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 range of the long-term economic impact of these disruptions in the case of the COVID-19 pandemic, 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. We find that: (i) Both lost schooling and experience can contribute to significant losses in global learning and output; and (ii) Developed countries incur *greater* losses than developing countries, because they have more schooling to start with *and* higher returns to experience. In addition, the returns to education and experience are separately estimated for men and women, to explore the differential effects *by gender* of the COVID-19 pandemic. While we uncover gender differences in returns to education and experience, gender differences in the impact of COVID-19 through human capital accumulation are small. 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 (World Bank, 2018; Lagakos et al., 2018b,a; Jedwab et al., 2022; Rossi, 2020). Macroeconomic downturns affect human capital accumulation at work. Downturns due to pandemics are different, however, as mitigation measures include workplace and school closures. As a result, they *disrupt human capital accumulation not just at work but also at school.* National school closures are also 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. Significant declines in employment occurred as a result of the initial lockdowns, and continued for a while due to behavioral changes as people avoided contact-intensive activities, as well as supply chain disruptions.

Given that future pandemics might have the potential to be similarly disruptive, we quantify the aggregate impact of pandemics 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 using 1,084 household surveys across 145 countries (1990-2016) following the methodology of Jedwab et al. (2022) who focus on estimating overall returns to experience and education. Finally, we use the framework to compute the 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. These losses are computed based on the missing human capital, *net* of the direct impact on output and welfare of the employment shock itself.

We first treat countries as though they were *symmetrically* affected by an identical pandemic shock. The long-term impact through human capital can be substantial, and for most scenarios is *higher in richer nations.* In the most severe scenario, welfare (measured relative to steady-state output) decreases in high-income countries (HICs) by 2.6 percent each year in perpetuity, 2.2 percent in middle-income countries (MICs) and 1.6 percent in low-income countries (LICs). Given a discount rate of 4%, this is equal to a one-time loss of 66 percent, 54 percent and 40 percent of GDP respectively.[1]

There are several reasons for the *asymmetric* impact of a *symmetric* shock on countries of different income levels. While the returns to education are highest in

[1] Even 40 years later, high-income countries remain 4.7 percent below steady state GDP, compared to 3.7 percent for middle-income countries and 2.7 percent for low-income countries.

the MICs, there is significantly less schooling to begin with in the MICs and LICs: the average years of schooling in the HICs, MICs and LICs is 13, 8 and 6 years, respectively. In addition, the returns to experience are highest in the HICs. In combination, these factors imply that the impact on HICs is greater than in MICs as well as the LICs.

We then use our framework to pinpoint *which pandemic scenario most closely reflects the COVID-19 shock* in each income group. We achieve this through an 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 the extent of disruption to employment for different types of workers.

Again, the impact of COVID-19 on the HICs and MICs turns out to be greater than in LICs. This finding is robust to using a number of different approaches to estimating the returns to schooling and experience, and to a number of different assumptions about the education and employment shocks and the form of the recovery. This contrasts with the policy literature on COVID-induced schooling disruptions that argues that the impact disproportionately falls on LICs.[2] However, the relatively lower impact does not imply that the effects on LICs should be discounted. Given the challenging context in many LICs, they are still heavily and durably impacted by the pandemic shock.

The potential welfare impact of the COVID shock is up to the equivalent of 1.01 percent of steady state income per year in perpetuity in HICs, compared to 0.91 percent in MICs and 0.56 percent in LICs. Based on GDP per capita in 2020, this is equivalent to $\$29,472$, $\$10,601$ and $\$2,473$. Alternatively, this is equivalent to a one-off hit of 25, 23 and 14 percent of income respectively. Overall, this amounts to 24 percent of global GDP (or $\$20.4$ trillion). In other words, even if the COVID shock is possibly over (at least at a global level), its human capital accumulation effects are long-lasting, as it takes time for impacted students to enter the labor market and for impacted workers to retire. In addition to the magnitudes and persistence of the effects over time, it is interesting to observe that the contribution of schooling and experience to these losses also varies by level of development. Experience accounts for over half of the losses in the HIC, as the returns to experience are very high. In contrast, experience accounts for about a third of the losses in the MIC and LIC. Finally, we can use our framework to consider the impact

[2]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 [...]."

of different scenarios of post-pandemic recovery in human capital accumulation.

Lastly, the policy literature suggests that COVID-19 had a disproportionate economic impact on female workers. To explore whether long-lasting human capital losses might play a role in this divergence, we repeat our quantitative exercise separately for men and women. We accomplish this through several steps.[3]

First, we find lower returns to experience for women, especially in richer nations. While this may be surprising given the likely lower rates of gender discrimination in richer nations, returns to experience are lower in poorer nations, which constrains the degree to which returns for men and women can differ in absolute terms. In contrast, returns to *education* are higher for women. Second, we use these returns along with data on the schooling and experience distributions for men and women to compute the long-term impact of the shock on the income and welfare of men and women separately. We find that differences are small: welfare differences peak at under 0.5% all three country groups. The reason is that measured differences in returns across genders, while leading to significant differences in average income across men and women, are not enough to substantially affect *transition dynamics* after the COVID-19 shock. Instead, the main factor behind differences in relative income across genders is the fact that the employment shock was simply more severe for women than for men.

Our study makes several contributions to the literature, for example on the macroeconomic impact of pandemics (Barro et al., 2020; Coibion et al., 2020; Fernandez-Villaverde and Jones, 2020; Guerrieri et al., 2020; Jorda et al., 2020; Kugler et al., 2021).[4] Given new technologies for mitigating schooling loss, these should be taken into account when assessing the impact of future pandemics on human capital.

While other studies on the global learning losses due to COVID-19 have appeared independently of this study – Azevedo et al. (2020, 2021), Hanushek and Woessmann (2020) and Psacharopoulos et al. (2021) estimate the impact of disruptions to schooling – we quantify the human capital effects of COVID-19 by income level: (i) considering *both* education and experience losses; (ii) relying on returns to education and experience that were consistently estimated using 1,084 household surveys across 145 countries;[5] (iii) performing a *global* analysis of the education and experience shocks

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

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

[5] In contrast, the three studies assume similar returns to education across countries. In Azevedo et

using evidence on school closures, access to and effectiveness of distance learning, non-employment for different types of workers, and post-pandemic human capital recovery rates;[6] (iv) examining the output dynamics associated with the shocks; and (v) studying how they vary by gender. Hanushek and Woessmann (2020) study OECD economies only, Fuchs-Schündeln et al. (2020) and Jang and Yum (2022) focus on the distributional, not aggregate, effects of school closures, Alon et al. (2022) study their effects on the employment of reproductive-age women in Nigeria, and Kugler et al. (2021) study COVID-19's employment effects in 40 countries.[7]

We also contribute to a sparse literature on the relationship between experience and economic development (Manuelli and Seshadri, 2014; Lagakos et al., 2018b,a; Jedwab et al., 2022), 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; Hanushek and Woessmann, 2012; Schoellman, 2012; Jones, 2014, 2019; Hanushek et al., 2017; Hendricks and Schoellman, 2018, 2022). While the macroeconomics literature has looked at the long-term impact of economic downturns or economic transitions or the impact of structural transformation through 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. We highlight the importance of experience when estimating global learning losses due to COVID-19.[9]

al. (2020, 2021) the returns also 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.

[6] Psacharopoulos et al. (2021) have a uniform assumption across countries about access to and effectiveness of distance learning. Azevedo et al. (2020, 2021) consider several school closure scenarