workers aged between 18 and 67 with data on age and education. The baseline sample that we obtain includes 24,437,020 individuals from 1,073 surveys and 11 censuses in 145 countries from 1990-2016 (median = 6; mean = 7.5; min = 1; max = 44). We include surveys from the 1990s to increase sample size. The 145 countries comprise 95% of the world's population.

Variables. We know the monthly wage, age, and number of years of education. For a substantial subsample, we know the hourly wage, the number of hours worked, and the employment status (e.g., self-employed or paid employee). Note that I2D2 calculates the wage of self-employed individuals as the amount of salary taken from the business.

We calculate *potential work experience* as follows: (i) For individuals with at least 12 years of education, we assume children start school at age 6 and experience equals age - years of education - 6; (ii) For individuals with less than 12 years of education, we assume that experience before age 18 is inconsequential and experience equals age - 18.

Model. For individual i and sample t, we first use OLS to estimate the following model for *each* country one by one, first for the whole population of 18-67 year-old workers, and then for 18-67 year-old male workers and 18-67 year-old female workers *separately*:

$$lnW_{it} = \sum_{e=1}^{7} \beta_e exp_{ite} + \gamma edu_{it} + \theta_t + \varepsilon_{it} \tag{3}$$

[16]We use the expanded December 2017 vintage of the database.

[17]World Bank (2013) writes that I2D2's aim is "to provide the World Bank and its client countries reliable micro economic data that is in an easy to use format. The data will be used to calculate a variety of indices and in the future can be used for complex economic analysis. The micro level data will be strictly confidential; however, the aggregate data can and will be used for information and research purposes."

[18]World Bank (2013) writes: "In practice we frequently see samples sizes of 10,000."

[19]They find that the samples are globally representative in terms of per capita income, age structure, education, and self-employment. The Mincerian R-squared are also not too different across countries.

where the dependent variable is the log of monthly earnings (lnW_{it}). Experience is categorized into seven bins (exp_{ite}). The bins are [5-9 years] (which we call 5), [10-14] (10), [15-19] (15), [20-24] (20), [25-29] (25), [30-34] (30), and [35+] (35). The omitted bin is [0-4] (0). We include the number of years of education (edu_{it}) and sample fixed effects (θ_t) to capture country-year-sample unobservables.[20] Note that having separate regressions for males and females has the advantage of making the sample fixed effects gender-specific. Finally, we omit samples without at least 10 observations in each bin.

Profiles. The coefficients of the experience dummies help construct wage-experience profiles for developing countries (G) and developed countries (D) (high-income countries in 2017 according to the World Bank classification). To obtain these profiles, we obtain the average wage differential for each country and construct the mean wage differentials for each group weighted by the population of each country in 2017. As seen in Fig. 1, in developed countries, a worker with 30 years of experience earns 80% more than a worker with zero experience. For developing countries, the difference is 45%. Note that differences in the profiles for males and females will be discussed later.

Returns. Measures of the returns to experience should take the integral below the profiles. For each bin one by one (5, 10, etc.), we estimate an annualized return. We then take the mean of the annualized returns across the seven bins to obtain the *mean annualized return* throughout the experience distribution. More precisely, for individuals belonging to bin e, we obtain the *bin-specific annualized return* as $ret_e = ((\beta_e + 1)^{(1/e)} - 1) * 100$, with β_e being the estimated coefficient for bin e in eq. (3). For this subgroup of individuals in the society, it tells us by how many percentage points wages increased on average for each extra year of experience. We then take the average of these seven bin-specific annualized returns so that each bin is equally represented.[21] For the returns to education, we consider the coefficient of the number of years of education.[22]

By College Status. To obtain the returns by college status, we estimate model 3 for workers without any college education and workers with some college education

[20]Most countries having several samples, we use individual weights divided by the size of the sample.

[21]More precisely, the overall return r_e is equal to $(\sum_{e=1}^{7} ret_e) \div 7$.

[22]Our specification has several advantages over the Mincerian specification: (i) Seven coefficients is more flexible and informative; (ii) Our returns are independent of the distribution of experience. Since we keep samples with at least 10 observations in each bin, and then give each bin the same weight, our returns are less affected by the facts that D and G countries have more experienced workers and more inexperienced workers, respectively; and (iii) We can construct measures using only the 0-25 bins.

separately.[23] Note that having separate regressions for each college status has the advantage of making the sample fixed effects college status-specific. We then proceed similarly for male workers only, and then female workers only. Again, in all cases, we omit samples without at least 10 observations left in each experience bin.

Figure 2 shows overall higher returns to education for college educated ("college+") workers than for other ("pre-college") workers.[24] The figure also shows the positive relationship between the returns to education for pre-college workers and log per capita GDP for the mean year in the data for each country (we use country populations c. 2018 as weights for the quadratic fit). For college+ workers, the relationship is U-shaped.[25]

Table 1 summarizes the resulting parameters for each country group. The returns to pre-college schooling are lowest in the LIC, possibly due to the fact that there is higher demand for human capital in the MIC and HIC, given their sectoral structure. Returns to college education are then higher in the LIC, perhaps due to the scarcity of college education, and the HIC, plausibly due to the higher demand for college education there. Indeed, average years of schooling in the LIC is 6, compared to 8 in the MIC and 13 in the HIC. This suggests that disruptions to schooling will be the most consequential in the HIC, as both the quantity of and returns to schooling are high. Finally, note that the returns implicitly take into account the quality of schooling. Indeed, in countries where the quality is low, the relative wages of more educated individuals will also be lower.

Figure 3 shows the returns to experience are also overall higher for college+ workers than for pre-college workers, except in the most developed countries.[26] The same figure then shows the positive relationship between both returns to experience and income.

Returns to experience are higher in the HIC than in the MIC and LIC, which are more similar (see Table 1 for the resulting parameters). Thus, a given disruption to employment will be more consequential in the HIC. For a pandemic shock to disrupt the economy of a MIC or LIC as much as that of the HIC, some aspect of the shock would have to be worse there than in the HIC. Given the higher returns for college workers, how the shock affects employment for college vs. non-college workers will also matter.

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[23]According to Unesco (2012), individuals finish high school after 12-13 years of education, thus 13 years is a reasonable cut-off. Results hold with other cut-offs (not shown, but available upon request).

[24]It is the case in 85% of countries. The mean difference in the other countries is small (about 0.7).

[25]The GDP is in PPP terms and constant 2011 USD. For countries with multiple years of data, the mean year is the average sample year using as weights the number of observations in each sample.

[26]It is the case for two thirds of countries. The mean difference in the other countries is small (0.6).

Finally, differences in the estimated returns for males vs. females will be discussed later.

3. Pandemic Shocks

We model pandemics as a temporary disruption to schooling and to employment.

The disruption to schooling means that, for the period of impact, less human capital is accumulated than usual. Possible scenarios include assuming that $r_s(s_{it}) = 0$ for the period of impact on schooling, which is equivalent to having no schooling at all. Another scenario could be that $r_s(s_{it})$ declines for a period but remains positive, which could be interpreted as a part-year disruption to schooling, or as a mode of schooling (e.g., online or hybrid schooling) that is not 100 percent effective. The transition probabilities for schooling $\pi_s(\cdot)$ do not change: in other words, students do not make up for a missed year of schooling later on, nor do they drop out early as a result. That said, dropping out temporarily can also be viewed as a factor behind declines in $r_s(s_{it})$.[27]

The disruption to employment involves a change in $\pi_e(\cdot)$. Broadly, we will assume an initial spike in non-employment (including unemployment, inactivity and reduced hours), which will decline over a transition period until it returns to normal.

Even though disruptions to $\pi_s(\cdot)$ and $\pi_e(\cdot)$ are temporary, the "lost years" of education and experience leave gaps in the human capital stock that do not disappear until all the students and workers who lost years of human capital accumulation retire.

3.1. Modeling the pandemic shock

We now discuss the range of scenarios we consider. To compile an empirically relevant range of pandemic shocks, we build on observed shocks to schooling and employment over the course of the COVID-19 pandemic, and use this to articulate the range between the best case scenario (no pandemic) and the worst case scenario. Doing so assumes that COVID-19 is a more or less representative of a severe pandemic.[28] Thus, both the spread of the pandemic through the community and the required mitigation measures would likely be similar.[29] As far as the disruption to schooling is concerned, COVID-

[27] The evidence suggests school dropouts rarely come back to school (see the discussion in Azevedo et al. (2020)). There is also evidence that students who temporarily leave school forget materials (Ibid.).

[28] Since 1900, global pandemics have indeed almost all been respiratory diseases: COVID-19 (2019-present), H1N1pdm09 (2009-2010, now endemic), H3N2 (1968-1969), H2N2 (1957-1958) and H1N1 (1918-1920). See U.S. Center for Disease Control and Prevention for details: https://www.cdc.gov/flu/pandemic-resources/basics/past-pandemics.html, last checked 10/28/2021.

[29] An exception is the HIV/AIDS global epidemic (1981-present). However, the HIV virus requires different mitigation measures (in particular, neither workplace nor school shut-downs are required).

19 was the first shock where schooling (particularly higher education) could switch to an online or hybrid system, particularly in wealthy countries, and as such it is likely to provide a relevant benchmarks for how schools might respond to future pandemics.[30]

We will first analyze pandemic shocks as though they affect countries *symmetrically*, in order to highlight the ways that a given shock might affect countries differently based on their level of development. Finally, note that we ignore the impact of mortality as it mostly affects the non-working population (see Web Appx. Section B for details).

3.1.1. Schooling shock

Incidence For primary and secondary students, the shock lowers the amount of schooling by some share $\nu \in [0,1]$ during the period of impact. Thus, we have that during equation (1) becomes: $h_{it} = h_{i,t-1} + (1-\nu)\, r_s\,(s_{it})$. Factors leading to values of $\nu > 0$ include school closures, imperfectly effective hybrid or online education, and temporary voluntary withdrawal from school. This does not affect the probability of proceeding to the following year $\pi_e\,(\cdot)$, but slows human capital accumulation.

On the other hand, we assume that the accumulation of human capital in college is not disrupted. This is because the evidence does not suggest significant disruption to college enrollment numbers nor to the effectiveness of college education during the COVID-19 pandemic. See Web Appx. Section C for further details.

Duration & Severity We explore all possibilities between no disruption and total disruption, over 2 years. We study scenarios whereby primary and secondary schooling is disrupted, i.e. we consider all values of $\nu \in [0,1]$. Later we discuss which values are most likely for each country group, depending on school closures, technology, etc.

3.1.2. Employment shock

Incidence The employment shock affects mainly workers with sub-college education and the young. We assume that, if the unemployment rate among adults without college education rises by a certain amount x, then unemployment among college-educated adults rises by one half of that amount $(0.5x)$. Youth unemployment is more severely affected so we assume that if unemployment among adults without college rises by x youth unemployment rises by $2x$. We explain in detail in Web Appx .Section D how we arrived at these factors, based on ILO (2020) data over the COVID-19 pandemic.

[30] There have also been severe pandemics in terms of mortality that were not airborne, such as the Black Death (14th century) and the American smallpox epidemic (16th). These are cases where mortality itself is a key channel of resource destruction (Jedwab et al., 2021a), rather than the mitigation measures.

Severity We examine an increase in overall unemployment rates ranging from zero to ten percentage points. This is achieved by varying x between 0 and the value that leads to overall unemployment increasing by 10 percentage points in each economy. Web Appx. Section D explains in detail how we arrived at this range, but note that the ILO (2020) nowcasting model estimates that total working hours (including unemployment, inactivity and reduced hours) lost worldwide in 2020 were 8.8 percent, varying from 6.7 percent in LIC up to 9.5 percent in MIC, making 10 percent a reasonable upper bound.

Duration Hall and Kudlyak (2021) find that recoveries from unemployment shocks regularly occur following a proportional factor $\rho \in (0,1)$ – that is, given an initial employment shock x_0, thereafter $x_{t+1} = x_t \times \rho$. Based on employment data from across the OECD, we calculate a proportional factor of $\rho = 0.7143$ (see Web Appx. Section D).

Of course such an economy would never fully recover: even though $\lim_{t\to\infty} x_t$, we would still have that $x_t > 0 \forall t$. Having a date at which the recovery is complete is necessary to distinguish cleanly between the direct impact of the shock through loss of employment and the long run impact through lost human capital. Based on these criteria, we proceed as follows. First, we assume that the full recovery takes 10 years. Assuming a decay factor of 0.7143, by ten years there would be very little residual deviation from steady state GDP ($0.7143^{10} \approx 0.03$).[31] Then, we subtract this deviation from x_t for all $t < 10$ – so the last factor is now zero. We set $x_t = 0$ for $t \geq 10$. Finally, we multiply all the factors by a number (slightly larger than one) to ensure that the initial deviation is of the initially assumed size x_0. This way we have the same initial shock size, zero residue after 10 years, and essentially the assumed constant decay factor.

4. Quantitative Impact of Pandemic Shocks

4.1. Impact on Output

We explore output dynamics when a pandemic has the maximal impact considered, on both schooling and unemployment. This assumes a disruption to pre-college schooling for two school years, and an initial increase in unemployment of 10 percentage points.

Figure 4(a) shows the results. The initial impact on GDP is similar in all countries, as employment has declined in all countries by ten percent. The losses are slightly less than ten percent, however, because the shock mostly affects the earnings of workers

[31] In addition, the employment recovery from the Great Recession of 2008 and onwards, which was a smaller employment shock, took over ten years to be completed: see Web Appx. Section D.

whose earnings were relatively low in the first place (the uneducated and the young).

76 percent of the global population lives in a MIC (World Bank, 2020b). Thus, the MIC trajectory is a good approximation for the average trajectory for the World.[32]

There are two phases to the output dynamics in Fig. 4(a). First, there is the direct impact, which ends in year 10. After year 10, output starts to decline again. Also note that the disruption to human capital accumulation has a greater impact on HICs.

Figure 4(b) displays what happens when there is no employment shock at all. The impact of the schooling shock is delayed, as it takes time for the students whose human capital was impacted to enter the job market. The impact is also highly persistent.

The impact of the schooling shock on the LIC is smaller, with maximum loss around 20 years out at 2.4 percent of steady state GDP. The maximum loss in the MIC is after 36 years (3.6 percent), while in the HIC the maximum loss is after fully 40 years (4.1 percent).[33] Thus, the impact of the schooling shock is most severe in the HIC, as the quantity of schooling was higher to begin with, so disruptions to schooling affect more workers. In addition, because more workers have college, their lost returns are higher.

Figure 4(c) displays what happens when there is no schooling shock. There are two phases to the employment shock. In the first phase, output is impacted negatively because employment has declined, so accumulated experience is not being used. As we enter the second phase, employment has already recovered yet output still remains below the steady state, due to the missing human capital from lost experience.

In the HIC, after 10 years GDP remains 1.0 percent down, and it actually continues to decline again until its trough after 23 years at 1.1 percent before recovering. In the MIC output remains down 0.35 percent after 10 years, and it continues to decline to 0.37 percent in year 20 before starting to recover. In the LIC, output is still down 0.45 after 10 years, again declining a little for a couple of years before recovering slowly. Thus, while the impact of lost experience is less than the impact of lost schooling, lost experience remains a factor keeping countries below steady state GDP for several decades.

The reason the value of lost experience is greater in the HIC is that, while the amount of affected workers was kept constant across countries, and while demographic

[32] Since our study is forward-looking, we count as MICs countries that recently entered that category, such as Bangladesh, Ghana and Laos. HICs include recent climbers such as Chile, Hungary and Poland.

[33] Ichino and Winter-Ebmer (2004) study the impact of disruptions to schooling in Germany and Austria due to World War II. 40 years later workers who were students at the time experience measurable earnings losses. GDP per capita in the 1980s was depressed by 1 percent in both Germany and Austria as a result.

variables are not too different among the working age population, the returns to experience in Table 1 are substantially higher for the HIC. Also, the reason why GDP continues to decline after year 10 is because youth unemployment is more affected than average unemployment, so the share of the workforce that was young at the time of the shock continues to increase for a while as older workers who were less affected retire.

To summarize: (i) the schooling shock has larger potential long-run impact; (ii) the experience shock delivers a sustained decrease in output over decades; and (iii) the shock mainly impacts HICs – since there is more schooling and the returns to experience are greater. These conclusions are drawn from striking countries with the same shock. Later, we analyze which specific shock scenario is more appropriate for each group.

4.2. Impact on Welfare

To compute the long-run welfare impact of the shock, suppose that all output is consumed, as our framework lacks capital. We assume that worker utility is defined as the natural log of consumption. Then, we assume that there is a representative agent.[34]

Our welfare measure is the percentage decrease in steady state consumption in *every period* that would make agents indifferent between experiencing and not experiencing the shock. If c^* is steady state consumption, c_t is steady state consumption with the shock and r is the discount rate, then the welfare measure is the value of Δ such that

$$\sum_{t=0}^{\infty} \left(\frac{1}{1+r}\right)^t \ln\left[c^*\left(1-\Delta\right)\right] = \sum_{t=0}^{\infty} \left(\frac{1}{1+r}\right)^t \ln c_t.$$

We assume a discount rate of 4 percent (Web Appx. Section E discusses why).

In the most severe scenario, welfare decreases in the LIC by 1.9 percent in perpetuity, 3.0 percent in the MIC and 4.3 percent in the HIC (see Figure 4(d)). Given the discount rate, this is equivalent to a one-time loss of 74 percent, 89 percent and 111 percent of GDP respectively.[35] This adds up to 102.4 percent of World GDP in 2019 ($\$86.7$ trillion). The cost of human capital decumulation is high also. In year 10, once the shock is over, $\Delta = 2.0$ percent in the LIC, 3.0 percent in the MIC and 3.4 percent in the HIC.[36]

As before, we decompose these losses based on the impact of the schooling shock

[34] An interpretation of this assumption is that agents derive utility from their families' outcomes, and their families are composed of a representative distribution of society (King et al., 1988; Lucas, 1990; Shi, 1997). One could also think of this in terms of an utilitarian social welfare criterion (Harsanyi, 1955).

[35] The losses equal $\$73$ in PPP terms per year in the LIC, $\$423$ per year in the MIC and $\$2,342$ per year in the HIC. Alternatively, this is equivalent to a one-off hit of $\$1,812$, $\$10,585$ or $\$58,549$ respectively.

[36] This is equivalent to a one-time hit in year 10 of $\$214$, $\$8,831$ or $\$44,339$ respectively.

as opposed to the experience shock. If the shock is to schooling only, then the shock lowers welfare by 1.3 percent in the LIC, 1.9 percent in the MIC and 1.8 percent in the HIC (Web Appx. Fig. A.5). In contrast, the experience shock alone reduces welfare by 1.6 percent in the LIC, 1.6 percent in the MIC, and 2.6 percent in the HIC (Ibid.). More generally, about 56 percent of the impact on LICs is from the shock to employment and experience, whereas this share is 45 and 57 percent in the MIC and HIC respectively.

That said, much of this has to do with the short run impact of the shock, whereas after 10 years (once the shock is over) it is the disruption to schooling that has the largest impact. At year 10, the total impact of schooling accounts for 86, 91 and 77 percent of the continuing welfare cost from the pandemic in the LIC, MIC and HIC respectively.

Finally, it is worth pointing out that the (conservative) assumption that college education is not disrupted implies that one effect of experience – its interaction with college schooling – is absent. Were it present, it would increase the impact of experience disruptions to some extent, primarily in the HIC where college education is common.

5. Welfare Impact for Different Scenarios

So far we examined the welfare impact of the extreme pandemic shock scenario, to get a sense of how different factors would impact economies at different income levels. In this section, a range of feasible scenarios are considered.

5.1. Symmetric Scenarios across Countries

Figures 5(a)-5(c) display the welfare impact for a variety of scenarios. The horizontal axis measures the extent of the unemployment shock between 0 and 10 (percentage points). The vertical axis measures the extent of the disruption to education, between 0 and 100 percent of our assumed maximum of full disruption for two years.

The contour lines are closer in the HIC (Fig. 5(a)) than in the MIC (Fig. 5(b)), and in the MIC than in the LIC (Fig. 5(c)). We call this the "compression" effect, as it is related to the proximity of different contour lines along the 45 degree line, indicating greater impact for a given scenario in richer countries than in poorer countries. The potential impact goes from 0 to 4.4 in HIC vs. 3.0 in LIC. Furthermore, the slopes differ. In the LIC the contour lines are steeper than in the MIC. We call this the "slope" effect. A steeper slope indicates that lost experience has a relatively greater impact on welfare than lost schooling. In the case of vertical lines, varying the education shock has no impact.

We consider points A $(25, 75)$ (25 percent of the full employment shock of +10 percentage points, and 75 percent of the schooling shock of two years lost), B $(50, 50)$ and C $(75, 25)$. Point B $(50, 50)$ has a welfare impact of $\Delta = 1.4$ in the LIC, compared to 1.8 in the MIC and 2.2 in the HIC economy. Thus, a symmetric shocks causes a greater welfare loss in richer nations. We then compare A and C to get a sense of the relative importance of disruptions that primarily affect schooling (A) or employment (C).

Point A $(25, 75)$, where schooling is largely disrupted, has an impact of 1.4 in the LIC, 1.8 in the MIC and 2.0 in the HIC. In contrast, C $(75, 25)$, where the main disruption is to employment, leads to an impact of 1.6 in the LIC, 1.7 in the MIC and a much larger 2.4 in the HIC. The MIC and HIC are closer for A. This is due to the compression effect, where the general proximity of contours for the HIC and MIC is more similar because both economies have more schooling, and the returns to schooling do not vary too much by levels of development. In contrast, the LIC and MIC are closer for C, due to the slope effect. Due to low levels of schooling, the schooling shock is relatively unimportant for the LIC, but remains important for the HIC and the MIC, where schooling is plentiful.

5.2. Modeling the COVID-19 Shock

We now use our framework to identify specifically for the case of COVID-19 which scenario is most appropriate for each income group. Answering this question requires determining the size of the employment and education shocks for each group.

5.2.1. Schooling and Employment Shocks

The size of the schooling shock amounts to an estimate of the value of the parameter ν in the education shock equation: $h_{it} = h_{i,t-1} + (1 - \nu)\, r_s\, (s_{it})$. For each group, we obtain ν in the following manner. First, we obtain estimates of the school closure rate s for each year (1, 2). Students at schools that were closed or partially closed continued their education in some form or another – through the internet, via TV or the radio, or by receiving work packs at home – with relative reach c and effectiveness e. Thus, the share $1-s$ children attend school as normal, and the share s of children participate in distance learning with reach c and effectiveness e. Finally, we set $\nu = s \times (1 - ce)$.

School closures UNESCO (2021) provides data on daily school closures globally. For each country and school day, we know the share of schools that are *fully open*, *partially open* or *closed*. The data cover the period 02-16-2020 until 10-31-2021. For days that schools are supposed to be open but are *closed*, we assume online instruction. For days that schools are *partially open*, we assume a hybrid system where half the students are present and half are online (see Web Appx. Section C for details on our assumptions).

A school year lasts 9.5 months on average globally. We thus examine the share of *not fully open* school days (using the formula "*closed* + 0.5 *partially open*") for the first 9.5 school months (starting 02-16-2020) against the last 5-8 school months (which depends on the country's school year schedule). We think of the last 5-8 school months as being representative of the second year of disruption. This provides estimates of s.[37]

Reach and Effectiveness To obtain estimates of the reach $(c) \times$ effectiveness (e) rate of school not in-person in each group, we first discuss data on the reach and effectiveness rates of different remote learning modalities in each group. However, as these rates are likely misestimated, we also rely on direct estimates of the reach $\times$ effectiveness rate.

UNESCO, UNICEF and the World Bank recently conducted a survey of ministries of education on national responses to COVID-19 (UNESCO, 2020b). Four remote learning modalities have been provided: *online platform* (mostly in HIC and MIC), *take-home packages* (HIC and MIC), *television* (MIC and LIC), and *radio* (LIC) (Appx. Table A.1). While take-home packages are accessible to all, we find lower reach rates of online platforms (as proxied by internet access) and television and radio programs (television and radio ownership) in LIC and MIC than in HIC (Appx. Table A.2).

The literature on primary and secondary schooling in a hybrid/online setting gives mixed results. While some studies find that remote learning modalities can improve student performance, most studies are pessimistic (see Web Appx. Section C).[38]

UNESCO (2020b) also asked ministries about how effective they think each modality has been over the past two years. Using their responses, we obtain a measure of the effectiveness (e) of each modality in each income group. Globally, online platforms were seen as the most effective modality (78%), followed by take-home packages and the television (75%), and finally the radio (67%) (see Web Appx. Table A.3).

Next, it is not obvious how to aggregate this information in order to obtain a reach (c) x effectiveness (e) rate for each group. We could thus make the following choices:

1. In HICs, the television and the radio are seen as much less effective, hence their reliance on online platforms and take-home packages. Reach $\times$ effectiveness is 77% for the former while it is 82% for the latter. Taking the lower bound of that

[37] Web Appx. Fig. A.3 shows for each school year and each income group the share of schools that are *fully open*, *partially open* or *closed* (using the child population of each country c. 2018 as weights).

[38] Azevedo et al. (2020) writes: "While mitigation strategies in the time of COVID-19 are often referred to as remote learning [...] in reality what many school systems rolled out was emergency response teaching."

range (take-home packages were used less often), $c \times e$ could be 75%.

2. In LICs, given the low reach of online platforms, the radio and the television are used the most. Reach $\times$ effectiveness is 32% for the former while it is 22% for the latter. Privileging the lower bound of the estimated range, $c \times e$ could be 25%.[39]
3. In MICs, the radio was the least effective modality. Focusing on the other ones, reach $\times$ effectiveness is 27% for online platforms, 53% for the television, and 79% for take-home packages. We could roughly assume $c \times e$ = 50% on average.

However, the estimates are provided by ministries of education that may have imperfect information, or incentives to over-estimate the effectiveness of their preferred modalities. For a few countries in late 2020, (pre-college) teacher surveys show much lower reach $\times$ effectiveness rates. For seven HICs with a large population, McKinsey (2020) finds an average rate of 4.2 out of 10, hence 42%. Given an effective closure rate of 44% in year 1 in HICs, ν = 0.44 (1-0.42) = 0.26, or a loss of 26%. Likewise, McKinsey (2020) explains that pre-college students were two months behind by November 2020, which suggests a loss ν of 29%. Were we to use the ministries' estimate, we would have ν = 0.44 (1-0.75) = 0.11, hence a 11% loss only. As a result, for HICs we assume that reach $\times$ effectiveness = 40% in year 1 and 45% in year 2, thus allowing improvement over time.

For MICs, the teacher survey from McKinsey (2020) reports reach $\times$ effectiveness rate = 54% for China. Given an effective closure rate of 43.5%, the loss is about 20%. Likewise, children were 1.4 months behind by November 2020, also a loss of 20%. In India, another large MIC, the ASER (2020, 2021) surveys suggest students were about 50% behind in 2020. Given an effective closure rate of 77%, reach $\times$ effectiveness = 35%. Since India is likely more representative of the MIC group's ability to provide effective remote learning than China, and since no improvement has been observed based on descriptive evidence, we assume reach*effectiveness $=$ 35% for MICs in both years.

Finally, for LICs we had obtained reach*effectiveness = 25% based on the ministries' data. Since we use 40-45% for HICs, 35% for MICs, we arbitrarily use 20% for LICs.

Computing the loss ν. The disruption to school was greatest in the MIC (33% of two years of education), due to their higher effective school closure rate (see Table 2). Schools were then slightly more open in LICs, but reach*effectiveness was much higher in HICs, making the shock less severe in HICs (21% vs. 28% for LICs).

[39] Take-home packages are less than 50% efficient in LICs given their lack of resources.

Employment Shock The ILO (2020) reports that the peak loss in total hours worked (from unemployment, inactivity and reduced hours) across the HICs, MICs and LICs are 15.8, 20.9 and 12.4 percent respectively. However, the peak is not indicative of the impact of the shock over the entire year. Instead, we assume a loss equal to the average over 2020, i.e. 8.3, 9.5 and 6.7 percent respectively (see Web Appx. Section D for details).

5.2.2. Results

For the HIC, the employment disruption is of 8.3 percent, and the schooling disruption is of 21 percent (South East of point C in Fig. 5(a)). For the MIC, the employment disruption is of 9.5 percent, and the schooling disruption is of 33 percent (middle near the right edge in Fig. 5(b)). For the LIC, the employment disruption is of 6.7 percent, and the schooling disruption is of 28 percent (point to the West of point C in Fig. 5(c)).

The welfare impact equals 2.5 percent of steady state income in perpetuity in the HIC, compared to 2.2 percent in the MIC and 1.5 percent in the LIC.[40] After ten years, when the direct impact of the shock has worn off, we get 1.2 percent in the HIC, compared to 1.2 percent in the MIC and 0.7 percent in the LIC.[41] LICs are, if anything, the *least* impacted group. Finally, the impact through schooling is highest for the MIC (see Web Appx. Section F for details). Indeed, the disruption to schooling is more severe in the MIC, even though the quantity of schooling is higher in the HIC. At the beginning, the employment shock accounts for 84, 70 and 75 percent of the welfare cost going forward in the HIC, MIC and LIC respectively (Ibid.). There is still some enduring cost from lost experience, particularly in the HIC. After 10 years, the losses from experience account for 52, 21 and 27 percent of the enduring cost of lost human capital.

6. Application to Gender

We turn to the question of whether pandemics, and COVID-19 in particular, has an asymmetric impact on workers by gender. To do so, we estimate the returns by gender.

6.1. Estimating the Returns by Gender

Profiles. As described in Section 2.2., for each country at a time we estimate eq. (3) for male workers and female workers *separately*, and use the coefficients of the experience

[40] This is equivalent to a one-off hit of 63, 55 and 36 percent of income respectively. Alternatively, this is equivalent to $\$15,478$, $\$3,478$ and $\$419$. Overall, this amounts to 59 percent of global GDP ($\$50.3$ trillion).

[41] This is equivalent to a one-off hit of 29, 29 and 17 percent of income respectively. Alternatively, this is equivalent to $\$15,478$, $\$3,478$ and $\$419$. Overall, this amounts to 29 percent of global GDP ($\$24.4$ trillion).

dummies to construct gender-specific wage-experience profiles for developing (G) and developed (D) countries (using as weights country populations in 2017).

As seen in Fig. 1, in D countries, a male worker with 30 years of experience earns twice (100%) more than a worker with zero experience. For female workers, the difference is lower (70%). In G countries, the profiles are flatter and corresponding differentials are 50% and 40% respectively. While women fare better in D countries (70% vs. 40% in G), the absolute gap is bigger in D (30 vs. 10 in G). In economies where experience is more valuable, factors that generate differences across gender are possibly more consequential in absolute terms. Thus, even if there is less gender discrimination in D countries, it may lead to bigger absolute gaps in the returns there.

For the World, we find average population-weighted returns to experience of 2.3% for male workers and 1.8% for female workers. Returns to education are 4-5 times higher, at 8.2% and 9.4%, respectively. While women show lower returns to experience, they have higher returns to education. The returns are indirectly related. While there are contexts where women have lower returns in both dimensions, there are more contexts where education may dampen the negative effects of discrimination. Indeed, studies show that education is disproportionately more important for economic minorities at the margin (e.g., Dougherty, 2005; The Atlantic, 2013). These facts are possibly corroborated by Fig. 6 which shows the correlation between the gaps in the returns to education and the gaps in the returns to experience. For both gaps, a positive value indicates higher returns for men. As seen, few countries have negative gaps for both dimensions. In most countries, a negative gap for experience is compensated by a positive gap for education.

Likewise, Figure 7 shows the strong positive relationship between the gap in the returns to experience (higher values indicate higher returns for men) and log per capita GDP for the mean year in the data for each country. Indeed, the absolute gap should be lower in countries where aggregate returns to experience are lower on average, i.e. poorer nations. Figure 8 then displays the same relationship for the returns to education. As expected, the gap in the returns to education is lower in richer nations. The aggregate returns for each income group are then reported in Table 3.

Now, if men have higher returns to experience than women, it could be that women have jobs that generate less human capital over time or that their experience is unfairly discounted by employers. We do not examine the drivers of such gaps. Instead, we take these as given in our calibration exercise below, thus allowing for the characteristics underlying the gaps to matter (via the returns) during the pandemic.

Returns for the Calibration. Finally, we use eq. (3) to estimate the returns for four subpopulations *separately* (considering only samples with at least ten observations per experience bin): pre-college male workers, college+ male workers, pre-college female workers, and college+ female workers. These returns are discussed below.

6.2. Calibrating the Steady State – Male vs. Female

We aim to see how the incomes of male and female workers are affected differentially by the shock. Of course, male and female workers may coexist within a household.

Parameters The control parameters are obtained from the same sources as the aggregated data. See Table 3. Participation rates for males are much higher, particularly in the MICs, consistent with the feminization U hypothesis (Goldin, 1995). Likewise, youth and adult unemployment rates are lower for men. Also, returns to experience are generally higher for men, whereas returns to schooling are generally higher for women. However, men have much more schooling than women in MICs and LICs and women get slightly more education than men in the HICs (Web Appx. Fig. A.2).

Steady State. Female GDP in the HIC is 64.3 percent of male GDP in the steady state. This is in large part due to differences in labor force participation. If we compare the average earnings conditional on working, in the HIC women earn 73.2 percent of male earnings on average. In the MIC, female GDP is 45.8 percent of male GDP, or 77.2 percent conditional on working. In the LIC, the corresponding shares are 82.1 and 103.3.[42]

6.3. Impact of the COVID-19 Shock – Male vs. Female

The schooling shock is as before – that is, we assume a schooling disruption of 21, 33 and 28 percent over two years in the HIC, MIC and LIC, respectively, for both men and women. If remote learning measures are taken, there is no clear reason to assume this would affect boys and girls differently – except inasmuch as the schooling distribution is different for boys and girls, something our framework already takes into account.

[42]Conditional on working, income inequality is smaller for lower levels of income. Indeed, the only potential source of differences in our framework is due to differences in human capital and in labor force participation. The lower the income group, the less human capital there is in the first place, and thus there is less scope for differences in earnings across gender net of labor force participation. Interestingly, conditional on working, women in the LIC earn slightly more than men, due to the fact that returns to schooling are higher for women, so those who do work earn slightly more than men.

The ILO (2020) reports the decrease in activity by gender. We use it to differentiate between the magnitude of the employment shock by gender. See Web Appx. Section G for details and see Table 2 for the resulting values. The shock disproportionately affects female workers in all country groups, but only by about 2 percentage points more.

Given the more severe employment shock, the initial impact on female income is greater than that on male income (Web Appx. Fig. A.9). After that, however, it is not easy to distinguish between the impact on male and female workers in each group. This is reflected in the welfare impact as well (Ibid.), which is similar after an initial stage where women are worse off relative to the steady state than men. However, these similarities mask the competing influence of the shocks to schooling and employment, which affect male and female workers differently. This is best seen by looking at changes over time in *relative* income, and by decomposing it based on the two different shocks.

In order to decompose relative income, we could simply plot deviations in relative income from its value in the steady state for female divided by male income. However, this would not be something we could easily decompose into a contribution due to the schooling shock and a contribution due to the employment shock. The reason is that income is based on an exponential function of human capital, which is accumulated linearly: thus, the shocks are multiplicative. As a result, we instead compare deviations in the difference between log income from the steady state value.

Results are reported in Figure 9. The relative log-income of women does not deviate much over the entire period of the shock (see the patterns for *Overall*), with the exception of the direct impact of the shock itself, which is more severe for women. In the HIC and the MIC, relative income declines by about 2.5 percent, slowly returning to zero after 10 years, whereas in the LIC it is closer to a decrease of 1.7 percent.

However, if we apply only the *employment/experience shock*, we see that relative female income gradually declines up to a minimum of -3 percent in the HIC after about 40 years. This is due to the fact that women have lost more experience than men due to the initial shock. The same is true, although less so, in the LIC. Interestingly the MIC shows no such difference, possibly because participation is so low among women in the MIC and because the lost experience of men appears to be more valuable in the MIC. More generally, the impact from a relatively larger employment shock among women is not so high because returns to experience are generally higher for men.

Conversely, if we have only the *schooling shock* we see that, in the HIC and LIC, relative female log income rises gradually for many years before declining again. In the LIC, it is because men have more schooling than women, so they lose more from the schooling shock. In the HIC, this is because more women have more college, so they are somewhat more insulated from the schooling shock than men. This turns out to have a large impact because the returns to college are significantly higher than the returns to regular education. In addition, women have slightly higher returns to education than men. In the MIC, the schooling shock slightly favors women but the effect is small.

Thus, gender differences are small and short-lived. While the employment shock is larger for women, their lower returns to experience dampen their income losses relative to men, especially in developed countries. The higher returns to education for women are then offset by higher schooling of men, especially in developing countries.

7. Robustness Checks

We first discuss the robustness of the gender analysis. We then explore the robustness of our main results on the aggregate implications of the COVID-19 pandemic.

7.1. Robustness Checks for the Analysis by Gender

The lack of differential impacts by gender is mostly due to: (i) returns to experience being smaller for women, especially in richer nations; and (ii) returns to education being higher for women. However, the returns could be misestimated due to selection or measurement issues. For example, in contexts where few women work, working women may be "selected". This affects the returns if experienced (i.e., older) women are differently selected than less experienced (younger) women due to social change.

Wep Appx. Table A.5 (Col. (3)) shows that gender differences in the returns are mostly preserved if we include *decadal* cohort fixed effects (FE) or cohort FE based on important *historical events* specific to each country, in order to reduce the experience-time-cohort problem. In doing so, we follow Heckman and Robb (1985, p.145) who propose to include cohort effects consisting of "a sequence of adjacent years (e.g., Depression or 1950s youth, etc.)", an approach previously implemented by Jedwab et al. (2022). Since we focus on workers aged 18-67 in samples from 1990-2016, we study individuals born between 1923 and 1998. We thus include 8 cohort FE (1920s, ..., 1990s) for countries with at least two years of data. Alternatively, we construct for each country periods based on important years, after identifying important events using information from standard sources such as Wikipedia and the BBC Profile of each country. We then include in the regressions estimating the returns the country-specific period dummies that equal to one if the individual was aged between 18 and 67 during the period(s), for countries with at least two years of data.[43] As such, the cohort FE are tailored to the country's history.[44] Furthermore, since we run separate regressions for female and male workers, the cohort FE are gender-specific. See Web Appx. Section H for details.[45]

Differences in the returns to experience are preserved if we include 10 industry FE and/or 10 occupation FE (Wep Appx. Table A.5).[46] For the returns to education, the occupation FE disproportionately reduce the returns for women in richer nations, which might indicate selection. At the same time, the ability to enter better (i.e., higher-return) occupations is part of the returns to education. In addition, overall patterns in the returns remain, and our simulation results should be largely unaffected.[47]

A related concern is whether there are differences in self-employment between men and women, as there could be issues with how self-employed individuals calculate and self-report the amount of salary taken from the business. Using the I2D2 data, we find that women are globally less self-employed: The self-employment rate is 36, 18 and 6% for women in LICs, MICs and HICs, respectively, vs. 44, 33 and 13% for men. If the salary of self-employed individuals includes some of the returns to capital, we may over-estimate the returns to experience of men, and the gender gap in the returns. However, the returns are similar when excluding the self-employed (Wep Appx. Table A.5).

Since women are more likely to be selected in contexts where they work less,

[43]For example, for the U.S., we consider 1923-1928, 1929-1932, 1933-1940, 1941-1944, 1945-1953, 1954-1961, 1962-1963, 1964-1967, 1968-1973, 1974-1979, 1980-1989, 1990-1993 and 1994-2000, due to important events in 1929 (Great Depression), 1933 (New Deal), 1941 (Pearl Harbor), 1945 (World War II ends), 1954 (ends of racial segregation in schools), 1962 (Cuban Missile Crisis), 1964 (Civil Rights Act), 1968 (Martin Luther King assassinated), 1974 (Watergate), 1980 (Reagan), 1990 (Gulf War starts, Cold War ends), 1994 (Nafta), 2001 (9-11), and 2007 (Great Recession). Of course, blindly following Wikipedia-BBC leads us to include events that might not be important for workers. At the same time, it is better if we blindly follow their selection of important events rather than cherry-picking the events ourselves.

[44]However, with events FE, the gender gap in the returns to experience is similar across *all* income groups. Nonetheless, the simulation results hold with return parameters estimated that way (not shown).

[45]Results hold if periods are based on other ages, controls for the country's average per capita GDP growth rate for those years during which the individual was aged between 18 and 67 are added, or combinations of the decade FE, events FE and growth rate approaches are implemented (not shown).

[46]We follow the International Standard Industrial Classification (ISIC revision 3.1) and the International Standard Classification of Occupations (ISCO-88). See Web Appx. Section H for details.

[47]We cannot examine if, for a given industry/occupation, women self-select into low-return positions.

Web Appx. Table A.5 shows that differences in the returns are preserved if we drop country-year-samples with disproportionately high non-employment rates for women, in particular samples with rates above the median (54%, which is also the mean) or 25th percentile (44%) in the sample.[48] Alternatively, we drop samples where the non-employment rate is much higher for women than for men, in particular samples with rates above the mean (25%), median (22%) or the 25th percentile (13%) in the sample.

Finally, we adjust the years of experience for female workers to account for the number of children they had. This is achieved by reducing experience by 1 year per child, or even 2 years (Web Appx. Table A.5). While that seems high, it may take into account the time cost of pregnancy as well as any negative effects on the career of mothers, due to discrimination or self-sorting into lower intensity lower-returns jobs.[49]

7.2. Robustness Checks and Other Issues for the Aggregate Impact

In Section 5.2., we identify the likely scenario for each country group, and compute the costs of the COVID shock to human capital using the baseline set of parameters. We find that HICs suffer more than MICs and LICs, and therefore the global economic impact of COVID-19 is mainly felt by HICs. This is largely as a result of the employment / experience shock. After ten years, once the direct unemployment effect has worn off, HICs and MICs suffer more than LICs. This is due to the education shock exceeding the experience shock in severity except in MICs. In HICs the losses after 10 years remain largely due to the experience shock as the returns to experience are high. It is important to establish whether these findings are sensitive to the parameters used. We thus repeat the analysis for a variety of different parameterizations. In all cases results hold. Indeed, the return parameter estimates are similar despite various alterations (Web Appx. Table A.6) and, as a result, so are the quantitative findings (Web Appx. Table A.7).

Child Labor. In the baseline estimation we assume that agents start accumulating work experience from age 18 at the earliest. Thus, even if agents were to work before 18, the associated experience is irrelevant later on. We repeat the estimation assuming work experience is accumulated from age 15, 13 or even 6, thus allowing for child labor.[50]

[48] For the population of 18-67 year-olds who are not attending school full-time, the *non-employment rate* is equal to 100 - the percentage of the population that is currently working.

[49] Note that we only know the number of children still in the household and for household heads and their spouse only. We thus only consider these workers for this robustness analysis.

[50] If we use age 15 (13), for individuals with at least 9 (7) years of education, experience is age - years of education - 9 (7). For individuals with less than 9 (7) years of education, experience is age - 15 (13).

Indeed, pandemics may increase child labor. However, in Web Appx. Section I we discuss how substitution effects due to worsening labor market conditions might compensate for income effects leading to reduced school enrolment, thus precluding any effects of COVID-19 on child labor as argued by ILO and UNICEF (2021).

In addition, even if child labor does increase during a pandemic, the evidence suggests that child labor only marginally contributes to total earnings. More precisely, using the I2D2 data for the World, we first show that the employment rate is much lower for children than for adults (Web Appx. Fig. A.8). While more than two thirds of 18-67 year-olds work across all countries regardless of the development level, only 3.9, 7.7 and 21.9% of 5-17 year-olds work in HICs, MICs and LICs, respectively. Children who work tend to work few hours and for low wages (Jedwab et al., 2021b). 5-17 year-olds thus only contribute 0.2, 3.1 and 1.9% of total wages in HICs, MICs and LICs, respectively. As such, ignoring the impact of child labor experience during a pandemic is likely to be inconsequential. Furthermore, allowing for increased work experience due to child labor during a pandemic to mitigate the negative effects of reduced schooling would if anything lower the losses for poorer nations, which would again reinforce our results.

Finally, children that attend school rarely work at the same time. Indeed, using I2D2 data for the World, we show in Web Appx. Fig. A.10 that children attending school on average work far fewer hours than children not attending school (note that these numbers include zeroes for children who do not work at all). Thus, we do not allow children to simultaneously accumulate human capital from education *and* work.

Cohort Effects, Measurement, and Selection. We include decadal cohort FE or important events FE. We then exclude self-employed individuals. Furthermore, we use parameters estimated for men only. Lastly, estimates could be sensitive to the extent of non-employment, which varies across countries and by level of development. This could be because workers with certain characteristics might be more likely to be unemployed or out of the labor force. To deal with this, we repeat the estimation using country-year-samples with unemployment or non-employment rates below the 25th percentile (7% and 35%, respectively) or 50th percentile (10% and 35%, respectively) in the sample, and separately for country-year samples above each of these thresholds.[51]

[51] We cannot use historical information on unemployment/participation to adjust the estimates of potential returns to experience to equal actual returns. Since we focus on workers aged 18-67 in samples from 1990-2016, we study individuals who worked in 1941-2016. Unfortunately, data on unemployment

Youth Unemployment. Returns to experience are higher among younger workers (Fig. 1). This could be important since employment was more severely disrupted by COVID-19 among younger workers (Section 5.2.1.). We repeat the simulation distinguishing between returns to experience in the 0-5 bin and the 10-25 bin.

School Remediation. We assume that the lost human capital cannot be made up for later.[52] Indeed, the literature indicates that disruptions to human capital accumulation have a significant long-term impact on earnings, focusing on schooling (see Azevedo et al. (2020) for a discussion). Notably, for the case of post-war Germany and Austria, Ichino and Winter-Ebmer (2004) show that this impact remains significant *even after 40 years*. This is inconsistent with students or teachers being able to significantly make up for gaps in schooling. Consider that, to make up for missed schooling, either students would need to spend extra time to catch up, spend more time in school, or the production of educational services would have to become more efficient. During the crisis and recovery phases of the pandemic, such remedial education is unlikely.[53]

In fact, the shock could instead be larger than we estimate for several reasons. First, we assumed that students did not drop out of school, whereas there is ample evidence that suggests that there has been some drop-out (UNESCO, 2020a). Second, to the extent that knowledge is cumulative, having missed certain topics or not learned them properly hampers progress in future years. Thus, we think our study provides a useful benchmark that is not too far from reality even if there is recovery among some students.

Selection in the Impact. Distance learning increases educational inequality between the children of wealthier/more educated families and other families (Fuchs-Schündeln et al., 2020; Jang and Yum, 2022). If the students from poorer/less educated families are disproportionately more impacted in less developed economies than in more developed economies, the selection effect would be larger in LICs than in MICs and accordingly in MICs than in HICs. Given complementarities between formal schooling and parental wealth/education, an education shock of a given magnitude should then

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and participation does not exist for *all* countries in *all* years. Unemployment data is typically only available from the 1990s. Also, since unemployment rates are higher in HICS and participation is lower in MICs (Table 1), we may under-estimate their returns, which should, if anything, reinforce our results.

[52] Of course, any speculation that x% of the loss can be made up for can be adjusted in our quantitative findings for each group accordingly: for such experimentation, our estimates provide a useful baseline.

[53] Fuchs-Schündeln et al. (2020) and Jang and Yum (2022) suggest that the ability of parents to substitute for formal schooling, as well as the elasticity of substitution, are key to mitigating schooling losses: we already factor this in as our estimates of losses are based on assessments of schooling loss over the period.

be less impactful in poorer nations (as the impacted students have lower educational potential). Accounting for this type of selection should thus reinforce our results on the asymmetry of the aggregate impact across countries.

8. Concluding Remarks

Pandemics are unique in that they disrupt human capital accumulation at both school and work. We present an accounting framework to improve our understanding of their impact. Poorer nations are *more* likely to be insulated from schooling shocks since there is little schooling initially. Richer nations are *less* likely to be insulated from employment shocks, due to higher returns to experience and higher quantity of schooling.

Through the lens of the COVID-19 pandemic, we find that the schooling shock is most significant for the middle- and high-income economies, causing significant economic damage in the long run. However, even after 10 years, the world economy will still continue to suffer significant losses due to lost experience in richer nations.

Finally, by estimating global returns to education and experience separately for men and women using household surveys for 145 countries, differential effects by gender of the COVID-19 pandemic are explored. Surprisingly, the effect on female relative income is small and short-lived. Indeed, while the employment shock is larger for women, the lower returns to experience for women dampen the losses for women. The higher returns to education for women are offset by higher schooling of men, especially in developing countries, resulting in *similar* human capital losses for men and women.

Our analysis has several implications for policy. First, recovery from the pandemic may require investments in remedial education for students who experienced schooling loss. Second, it suggests that payment protection programs are likely preferable to unemployment insurance, at least to the extent that they can protect jobs that continue to provide experience that generates human capital without exacerbating the spread of infection. Alternatively, retraining programs may be useful. Third, given the magnitude and persistence of the pandemic, the costs of these adjustments are likely worthwhile.

Our analysis also has limitations. We do not model the impact of pandemics on human capital through deteriorating health of survivors. For example, there is growing evidence that some COVID-19 patients may have long-term health effects.[54]

We also do not model the impact of pandemics on mortality. However, in the case of

[54] See, for example, https://www.nature.com/articles/d41586-021-01693-6, last checked 10/25/2021.

COVID-19, mortality among working-age individuals, although non-zero, is very low,[55] so their influence on the human capital stock is small compared to the impact from the disruption to schooling and experience for large numbers of students and workers.[56]

Finally, we do not account for the value of, for example, learning or utility from contact with older relatives, those most vulnerable to the virus. We note in addition that over $140,000$ children have lost a caregiver due to COVID-19 just in the United States.[57] We also assume a closed economy framework in that there are no economic or human capital spillovers from HICs to MICs and LICs. Lastly, we ignore indirect effects that human capital might have on social cohesion and political stability. Integrating all of this in our framework could be a challenging but valuable endeavor.

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[55] See, for example, Mallapaty (2020), as well as https://www.cdc.gov/coronavirus/2019-ncov/covid-data/investigations-discovery/hospitalization-death-by-age.html, last checked 11/11/2021.

[56] The H1N1 epidemic of 1918-20 was different with peak mortality at age 28 (Gagnon et al., 2013). Thus, in future pandemics, case mortality might be a significant channel of human capital decumulation).

[57] See, for example, https://www.nih.gov/news-events/news-releases/more-140000-us-children-lost-primary-or-secondary-caregiver-due-covid-19-pandemic, last checked 11/11/2021.

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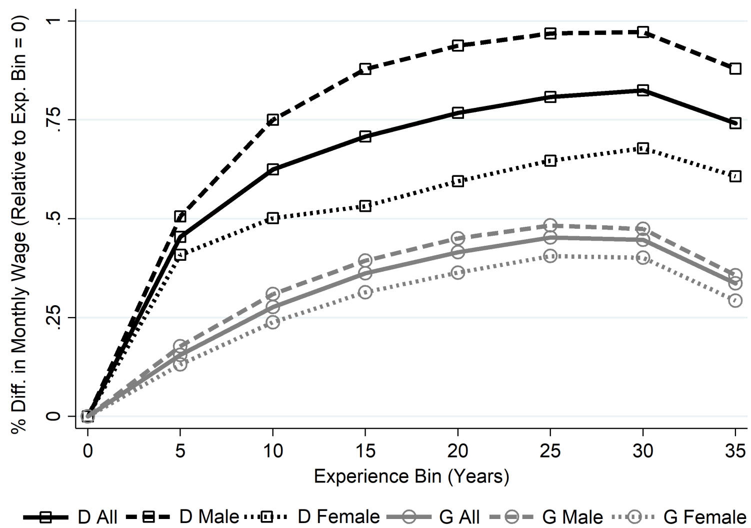
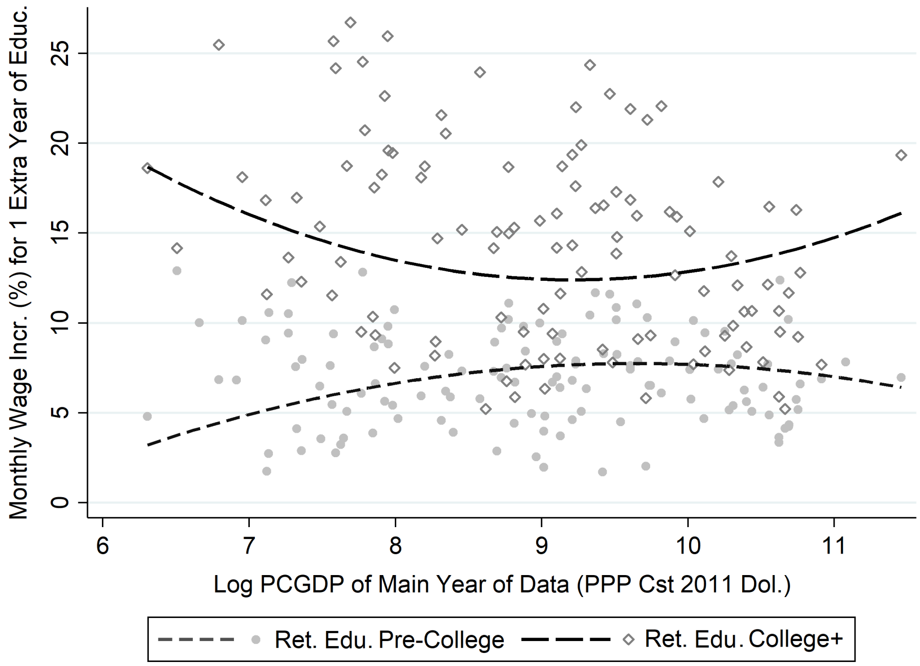
Figure 1: Wage-Experience Profiles by Development Status and Gender



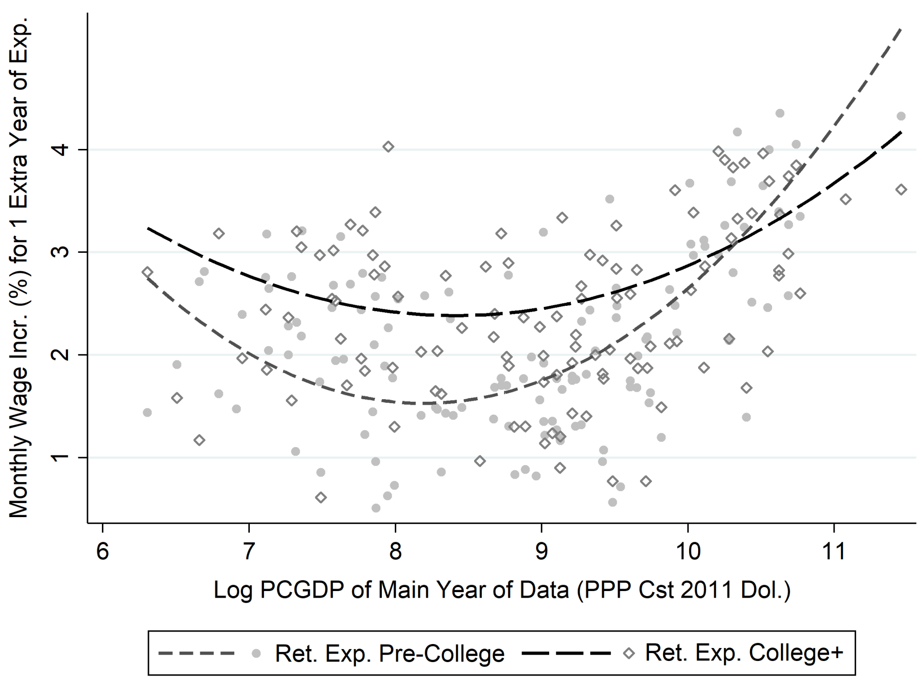
Notes: This figure shows the average wage differential for the seven experience bins for all, male and female workers in developed countries (devD) and developing countries (devG) (using population ca. 2018 as weights). The 0 experience bin is the omitted group. Only samples from 1990 to 2016 are used.

Figure 2: Returns to Education by College Status and Log Per Capita GDP



Notes: This figure shows the correlation between the estimated returns to education for pre-college vs. college+ workers (estimated using data for the period 1990-2016 depending on the country) and log per capita GDP (PPP; cst 2011 USD; for the mean year in the data for each country) (using pop. c. 2018 as weights for the quadratic fit). We exclude outlying countries in the top and bottom 5% in the returns.

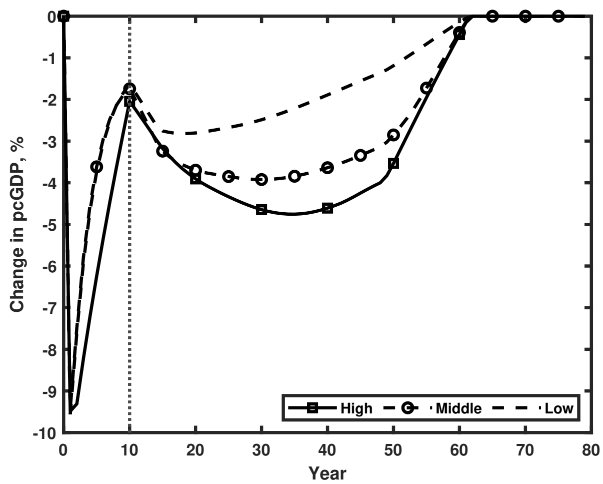
Figure 3: Returns to Experience by College Status and Log Per Capita GDP



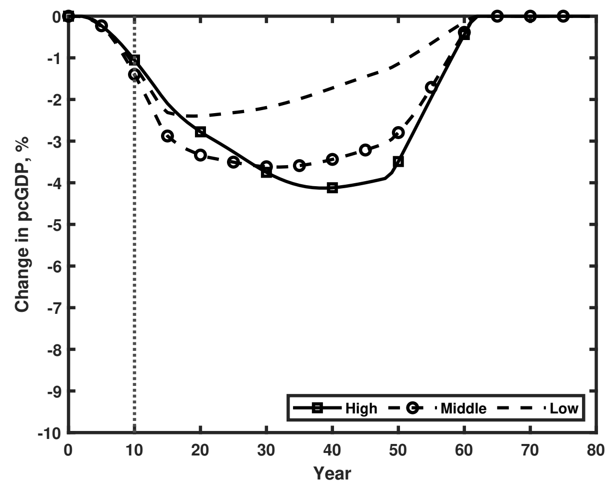
Notes: This figure shows the correlation between the estimated returns to experience for pre-college vs. college+ workers (estimated using data for the period 1990-2016 depending on the country) and log per capita GDP (PPP; cst 2011 USD; for the mean year in the data for each country) (using pop. c. 2018 as weights for the quadratic fit). We exclude outlying countries in the top and bottom 5% in the returns.

Figure 4: Impact of the Maximal Shock Year-by-Year Compared to the Steady State

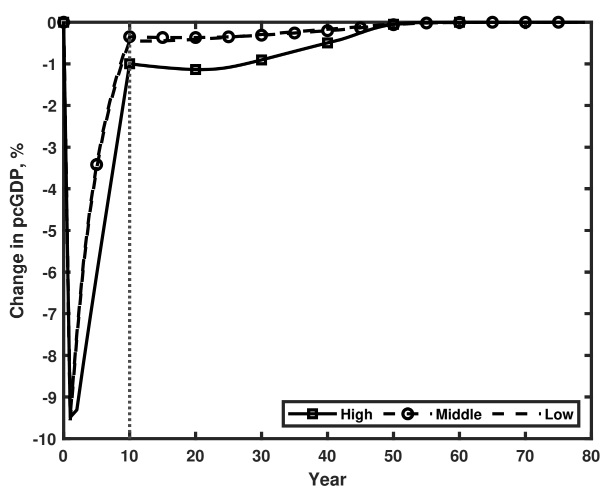
(a) Total Impact on Current pcGDP



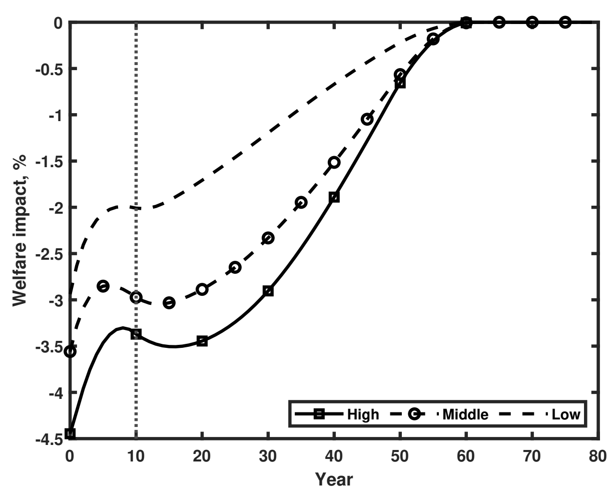
(b) Disruptions to Schooling Only



(c) Disruptions to Employment Only



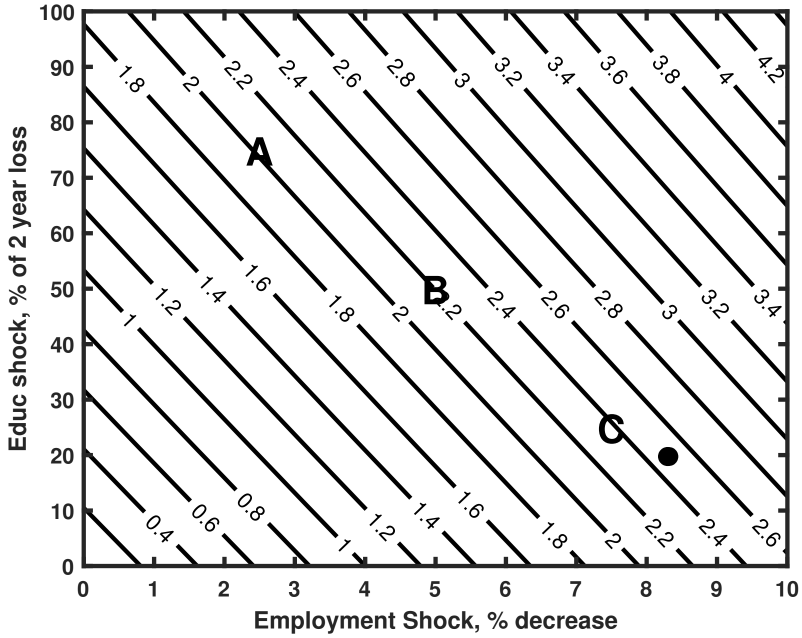
(d) Total Impact on Welfare



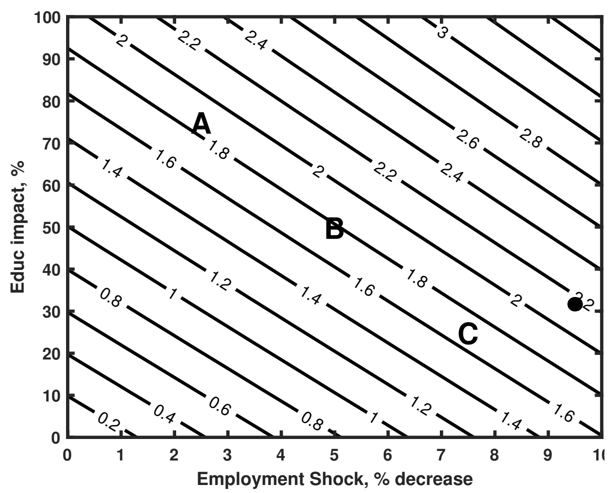
Notes: Figure 4(a): The pandemic shock is assumed to disrupt both schooling and employment. Figure 4(b): The pandemic shock is assumed to disrupt only schooling. Figure 4(c): The pandemic shock is assumed to disrupt only employment. Figure 4(d): The welfare measure is the percent of GDP that would have to be added in each period in order to make agents indifferent between the pandemic shock and remaining in the steady state. The shock is assumed to disrupt both schooling and employment.

Figure 5: Welfare Impact of the Pandemic Shock under Different Scenarios

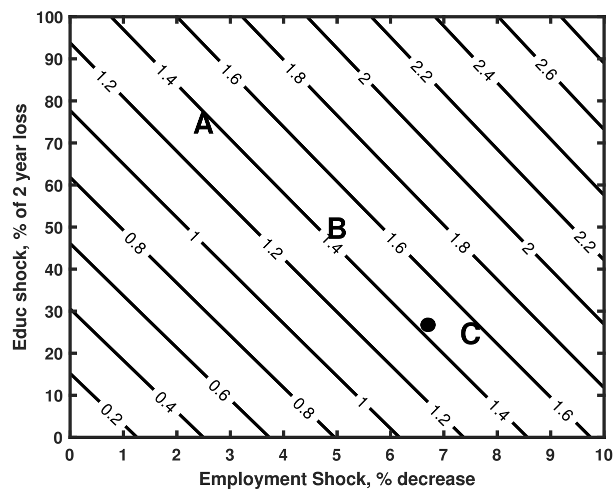
(a) High-Income Economies (HICs) Only



(b) Middle-Income Economies (MICs) Only

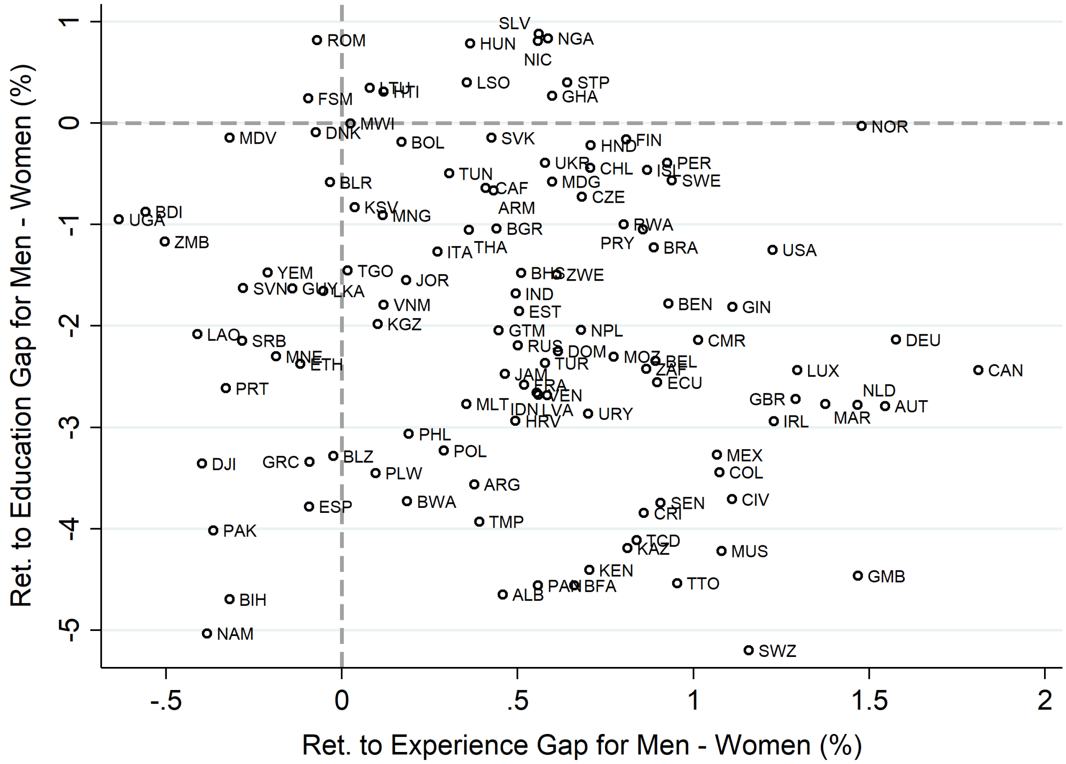


(c) Low-Income Economies (LICs) Only



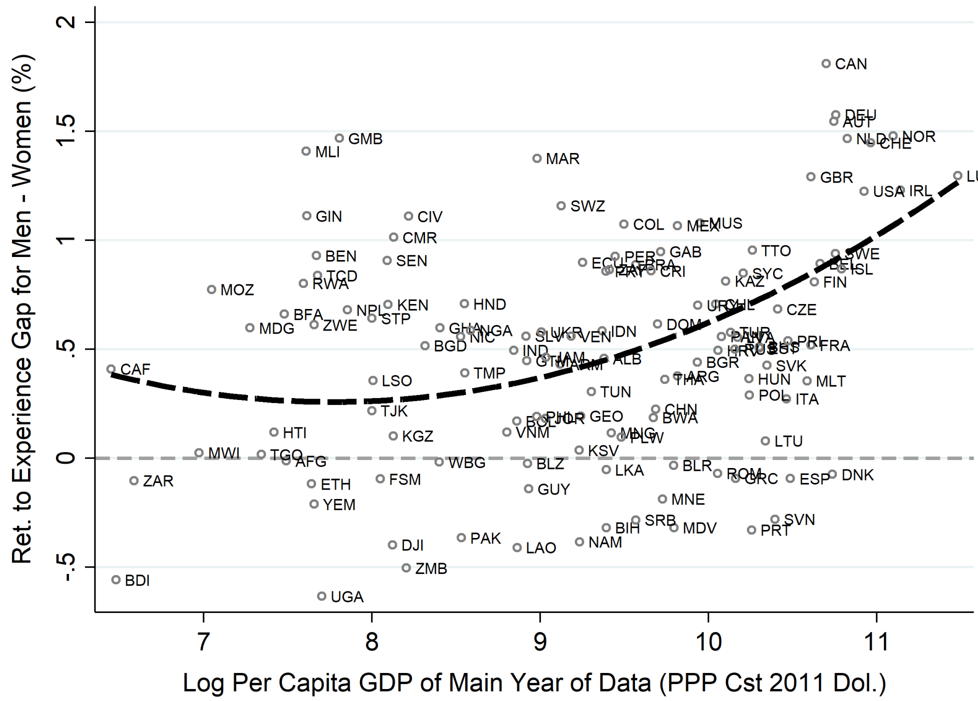
Notes: The horizontal axis measures the unemployment shock of between 0 and 10 percentage points. The vertical axis describes the extent between 0% and 100% of our maximal shock to schooling, a total disruption for two years. The dot represents the most likely scenario in each group of countries.

Figure 6: Returns to Education Gap vs. Returns to Experience Gap



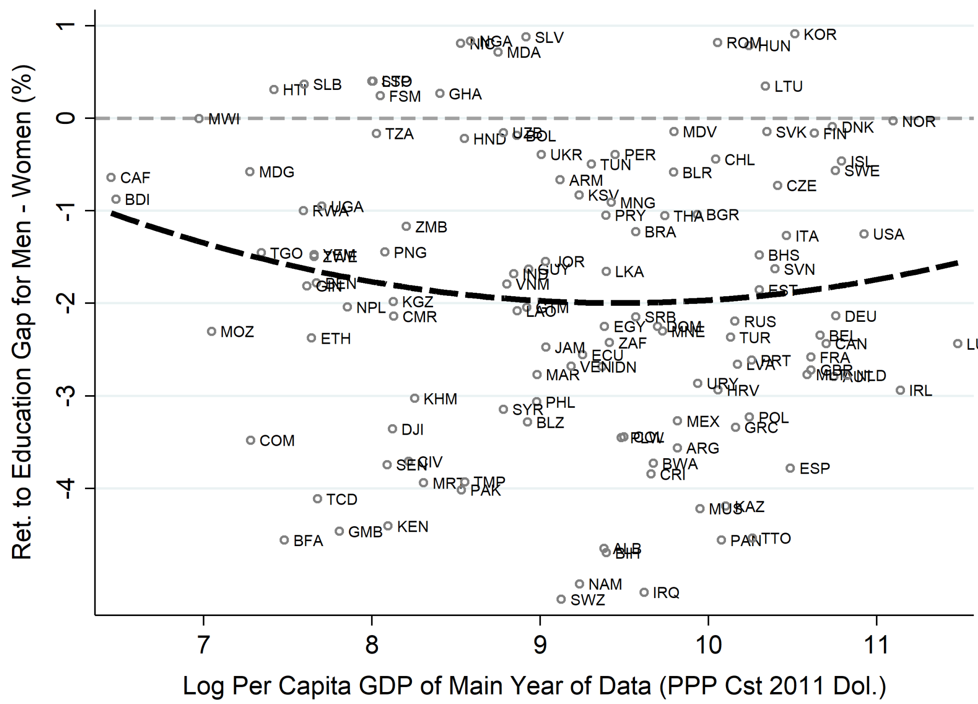
Notes: This figure shows the correlation between the absolute difference between the estimated returns to education for male workers and the estimated returns to education for female workers (a positive value indicates higher returns for men) and the absolute difference between the estimated returns to experience for male workers and the estimated returns to experience for female workers (a positive value indicates higher returns for men). We exclude outlying countries in the top and bottom 5% in the gaps.

Figure 7: Difference in the Returns to Experience for Men vs. Women by Income Level



Notes: This figure shows the correlation between the difference between the returns to experience for male workers and the returns to experience for female workers (positive value = higher returns for men) and log pcGDP (PPP; cst 2011 USD; for the mean year in the data for each country) (using pop. c. 2018 as weights for the quadratic fit). We exclude outlying countries in the top and bottom 5% in the gaps.

Figure 8: Difference in the Returns to Education for Men vs. Women by Income Level



Notes: This figure shows the correlation between the difference between the returns to education for male workers and the returns to education for female workers (negative value = higher returns for women) and log pcGDP (PPP; cst 2011 USD; for the mean year in the data for each country) (using pop. c. 2018 as weights for the quadratic fit). We exclude outlying countries in the top and bottom 5% in the gaps.

Figure 9: Relative Log Income of Women Compared to Men After the COVID-19 Shock, and Decomposition by Schooling and Employment Shocks.

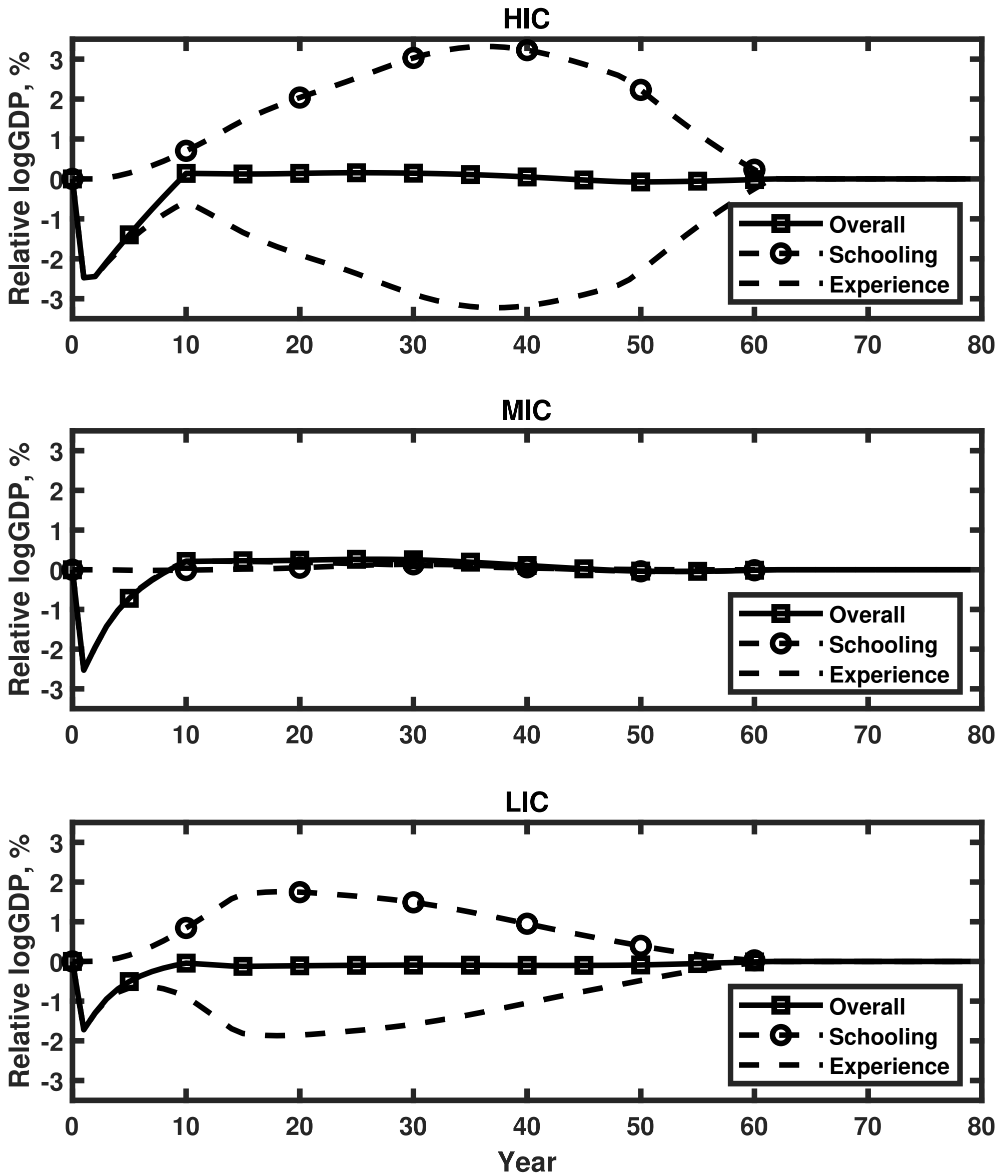


Table 1: Calibration Statistics: Aggregate Analysis

A. Control Parameters	Parameter	High (HIC)	Middle (MIC)	Low (LIC)
Population growth rate	g_b	0.5%	0.6%	2.2%
Labor force participation	l_p	84.0%	75.7%	89.6%
Youth unemployment	u_y	13.7%	13.8%	6.3%
Adult unemployment	u	4.9%	3.8%	2.5%
Retirement age	R	65	65	65
Schooling	π_s	See text	See text	See text
Mortality function	$\delta(\cdot)$	See text	See text	See text
B. Return parameters	Parameter	High (HIC)	Middle (MIC)	Low (LIC)
Returns to education, before college	$\underline{r}_s$	6.7%	8.8%	5.5%
Returns to education, college +	$\bar{r}_s$	13.0%	11.5%	13.6%
Returns to experience, before college	$\underline{r}_e$	4.4%	2.1%	1.9%
Returns to experience, college +	$\bar{r}_e$	4.2%	2.7%	3.2%

Notes: Calibration parameters for the stationary equilibrium of the model economy.

Table 2: Calibration Statistics: Magnitude of the Education and Experience Shocks

Group	Year	Effective Closure Rate (s)	Reach (c) $\times$ Effectiveness (e)	Lost Educ. $\nu = s \times (1 - ce)$	Education Shock %	Employment Shock % All	Male	Female
HIC	1	44.0	40	26.4	21	8.3	7.2	9.5
HIC	2	32.5	50	16.3				
MIC	1	63.5	35	41.3	33	9.5	8.8	10.9
MIC	2	37.5	35	24.4				
LIC	1	53.0	20	42.4	28	6.7	6.2	7.7
LIC	2	18.0	20	14.4				

Notes: Calibration parameters for the education and employment shocks in different groups. The effective closure rate is equal to the share of open schools + 0.5 $\times$ the share of partially open schools.

Table 3: Overall Returns and Calibration Statistics: Aggregate Analysis

Group:	Male			Female			Diff. Male - Female		
A. Overall Returns	HIC	MIC	LIC	HIC	MIC	LIC	HIC	MIC	LIC
Ret to education	9.4	7.9	8.5	11.1	9.0	9.9	−1.7	−1.1	−1.4
Ret to experience	4.1	1.9	2.2	3.0	1.5	2.1	1.1	0.4	0.1
B. Parameters	HIC	MIC	LIC	HIC	MIC	LIC	HIC	MIC	LIC
Pop. growth	0.5	0.6	2.2	0.5	0.6	2.2	0.0	0.0	0.0
Labor force part.	91.6	94.9	96.7	74.8	55.2	81.2	16.8	39.7	15.5
Youth unemp.	14.0	15.9	7.0	14.2	18.4	7.4	−0.2	−2.5	−0.4
Adult unemp.	4.7	4.0	2.9	5.5	5.1	3.5	−0.8	−1.1	−0.6
Ret to edu, pre-coll.	6.4	9.0	5.1	7.1	9.2	6.8	−0.7	−0.2	−1.7
Ret to edu, coll. +	12.6	11.2	13.7	13.3	11.8	13.5	−0.7	−0.6	0.2
Ret to exp, pre-coll.	4.8	2.3	2.0	3.8	1.8	1.4	1.0	0.5	0.6
Ret to exp, coll. +	5.0	2.8	3.2	3.5	2.6	3.2	1.5	0.2	0.0

Notes: Calibration parameters for the stationary equilibrium of the model economy - male and female workers. Retirement age = We use 65 for all. Schooling and Mortality function: See text.

WEB APPENDIX NOT FOR PUBLICATION

A Calibration: Distributions of Schooling and Mortality

Here we discuss some details of the parameterization of the accounting framework. We calibrate the economy to match a representative LIC, MIC and HIC.

We begin with the mortality function $\delta(\cdot)$. United Nations (2019) reports δ only for ages zero, 1, 5 and for five year intervals henceforth. As a result, we need to interpolate $\delta(\cdot)$ for other ages. We develop a smooth function $\delta(\cdot)$ by computing the step function implied by taking the UN's reported values of $\delta(\cdot)$ and assuming the unreported years equal the nearest lowest value (e.g. $\delta(2) = \delta(1)$), and then smoothing the step function with the Hodrick-Prescott filter. We used a parameter of $\lambda = 10$, a value that was both low yet smooths out the "steps" in the step function.[58] Then, we set $\bar{a} = 99$ as the population aged 100 and above is very small everywhere.

We also match the distribution of schooling, based on the I2D2 data ($1990-2016$; see Section 6.1. for details on the data). We assume that agents may only accumulate up to 25 years of schooling because some countries only record schooling up to 25 years. See Web Appx. Fig. A.1 for the resulting distributions of mortality and schooling.

Finally, we proceed similarly to obtain the distributions by gender. Web Appx. Fig. A.2 then shows the distributions of schooling for male and female workers separately.

B COVID-19, Mortality and Human Capital

The focus of this study is on education and work experience. Mortality is unlikely to be an important driver of the COVID-19 pandemic's impact on human capital. COVID mortality among the working-age population is only a small share of that population.

For the U.S., the CDC provides data on the number of deaths associated with COVID-19.[59] Web Appx. Table A.4 indicates that the share of deaths from COVID-19 is a non-trivial (10% or above) share of deaths for the population aged 40 and above. However, as a share of the population within a given age group, COVID-19 deaths are below 0.5 percent of the population, and only increase for the 65-74 age group. In contrast, returns to experience are an order of magnitude larger per year of work experience for all survivors. Consequently, welfare losses due to lost schooling and work experience of survivors should be far larger than any losses through increased mortality (and also smaller than any apparent increase in GDP per capita from the decline in population).

[58] Ravn and Uhlig (2002) recommend a smoothing parameter of 6.25 for annual business cycle data. However, business cycle data are fluctuations around a trend, whereas we smooth a step function, so we prefer a higher coefficient to ensure a smooth hazard rate that does not appear like a step-function.

[59] "Deaths with confirmed or presumed COVID-19, coded to ICD–10 code U07.1." See https://www.cdc.gov/nchs/nvss/vsrr/covid_weekly/index.htm, last checked 11/20/2021

Bauer et al. (2021) examine a sample of European countries as well as the U.S., and find that relationships between mortality rates up to December 2020 and age have an exponential relationship with age. Thus, while many prime-aged workers died from COVID, their impact on the global stock of human capital is likely small. More broadly, given that the U.S. was one of the worst affected countries in the world by COVID-19, it is reasonable to extrapolate that few parts of the world are likely to experience as severe a human capital loss from COVID-19 through the mortality channel.

Finally, while Demombynes (2020) and Demombynes et al. (2021) show using official and excess deaths data from 26 and 64 countries that age-mortality curves for 2020 were flatter in developing countries than in developed countries, their Figures 4 confirm that COVID-19 mortality rates were relatively low below age 60 in most countries.

C Calibration: Defining the Pandemic: Schooling Shock

College Shock and Effectiveness of Online College. We assume that the returns to college $\bar{r}_s$ are not disrupted. This is because the evidence so far on COVID-19 does not suggest significant disruption to college enrollment numbers – and, while this may not have been the case for past pandemics, technological advances suggest that the COVID-19 pandemic is a good benchmark looking forward.[60] Additionally, the literature on the effectiveness of online college is mixed. Some studies finds that online education can be highly effective (sometimes more effective than in-person education – see Jaggars and Bailey (2010)) while others suggest it is not, e.g. Alpert et al. (2016) and Bettinger et al. (2017). Selection effects may cloud the results (Xu and Jaggars, 2013). A few studies on online education during the pandemic find that it was less effective than in-person instruction, but the effect is not large – e.g. Kofoed et al. (2021) find that online instruction lowered average grades by one half of a grade step (e.g. the difference between a B and a B+). Given this lack of decisive evidence either way, we make a conservative assumption that college is unaffected. Note that assuming that college returns are also lowered during the pandemic will only exacerbate the finding that HICs are more affected through human capital losses than MICs and LICs.

Effectiveness of Primary and Secondary Schooling. The literature provides mixed results. In a panel of Dutch schools, Engzell et al. (2021) find that the learning loss during 5 months of online and hybrid schooling was equivalent to 5 months of schooling loss, suggesting that online instruction is entirely ineffective. Maldonado and De Witte (2021) for the case of Flanders find that students' exam performance is consistent with

[60] Based on National Student Clearinghouse data, undergraduate enrollment was down 3.5 percent in the U.S. from Spring 2019 to Spring 2020. This was offset by an increase in graduate enrollments of 4.6 percent. See https://nscresearchcenter.org/current-term-enrollment-estimates/, last checked 10/1/21.

having gained only between a half and a quarter of what was expected in terms of knowledge, indicating that effectiveness e=1 is not realistic. On the other hand, Thorn and Vincent-Lancrin (2022) report that performance on the French national exams during the pandemic was similar to or even exceeded performance in 2019. Thus, e=0 is unrealistic. Thorn and Vincent-Lancrin (2022) find that, in studies for the US and UK, learning is somewhat hampered but not to the degree observed in the other studies. We conclude conservatively that online instruction is imperfectly effective.

School Closure Data. UNESCO (2021) classify school days as: (i) *open*; (ii) *closed* (in which case remote learning options are almost always offered); or (iii) *partially open*. According to their methodological note, *partially open schools* are schools that are: "*(a) open/closed in certain regions only; and/or (b) open/closed for some grade levels/age groups only; and/or (c) open but with reduced in-person class time, combined with distance learning (hybrid approach)*". As there is limited information on which situation prevailed in the aggregate in each country in each year, i.e. (a), (b) or (c), we assume a hybrid system where half the students are present and half are online.

In the data, U.S. schools are coded as *partially open* throughout the period since March 2020. Between March and May 2020, most schools were online. During the 2020-21 school year, hybrid learning dominated. At the beginning of the 2021-22 school year, many schools went online within a few weeks of opening due to COVID-19 outbreaks. While most schools are now fully open, the Omicron variant threatens to shift schools to online again.[61] Therefore, we believe that assuming a hybrid system in the case of partially open schools makes sense for developed countries.

D Calibration: Defining the Pandemic: Employment Shock

Severity. We examine an increase in overall unemployment rates in the range of zero to ten percentage points. This is achieved by varying x between 0 and the value that leads to overall unemployment increasing by 10 percentage points in each economy. We arrive at this range for the following reasons. Note that the objective is to capture lost learning from work experience. Learning from work was lost in several ways.

One was that unemployment increased. Another was that labor force participation decreased. For example, for the U.S., the Pew Research Center computes an adjusted unemployment rate that counts workers who were not in the labor force based on two variables compared with the same month in the previous year - the participation rate and the number listed as "employed but absent for other reasons".[62] While the official

[61] See www.edweek.org/leadership/a-year-of-covid-19-what-it-looked-like-for-schools/2021/03 and www.washingtonpost.com/world/2022/01/07/global-school-closures-omicron/, last checked 01-15-22.

[62] See www.pewresearch.org/fact-tank/2021/04/14/u-s-labor-market-inches-back-from-the-covid-19-

unemployment rate went from 3.8 to 14.4 in April 2020 and down to 6.6 by February 2021, the adjusted number increases from 3.4 to 22.7 and then declines to 9.9 a year later. This implies an average increase in non-employment over the course of the year since the pandemic of 8.4 percent. Considering that hours worked also declined, the total increase in non-employment must have been higher than 8.4 percent.

Globally, the ILO (2020, Fig. 5) reports that the peak loss in total hours worked (from unemployment, inactivity and reduced hours) across the HICs, MICs and LICs are 15.8, 20.9 and 12.4% respectively. However, the peak is not indicative of the impact of the shock over the entire year. Thus, we assume a loss equal to the average over 2020, i.e. 8.3, 9.5 and 6.7% respectively (ILO, 2020, Fig. 7). 10% is a reasonable upper bound.

Workers with Sub-College Education and the Young. Based on the COVID-19 experience, we assume that the employment shock affects mainly workers with sub-college education and the young. We assume that if the unemployment rate among adults without college education rises by a certain amount x, then unemployment among college-educated adults rises by one half of that amount ($\frac{1}{2}x$). The factor of $\frac{1}{2}$ is based on comparing employment rates for workers of different skill levels, as estimated by the ILO (2020, Box 2).[63] The ILO finds that, globally, “the mean loss for low-skilled workers was 10.8 per cent in the second quarter of 2020, compared with 7.5 per cent for medium-skilled workers and 2.2 per cent for high-skilled workers.” The ILO defines low-, medium- and high-skilled workers as follows: “*Low-skill* = elementary occupations and skilled agricultural, forestry and fishery workers; *Medium-skill* = clerical support workers, service and sales workers, craft and related trades workers, plant and machine operators, and assemblers; *High-skill* = managers, professionals and technicians, and associate professionals.” Using the I2D2 data and the same classification, we obtain the average employment share and college share of each skill group for the World. Using back-of-the-envelope calculations, we then obtain the percentage employment loss by college status, finding 9.5% for pre-college workers and 4.8% for college workers. Thus, the loss was twice higher for the former group than for the latter group.

Regarding youth unemployment, the ILO (2020, p. 10) states: “Young workers were particularly hard hit by the crisis in 2020 across all regions and country income groups, resulting in an [global] employment loss of 8.7 per cent, as opposed to 3.7 per cent for adults (figure 8) [4.3% in total]. However, outside high-income countries, jobless young people, or those who were about to enter the labour market, did not generally move into

shock-but-recovery-is-far-from-complete/, last checked 10/1/2021.

[63]The ILO (2020, p. 19) writes: “The uneven impact of the crisis on workers with different skill levels can be seen not only in terms of income but also when observing decreases in employment. A sample of 50 countries shows that the magnitude of job losses tended to be much larger for low-skilled workers.”

unemployment but, rather, dropped out of the labour force, or delayed their entry into it." These numbers suggest that young workers were at least twice as much impacted than adult workers. However, the ILO only includes unemployment and inactivity for this analysis, not reduced hours which account for about half of the total employment loss (Fig. 7). Since the employment loss for young workers is twice the average loss in the society (8.7/4.3 = 2.0), and since the average total employment loss for the society (including reduced hours) is 8.8% globally (Fig. 5), we obtain 8.8 x 2 = 17.6% for the youth. Since we obtained 9.5% for pre-college workers, the loss for the youth is about twice the loss for the latter (17.6/9.5 = 1.9). Therefore, we assume that if unemployment among adults without college rises by x youth unemployment rises by $2x$.

Duration. Hall and Kudlyak (2021) find that recoveries from unemployment shocks tend to happen at a proportional rate. Using data from across the OECD on the rate of recovery in employment, we calculate a proportional factor such that, given an initial employment shock x_0, thereafter $x_{t+1} = x_t \times 0.7143$. We arrive at this factor by looking at data on employment to population ratios from the *OECD.Stat* database. The employment to population ratio of the OECD, i.e. developed countries, deviated on average during 2020 from its value in the last quarter of 2019 by 2.8 percent. The average deviation over 2021 compared to the last quarter of 2019 was 2.0 a year later. Thus, we set our recovery factor equal to $x_t/x_{t-1} = 2.0/2.8 = 0.7143$.

Of course such an economy would never fully recover: even though $\lim_{t\to\infty} x_t$, we would still have that $x_t > 0 \forall t$, so we could not speak of a date at which the recovery is complete. Having a date at which the recovery is complete is necessary to distinguish cleanly between the direct impact of the shock through loss of employment and the long run impact through lost human capital. As discussed in the text, we make an adjustment to ensure that the recovery is complete after 10 years. We choose 10 years because $0.7143^{10} = 0.346$ is very small compared to whatever the initial shock was.

We also note that Web Appx. Fig. 4(a) shows that, after the Great Recession that began in 2008, U.S. unemployment did not recover to pre-2008 levels for 10 years, whereas the employment to population ratio was still not back to it's pre-2008 level even by January 2020. The Great Recession was a significant employment shock, albeit of lesser magnitude than the COVID-19 shock, so 10 years again seems reasonable.

The procedure to compute x_t using the recovery factor 0.7143 with a complete recovery after 10 years is as followed. First we compute x_t assuming a particular initial shock and the recovery factor. Then, subtract from all the x_t the number $0.7143^{10} x_t$. Finally, we multiply all the x_t for $t < 9$ by $\frac{1}{1-0.7143^{10}}$ to obtain an initial shock of the original size, and set $x_t = 0$ for $t \geq 10$. Web Appx. Fig. 4(b) shows the resulting deviations from steady state unemployment, assuming an initial shock of ten percentage points.

E Choice of the Discount Rate

4% is a compromise between the fact that the historical annual rate of return on U.S. Treasury bills is around 1 percent whereas the rate of return on equity is around 7 percent, see Mehra and Prescott (1985). Related studies such as Azevedo et al. (2020) and Psacharopoulos et al. (2021) assume a lower discount rate of 3 percent. They use 3 percent as it is consistent with the standards in global health analyses, established primarily through the recommendations of the *Panels on Cost-Effectiveness in Health and Medicine* (Gold et al., 1996; Neumann et al., 2016). The Gates reference case (Wilkinson et al., 2014), developed to support health economic evaluations funded by the Bill and Melinda Gates Foundation globally also endorses a discount rate of 3 percent. However, our purpose is not to evaluate the health costs of the pandemic, but its economic impact, so we prefer a rate drawn from the macroeconomics literature.

F Most Likely Impact of the Actual COVID-19 Shock

The left panel of Figure A.6 shows the impact on GDP per capita of these calibrated shocks. On impact, output decreases more in the MIC, simply because the initial shock is larger. After that, however, it is the HIC which suffers more, due to the greater importance of schooling to output. Once the pandemic is over, the HIC and the MIC look similar in terms of income dynamics. Below we shall analyze why this might be.

The right panel of Figure A.6 displays the welfare impact, equivalent to 2.5 percent of steady state income in perpetuity in the HIC, compared to 2.2 percent in the MIC and 1.5 percent in the LIC. This is equivalent to a one-off hit of 63, 55 and 36 percent of income respectively. Alternatively, this is equivalent to $\$15,478$, $\$3,478$ and $\$419$. Using population shares as before, this amounts to 59.4 percent of global GDP ($50.3 trillion). HICs account for 66.6 percent of the global cost of the COVID-19 shock through disruptions to human capital, because they make up such a large share of global GDP in the first place, as well as because they are severely impacted.

After ten years, when the direct impact of the shock has worn off, the impact is equivalent to 1.2 percent of steady state income in perpetuity in the HIC, compared to 1.2 percent in the MIC and 0.7 percent in the LIC. This is equivalent to a one-off hit of 29, 29 and 17 percent of income respectively. Alternatively, this is equivalent to $\$15,478$, $\$3,478$ and $\$419$. Using population shares as before, this amounts to 28.7 percent of global GDP ($24.4 trillion). HICs account for 63.3 percent of the global cost of the shock through disruptions to human capital, because they make up such a large share of global GDP in the first place, and because the impact there is highly persistent.

In Figure A.7, we can also break down this impact by schooling and experience. The left panel shows that the impact through schooling is highest for the MIC than for the HIC and the LIC. The reason is that, as discussed earlier, the disruption to schooling is more severe in the MIC than in other countries, even though the returns to schooling and the quantity of schooling are higher in the HIC. On impact this amounts to a one-off hit of 10.0, 16.6 and 9.2 percent of GDP in the HIC, MIC and LIC respectively, amounting to 10.45 trillion or about 12.3 percent of global GDP – 51 percent of which is borne by the HICs and 49 by the MICs. However, the peak welfare loss from schooling does not arrive until around year 19, which amounts to about 15 trillion looking ahead.

Finally, the right panel of Figure A.7 displays the ongoing cost from the disruption to employment and experience. The main cost is from the employment shock: at the beginning, the employment shock accounts for 84, 70 and 75 percent of the welfare cost going forward. That said, there is still some enduring cost from lost experience, particularly in the HIC. The losses from experience account for 52.3, 20.8 and 27.2 percent of the enduring cost of lost human capital after 10 years in the HIC, MIC and LIC respectively. The forward-looking cost of lost experience in year 10 is about 10 trillion, or 12 percent of global GDP – 81 percent of which comes from the HICs.

G COVID-19 Employment Shock by Gender

The ILO (2020, p. 9) reports the decrease in activity by gender, explaining that "across all regions and country income groups, women have been affected by employment loss to a greater extent than men." They find that "at the global level, the employment loss for women stands at 5.0 per cent in 2020, versus 3.9 per cent for men" [and 4.3 per cent for the whole society].[64] As such, women were (5.0 ÷ 3.9 - 1)*100 = 28% more impacted than men and (5.0 ÷ 4.3 - 1)*100 = 16% more impacted than the society overall. Since the report explains that *all* regions and country income groups were similarly impacted, and given the lack of better global data, we use these numbers to infer the employment losses of women and men for each income group. Furthermore, for selected developed and developing countries the ILO (2020, p. 16-17) reports the percentage changes in post-support labor income by gender, explaining that "women experienced greater losses in post-support labour income than men" in almost all countries. On average, women lost 15% more income than men and 10% more than society overall.[65] Comparing women to the overall population, we thus find that they

[64]Their measurement is based on both unemployment and inactivity. As such, it does not include any reduction in working hours. However, the fact that it includes inactivity is important. The ILO (2020, p. 9) writes: "Across all regions, women have been more likely than men to become economically inactive [...]."

[65]This is the change between the first and second quarter of 2020, which is the shock that we are interested in measuring. Post-support labour income is "labour income that takes into account income

lost 10-16% more. To make our results more salient, we assume a larger average shock of 15%. Next, knowing the overall employment shock of each income group (e.g., 8.3% in HICs), we obtain the shock for women only (e.g., 8.3*1.15 = 9.5% in HICs). Lastly, knowing the female share in the labor force before the shock, we estimate the shock for men only (e.g., 7.2% in HICs). See Table 2 for the resulting values.

H Robustness for the Analysis by Gender

Important Events FE. Since we focus on workers aged 18-67 in samples from 1990-2016, we study individuals born between 1923 and 1998. For this approach, we thus construct for each country periods based on important years, e.g. for the U.S., 1923-1928, 1929-1932, 1933-1940, 1941-1944, 1945-1953, 1954-1961, 1962-1963, 1964-1967, 1968-1973, 1974-1979, 1980-1989, 1990-1993 and 1994-2000, due to important events in 1929 (Great Depression), 1933 (New Deal), 1941 (Pearl Harbor), 1945 (World War II ends), 1954 (ends of racial segregation in schools), 1962 (Cuban Missile Crisis), 1964 (Civil Rights Act), 1968 (Martin Luther King assassinated), 1974 (Watergate), 1980 (Reagan), 1990 (Gulf War starts, Cold War ends), 1994 (Nafta), 2001 (9-11), and 2007 (Great Recession). For Kenya, we use 1920 (Crown Colony), 1940 (Italian attack), 1944 (Kenyan African Union), 1947 (Kenyatta becomes KAU leader), 1952 (Mau Mau rebellion), 1956 (rebellion ends), 1960 (state of emergency ends), 1963 (Independence), 1969 (Mboya assassinated), 1978 (Kenyatta dies, rule of Moi), 1982 (one-party state), 1987 (opposition suppressed), 1992 (elections, conflict), 1996 (constitution amended), 2002 (Moi's reign ends), 2007 (electoral violence), 2010 (constitution, East African market), 2013 (terrorist attacks).

We identify these important events using information from standard sources such as Wikipedia. For each country, we read the top of the Wikipedia webpage of the country (in English as well as in the main language of the country) as well as the "contemporary/modern period" and "colonial period" sections.[66] We cross-check this information using other sources, e.g. the BBC Profile of each country.[67] We then include in the regressions estimating the returns country-specific period dummies equal to one if the individual was aged between 18 and 67 during the period(s), for countries with at least two years of data. Doing so captures the fact that each person was affected by multiple events during her lifetime. For example, an American person born in 1931 was 18 in 1949 and 67 in 1998. For her, the 1945-1953, 1954-1961, ..., 1990-1993 and 1994-2000 period dummies are equal to one. Of course, blindly following Wikipedia-BBC may lead us to include events that might not be that "important" for workers. At the

support measures". The countries in the analysis are Brazil, Italy, Peru, the UK, the US and Vietnam.

[66] See https://en.wikipedia.org/wiki/United_States for the U.S. Accessed 03-15-2019.

[67] See https://www.bbc.com/news/world-us-canada-16761057 for the U.S. Accessed 03-15-2019.

same time, it is better if we blindly follow their selection of important events rather than us cherry-picking the events ourselves. Selecting too many events by including events that might not appear so "important" should also lead to more conservative estimates because the included cohort fixed effects are then more refined, i.e. lump together fewer years than if we were not using these events, leading to more conservative estimates.

Classification of Industries (N = 10). The 10 industries are based on revision 3.1 of the International Standard Industrial Classification: 1 = Agriculture, Hunting, Fishing (01-05); 2 = Mining (10-14); 3 = Manufacturing (15-37); 4 = Electricity and Utilities (40-41); 5 = Construction (45); 6 = Commerce (50-55); 7 = Transportation, Storage and Communication (60-64); 8 = Financial, Insurance and Real Estate (65-74); 9 = Services: Public Administration (75); 10 = Other Services & Other/Unspecified Sectors (80-99).

Classification of Occupations (N = 10). The 10 occupations are based on International Standard Classification of Occupations 88: 1 = Managers; 2 = Professionals; 3 = Technicians and associate professionals; 4 = Clerical support workers; 5 = Service and sales workers; 6 = Skilled agricultural, forestry and fishery workers; 7 = Craft and related trades workers; 8 = Plant and machine operators, and assemblers; 9 = Elementary occupations; 10 = Armed forces occupations/Other/Unspecified occupations.

I The COVID-19 Pandemic and Child Labor

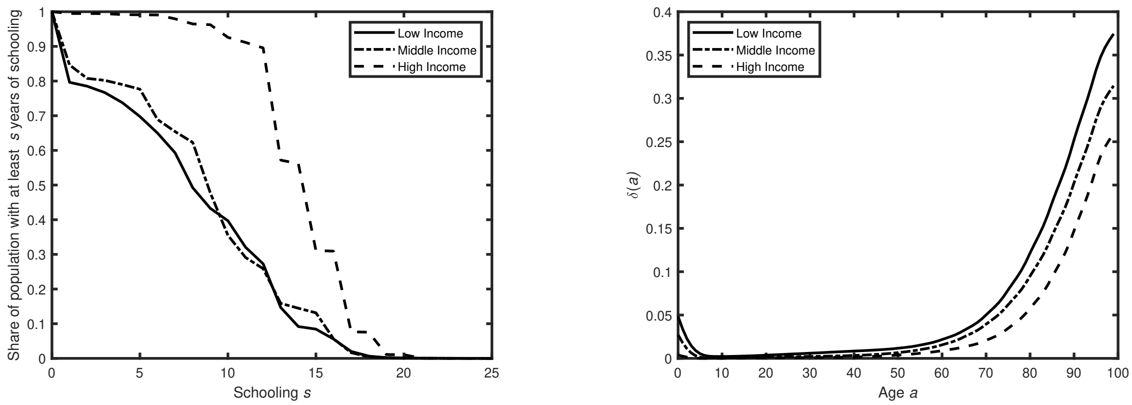
Negative aggregate shocks may increase or decrease child labor (e.g., Ferreira and Schady, 2009; Cogneau and Jedwab, 2012). Given such shocks worsen labor market conditions and reduce the opportunity cost of time for children, children may work less. This substitution effect may even dominate the income effect and result in countercyclical human capital investments, hence *less* child labor. In HICs, the income effect is typically small so the substitution effect tends to dominate. For example, Ahn et al. (2020) find that for the U.S., high school completion rates increased in 2020 relative to previous years, and these can largely be explained by worse labor market conditions.

The question then is how the income effect and substitution effect compare in both LICs and MICs. In the case of COVID-19, ILO and UNICEF (2021, p. 8) says that "the predicted additional rise in child labour is by no means a foregone conclusion." The reduction in economic activity due to the pandemic dramatically reduced employment, and youth unemployment increased 2.4 times more than adult unemployment (ILO, 2020, p. 10). Thus, older workers were more protected than younger workers when total employment decreased. As such, it could be child employment did not increase despite falling incomes. More generally, to our knowledge, no studies have quantitatively and rigorously established that COVID-19 increased child labor in developing economies.

A. Appendix Figures and Tables

Figure A.1: Distributions of Schooling and Mortality in the Model Economy.

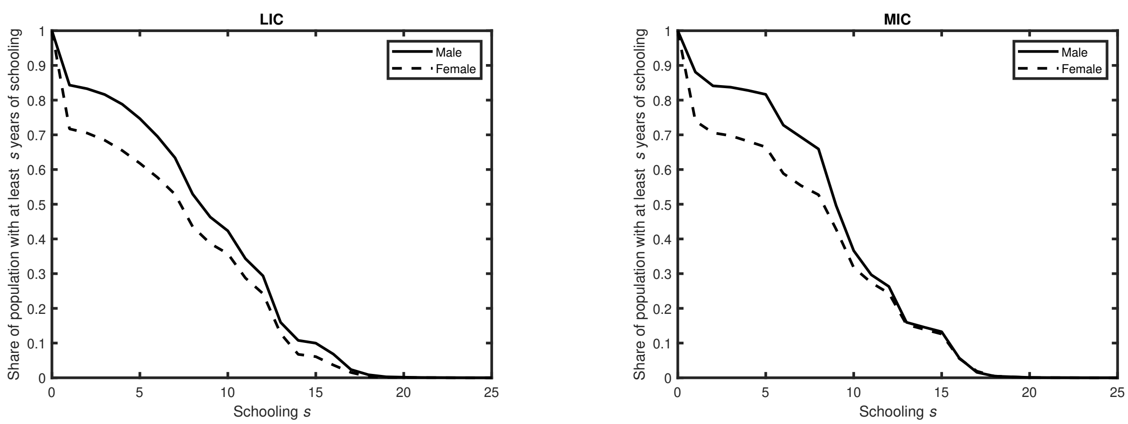
(a) Distributions of Schooling **(b)** Distributions of Mortality



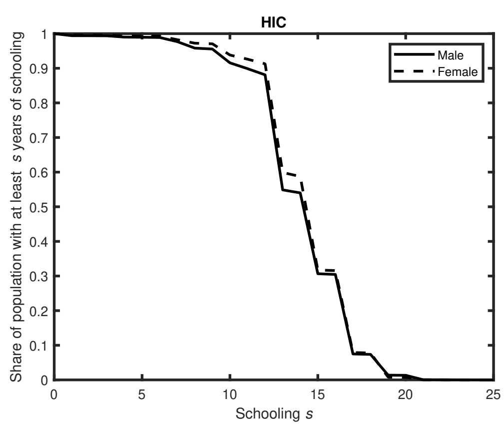
Sources – United Nations (2019), I2D2 database.

Figure A.2: Distributions of Schooling by Gender and Income Level

(a) Low-Income Economies **(b)** Middle-Income Economies



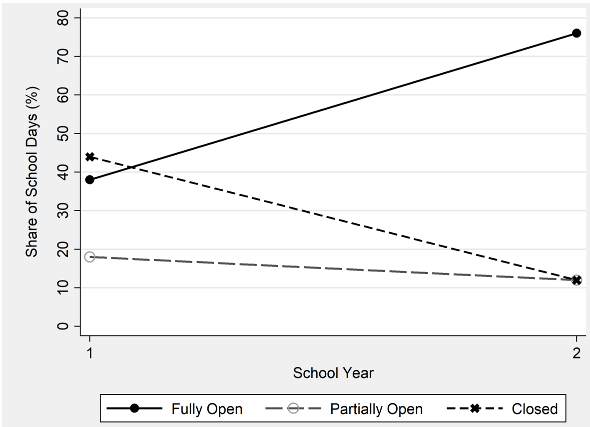
(c) High-Income Economies



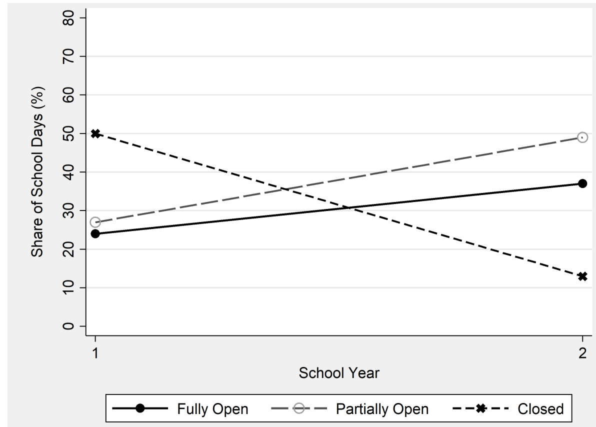
Sources – I2D2 database.

Figure A.3: Distributions of School Closures by Income Level

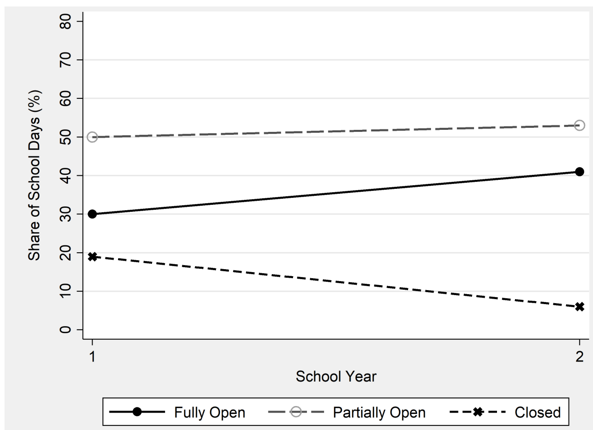
(a) Low-Income Economies



(b) Middle-Income Economies



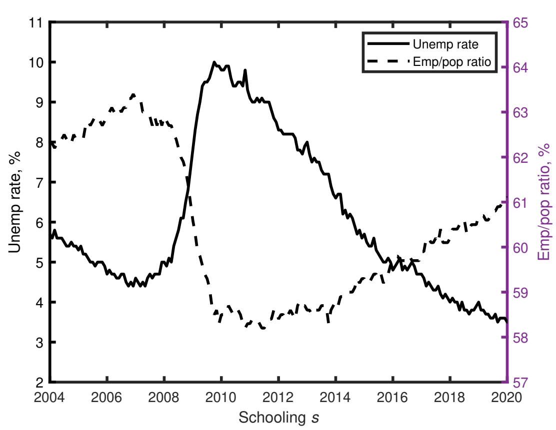
(c) High-Income Economies



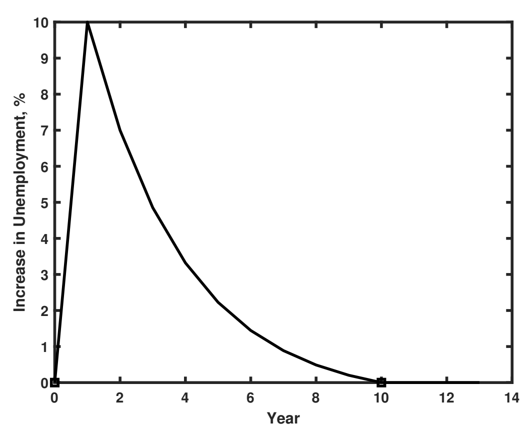
Sources – UNESCO (2021). According to their methodological note, *partially open schools* are schools that are: "*(a) open/closed in certain regions only; and/or (b) open/closed for some grade levels/age groups only; and/or (c) open but with reduced in-person class time, combined with distance learning (hybrid approach)*".

Figure A.4: Duration of the Employment Shock

(a) The Great Recession and Employment



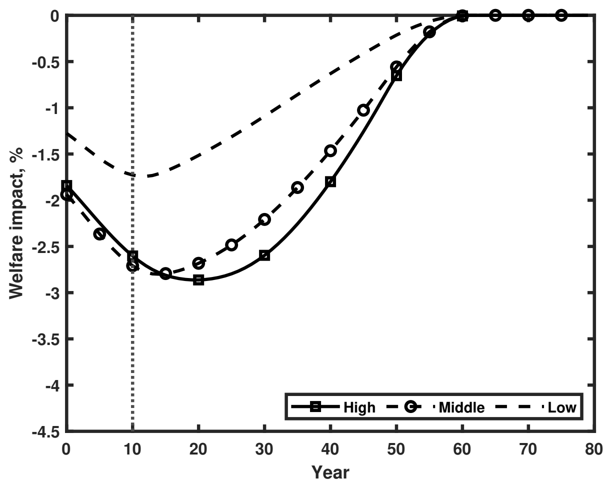
(b) Maximal Employment Shock



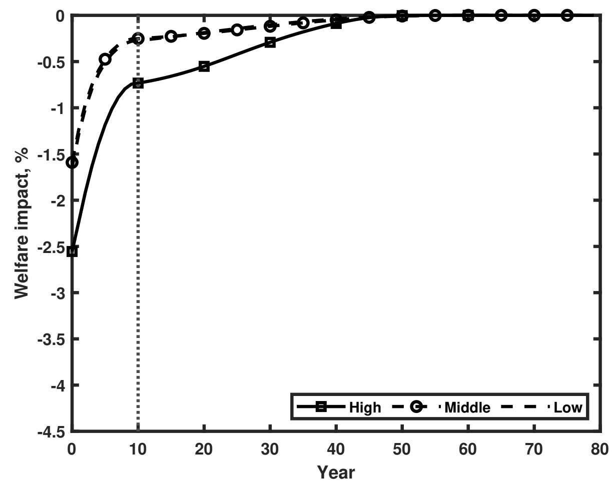
Left figure: Source – Federal Reserve Bank of St. Louis. Right figure: See text for construction details..

Figure A.5: Impact of the Maximal Shock on Welfare

(a) Disruptions to Schooling Only



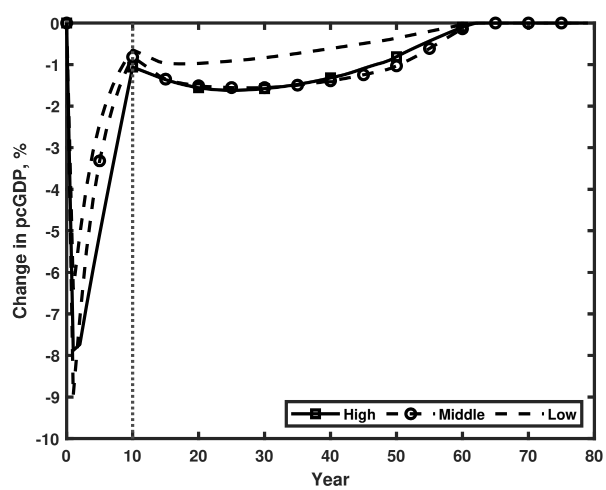
(b) Disruptions to Employment Only



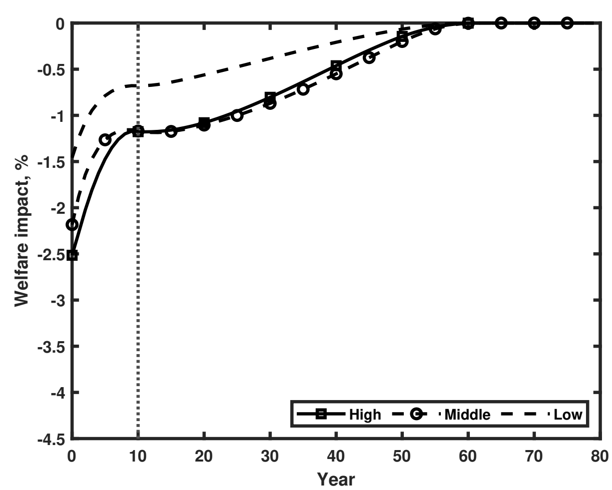
Notes: Welfare measure = the percent of GDP that would have to be added in each period in order to make agents indifferent between the pandemic shock and remaining in the steady state. Left fig.: The shock is assumed to disrupt schooling only. Right fig.: The shock is assumed to disrupt employment only.

Figure A.6: Most Likely Impact of the COVID-19 Shock

(a) pcGDP Compared to the Steady State

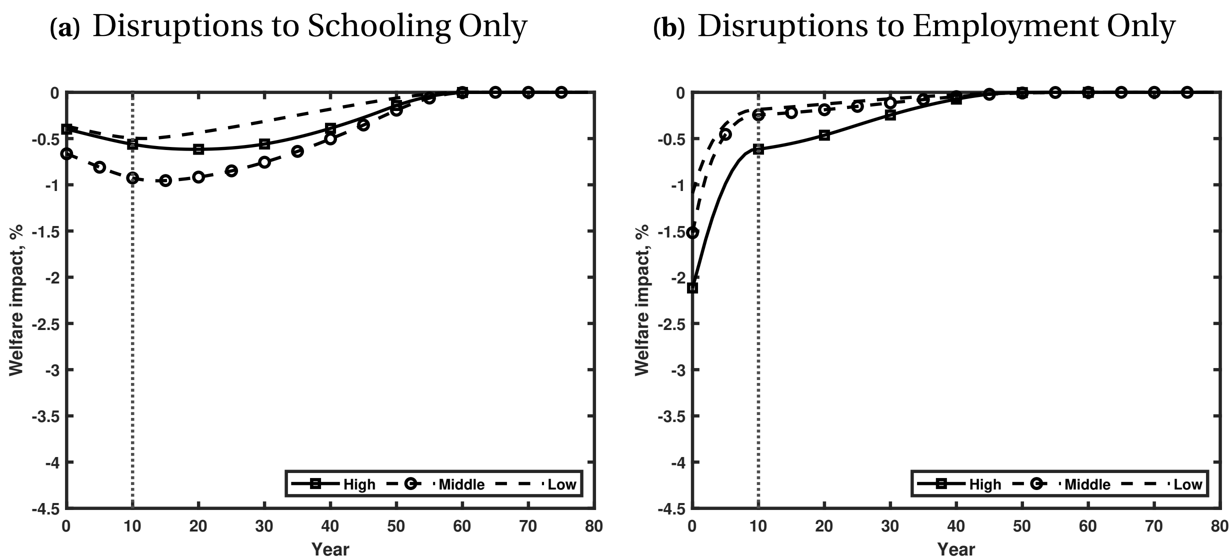


(b) Welfare



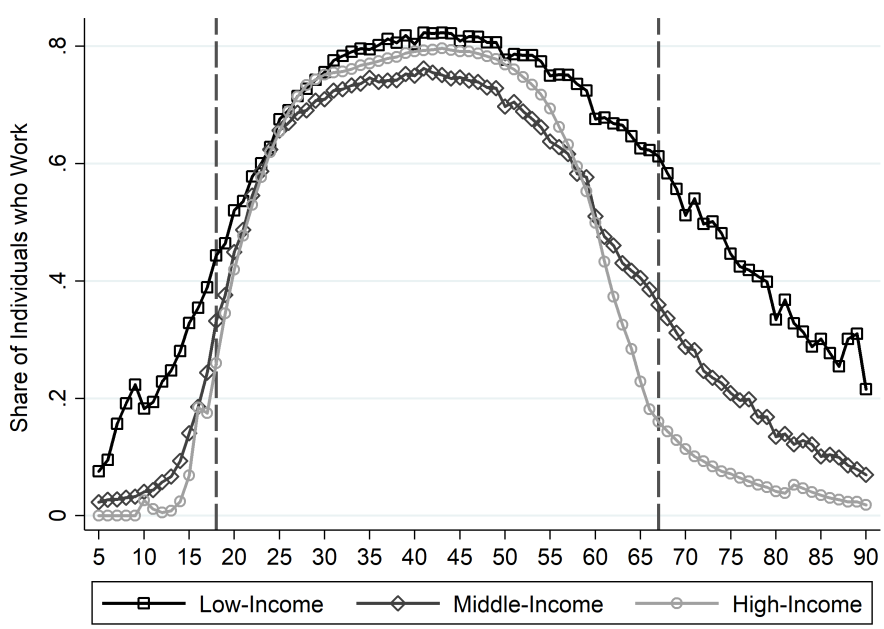
Notes: Left figure: Impact on current per capita GDP of the shock year-by-year compared to the steady state for economies at different levels of development. Right figure: Impact of the shock on welfare in economies at different levels of development. The welfare measure is the percent of GDP that would have to be added in each period in order to make agents indifferent between the COVID-19 shock and remaining in the steady state. The shock is assumed to disrupt both schooling and employment.

Figure A.7: Most Likely Impact of the COVID-19 Shock, Education vs. Employment



Notes: Welfare measure = the percent of GDP that would have to be added in each period in order to make agents indifferent between the pandemic shock and remaining in the steady state. Left fig.: The shock is assumed to disrupt schooling only. Right fig.: The shock is assumed to disrupt employment only.

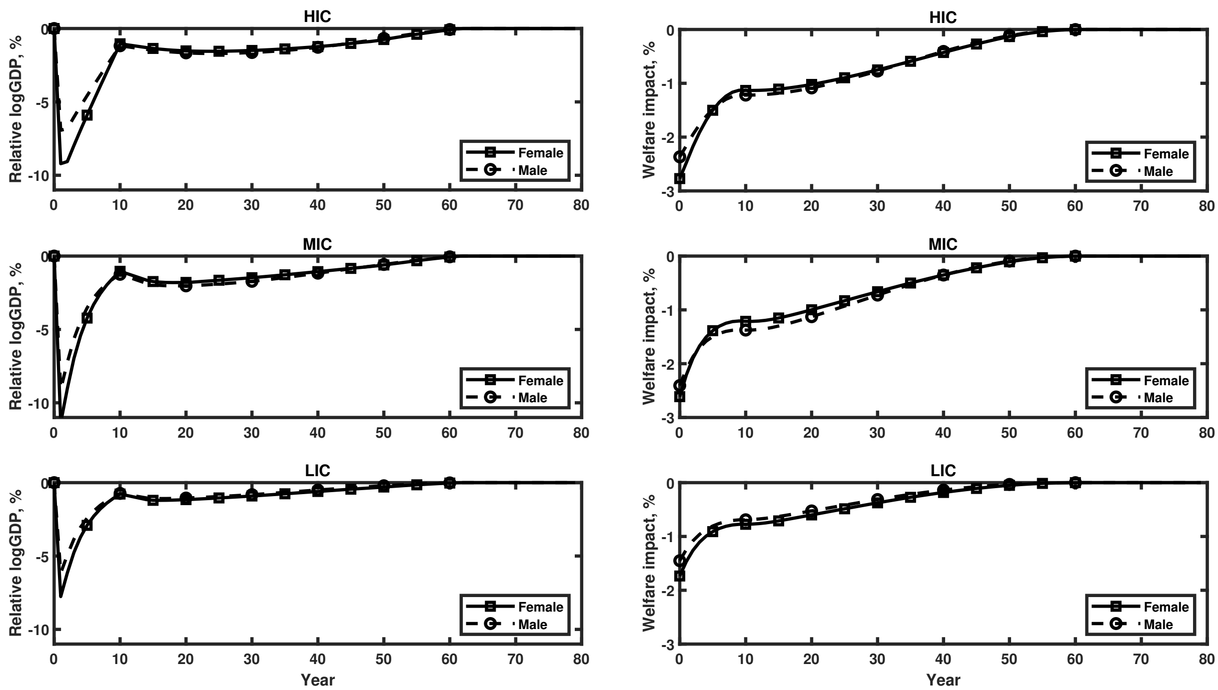
Figure A.8: Employment Rate by Age and Income Group, 5-90 Year-Olds



Notes: These figures show for each age from 5 to 90 in LICs, MICs and HICs the share of individuals who work (no matter the number of work hours). These graphs were created using the I2D2 data (1990-2016), only for country-year-samples and ages with available information on employment. We then use the population of each country c. 2018 to obtain the average distributions for each income group.

Figure A.9: Most Likely Impact of the COVID-19 Shock by Gender

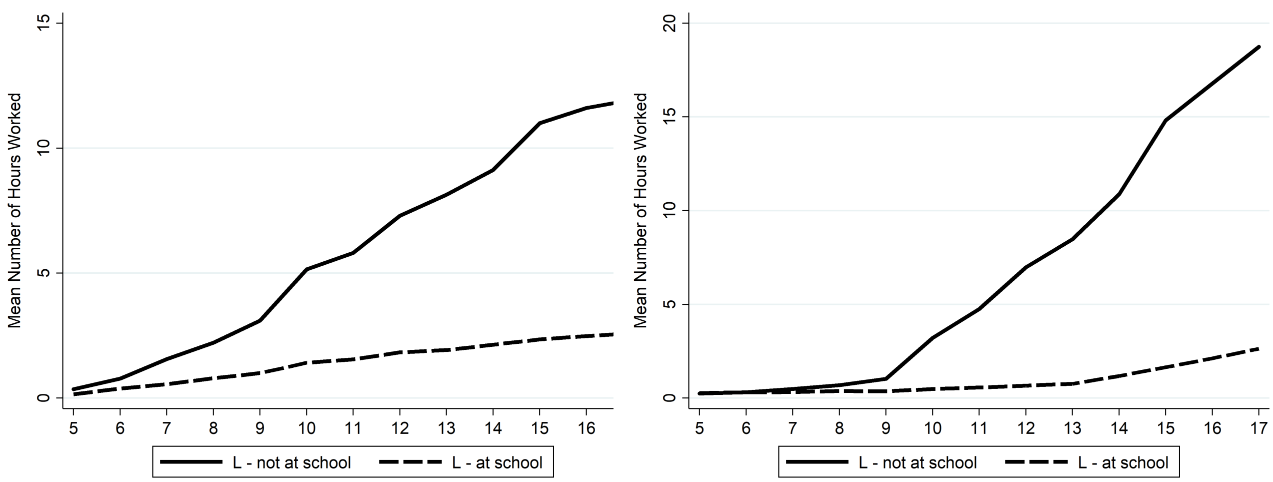
(a) pcGDP Compared to the Steady State **(b)** Welfare



Notes: Left figure: Impact on current per capita GDP year-by-year compared to the steady state for economies at different levels of development and by gender. Right figure: Impact on welfare in economies at different levels of development and by gender. The welfare measure is the percent of GDP that would have to be added in each period in order to make agents indifferent between the COVID-19 shock and remaining in the steady state. The shock is assumed to disrupt both schooling and employment.

Figure A.10: Average Number of Work Hours by Age, 5-17 Year-Olds

(a) Distributions in LICs **(b)** Distributions in MICs



Notes: These figures show for 5-17 year-old children in LICs and MICs the average number of work hours (including the 0s) by age and school attendance status. These graphs were created using the I2D2 data (1990-2016), only for country-year-samples and ages with available information on work hours. We then use the population of each country c. 2018 to obtain the average distributions for each income group.

Table A.1: Provision of Remote Learning Modalities by Income Group

Modality \ Income Group	LIC	MIC	HIC
Online Platform	64	93	95
Television	92	98	63
Radio	93	76	22
Take-Home Packages	64	88	89
Highest	Radio	Television	Online
2nd Highest	Television	Online	Take-Home
2nd Lowest	Take-Home	Take-Home	Television
Lowest	Online	Radio	Radio

Notes: Sources - UNESCO (2020b).

Table A.2: Access to the Internet, the Television and the Radio, 2010s

Mean	Share with Internet (%)	Share with Television (%)	Share with Radio (%)
HIC	86	98	99
MIC	34	69	47
LIC	6	35	35

Notes: Sources - Internet: World Bank (2020b) (among 3-17 year-old children); Television and Radio: ITU (2010); UNICEF (2020) (for all households).

Table A.3: Implied Effectiveness Rate for Each Remote Learning Modality

Modality \ Income Group	LIC	MIC	HIC	Global
Online Platform	65	80	89	78
Television	63	77	74	75
Radio	65	69	54	67
Take-Home Packages	48	80	82	75

Notes: Sources - UNESCO (2020b). The effectiveness rate of each modality is calculated as the percentage share of *Very Effective* + 0.8 × the percentage share of *Fairly Effective*. We arbitrarily assume 80% given the lack of information on what *Fairly Effective* implies in UNESCO (2020b).

Table A.4: COVID and Mortality in the U.S., 2020-2021

	COVID Deaths as % of	
Age	Deaths	Population
0-17	0.97	0.00
18-29	2.67	0.01
30-39	7.63	0.03
40-49	12.4	0.08
50-64	13.3	0.22
65-74	13.7	0.55
75-84	13.2	1.23
85+	11.4	3.20

Sources: US Center for Disease Control, US Census Bureau and authors' calculations

Table A.5: Returns to Experience and Education for Women vs. Men, Robustness

Group:	(1) Male			(2) Female			(3) Male - Female		
***Panel A:* Returns to Experience**	HIC	MIC	LIC	HIC	MIC	LIC	HIC	MIC	LIC
1. Baseline	4.1	1.9	2.2	3.0	1.5	2.1	1.1	0.4	0.1
2. Decadal Cohort FE & $\geq$ 2 Yrs of Data	3.5	1.8	1.4	2.5	1.1	0.8	1.0	0.7	0.6
3. Important Events FE & $\geq$ 2 Yrs of Data	3.4	1.7	0.6	2.3	0.7	-0.5	1.1	1.0	1.1
4. Industry (10) FE	3.9	1.9	2.3	2.9	1.6	1.9	1.0	0.3	0.4
5. Occupation (10) FE	3.9	1.7	2.0	2.8	1.4	1.9	1.1	0.3	0.1
6. Industry (10) FE & Occupation (10) FE	3.9	1.7	2.0	2.8	1.4	1.9	1.1	0.3	0.1
7. Excluding Self-Employed Individuals	4.2	1.9	2.2	3.2	1.5	1.7	1.0	0.4	0.5
8. Female Non-Empl. Rate $<$ 54%	4.1	2.1	2.2	3.2	1.5	2.0	0.9	0.6	0.2
9. Female Non-Empl. Rate $<$ 44%	4.2	2.0	2.3	3.2	1.7	2.1	1.0	0.3	0.2
10. Diff Female - Male Non-Empl $<$ 25%	4.1	2.0	2.3	3.1	1.6	2.2	1.0	0.4	0.1
11. Diff Female - Male Non-Empl $<$ 22%	4.2	2.0	2.3	3.2	1.6	2.2	1.0	0.4	0.1
12. Diff Female - Male Non-Empl $<$ 13%	4.5	2.0	2.3	3.5	1.3	2.0	1.0	0.7	0.3
13. HH Head/Spouse & Child Costs 1 Year	3.3	1.4	1.6	2.4	1.1	1.9	0.9	0.3	-0.3
14. HH Head/Spouse & Child Costs 2 Years	3.3	1.4	1.7	2.5	1.2	1.6	0.8	0.2	0.1
***Panel B:* Returns to Education**	HIC	MIC	LIC	HIC	MIC	LIC	HIC	MIC	LIC
1. Baseline	9.4	7.9	8.5	11.1	9.0	9.9	-1.7	-1.1	-1.4
2. Decadal Cohort FE & $\geq$ 2 Yrs of Data	9.1	7.8	8.8	10.8	8.8	10.5	-1.7	-1.0	-1.7
3. Important Events FE & $\geq$ 2 Yrs of Data	9.0	7.7	8.7	10.7	8.7	10.4	-1.7	-1.0	-1.7
4. Industry (10) FE	8.7	6.6	6.8	10.0	8.1	7.7	-1.3	-1.5	-0.9
5. Occupation (10) FE	6.0	5.3	6.1	6.1	5.9	7.4	-0.1	-0.6	-1.3
6. Industry (10) FE & Occupation (10) FE	6.0	5.4	6.1	6.2	5.9	7.3	-0.2	-0.5	-1.2
7. Excluding Self-Employed Individuals	9.7	7.0	8.2	11.6	8.1	10.1	-1.9	-1.1	-1.9
8. Female Non-Empl. Rate $<$ 54%	9.5	9.8	8.7	11.2	10.1	9.9	-1.7	-0.3	-1.2
9. Female Non-Empl. Rate $<$ 44%	9.1	10.4	9.3	11.4	9.9	10.9	-2.3	0.5	-1.6
10. Diff Female - Male Non-Empl $<$ 25%	9.4	9.8	9.1	11.1	9.9	10.7	-1.7	-0.1	-1.6
11. Diff Female - Male Non-Empl $<$ 22%	9.6	10.0	9.3	11.4	9.8	10.9	-1.8	0.2	-1.6
12. Diff Female - Male Non-Empl $<$ 13%	10.2	6.9	8.7	11.9	8.6	9.4	-1.7	-1.7	-0.7
13. HH Head/Spouse & Child Costs 1 Year	9.4	8.6	9.1	11.5	9.5	10.5	-2.1	-0.9	-1.4
14. HH Head/Spouse & Child Costs 2 Years	9.4	8.6	9.1	11.5	9.6	10.4	-2.1	-1.0	-1.3

Notes: This table shows the returns to experience and the returns to education by gender, as well as the gender gaps, when implementing various robustness checks. See text for details.

Table A.6: Returns to Experience and Education by College Status, Robustness

Group:	(1) Pre-College Workers			(2) College Workers		
***Panel A:* Returns to Experience**	LIC	MIC	HIC	LIC	MIC	HIC
Baseline	1.9	2.1	4.4	3.2	2.7	4.2
Incl. Child Labor Exp from 15	2.2	2.4	4.8	2.9	2.7	4.2
Incl. Child Labor Exp from 13	2.7	2.5	4.8	2.9	2.7	4.2
Incl. Child Labor Exp from 6	2.5	2.4	4.8	2.9	2.7	4.2
Decadal Cohort FE	1.9	2.1	4.4	3.2	2.7	4.2
Important Events FE	1.6	2.4	4.0	2.4	1.5	3.7
Excl. Self-Employed Workers	1.8	2.0	4.5	3.3	2.7	4.3
Estimated Using Males Only	2.0	2.3	4.8	3.2	2.8	5.0
Unemployment $<$ 7% (25p)	1.9	2.2	4.3	3.2	2.7	4.0
Unemployment $<$ 10% (50p)	1.9	2.1	4.4	3.2	2.7	4.0
NLF $<$ 35% (25p, 50p)	2.3	2.1	4.4	3.1	2.7	4.1
Unemployment $>$ 7% (25p)	2.1	2.2	4.8	2.6	2.7	4.5
Unemployment $>$ 10% (50p)	2.4	2.2	4.3	2.3	2.3	4.3
NLF $>$ 35% (25p, 50p)	1.8	2.0	4.0	3.1	2.3	4.2
Non-Linear: Bin 5 Only	2.7	2.8	7.9	4.6	3.5	7.3
Non-Linear: Bins 10-25 Only	1.4	1.6	2.9	2.5	2.1	2.8
***Panel B:* Returns to Education**	HIC	MIC	LIC	HIC	MIC	LIC
Baseline	5.5	8.8	6.7	13.6	11.5	13.0
Incl. Child Labor Exp from 15	5.7	9.1	7.6	15.2	12.2	13.0
Incl. Child Labor Exp from 13	6.0	9.3	7.8	15.2	12.2	13.0
Incl. Child Labor Exp from 6	6.8	9.6	8.0	15.2	12.2	13.0
Decadal Cohort FE	5.4	8.8	6.7	13.5	11.5	13.0
Important Events FE	5.4	8.7	6.6	12.7	10.7	12.7
Excl. Self-Employed Workers	4.7	8.0	6.8	11.9	11.3	13.7
Estimated Using Males Only	5.1	9.0	6.4	13.7	11.2	12.6
Unemployment $>$ 7% (25p)	5.5	9.2	6.4	13.5	11.3	13.2
Unemployment $<$ 10% (50p)	5.5	8.7	6.8	13.6	11.5	12.3
NLF $<$ 35% (25p, 50p)	7.7	8.9	6.6	20.4	11.9	13.4
Unemployment $>$ 7% (25p)	8.1	7.5	6.4	19.1	16.8	14.3
Unemployment $>$ 10% (50p)	8.6	7.8	7.3	19.3	12.9	12.1
NLF $>$ 35% (25p, 50p)	4.9	7.0	7.8	12.6	14.1	11.1
Non-Linear: Education	5.5	8.8	6.7	13.6	11.5	13.0

Notes: This table shows the returns to experience and the returns to education by college status when implementing various robustness checks. See text for details.

Table A.7: Robustness of the Welfare Impact of Disruptions to Human Capital

	(1) Summing Across All Years				(2) From Year 10 Only			
Scenario	Shock	HIC	MIC	LIC	Shock	HIC	MIC	LIC
Baseline	Empl	2.1	1.5	1.1	Empl	0.6	0.2	0.2
	School	0.4	0.7	0.4	School	0.6	0.9	0.5
	Total	2.5	2.2	1.5	Total	1.2	1.2	0.7
Incl. Child Labor Exp from 15	Empl	2.1	1.5	1.0	Empl	0.6	0.3	0.2
	School	0.5	0.7	0.4	School	0.6	0.9	0.5
	Total	2.6	2.2	1.4	Total	1.3	1.2	0.7
Incl. Child Labor Exp from 13	Empl	2.1	1.5	1.1	Empl	0.6	0.3	0.2
	School	0.5	0.7	0.4	School	0.6	0.9	0.5
	Total	2.6	2.2	1.5	Total	1.3	1.2	0.7
Incl. Child Labor Exp from 6	Empl	2.1	1.4	1.0	Empl	0.6	0.3	0.2
	School	0.5	0.7	0.5	School	0.7	1.0	0.6
	Total	2.6	2.1	1.4	Total	1.3	1.2	0.8
Decadal Cohort FE	Empl	2.1	1.5	1.1	Empl	0.6	0.2	0.2
	School	0.4	0.7	0.4	School	0.6	0.9	0.5
	Total	2.5	2.2	1.4	Total	1.2	1.2	0.7
Important Events FE	Empl	2.1	1.5	1.1	Empl	0.5	0.3	0.2
	School	0.4	0.6	0.4	School	0.6	0.9	0.5
	Total	2.5	2.2	1.4	Total	1.1	1.1	0.6
Excl. Self-Employed Workers	Empl	2.1	1.5	1.1	Empl	0.6	0.2	0.2
	School	0.4	0.7	0.3	School	0.6	0.8	0.4
	Total	2.5	2.1	1.4	Total	1.2	1.1	0.6
Estimated Using Males Only	Empl	2.2	1.5	1.1	Empl	0.7	0.3	0.2
	School	0.4	0.7	0.3	School	0.5	0.9	0.5
	Total	2.6	2.2	1.4	Total	1.2	1.2	0.6
Unemployment $<$ 7% (25p)	Empl	2.1	1.5	1.1	Empl	0.6	0.3	0.2
	School	0.4	0.7	0.4	School	0.5	1.0	0.5
	Total	2.5	2.2	1.5	Total	1.1	1.2	0.7
Unemployment $>$ 7% (25p)	Empl	2.1	1.5	1.1	Empl	0.7	0.3	0.2
	School	0.4	0.6	0.6	School	0.5	0.8	0.8
	Total	2.5	2.1	1.7	Total	1.2	1.0	1.0
Unemployment $<$ 10% (50p)	Empl	2.1	1.5	1.1	Empl	0.6	0.2	0.2
	School	0.4	0.7	0.4	School	0.6	0.9	0.5
	Total	2.5	2.2	1.5	Total	1.2	1.2	0.7
Unemployment $>$ 10% (50p)	Empl	2.2	1.5	1.1	Empl	0.6	0.2	0.2
	School	0.4	0.6	0.6	School	0.6	0.8	0.8
	Total	2.5	2.1	1.47	Total	1.2	1.1	1.0
Unemployment $<$ 7% (25p)	Empl	2.1	1.5	1.1	Empl	0.6	0.2	0.2
	School	0.4	0.7	0.4	School	0.6	0.9	0.7
	Total	2.5	2.2	1.5	Total	1.2	1.2	0.9
Unemployment $>$ 7% (25p)	Empl	2.1	1.5	1.1	Empl	0.6	0.2	0.2
	School	0.4	0.6	0.6	School	0.7	0.7	0.4
	Total	2.5	2.1	1.7	Total	1.2	0.9	0.6
Non-Linear Returns (0-5 vs. 10-25)	Empl	2.2	1.5	1.1	Empl	0.7	0.3	0.2
	School	0.4	0.7	0.3	School	0.6	0.9	0.5
	Total	2.6	2.2	1.5	Total	1.3	1.2	0.7

Notes: See text for details.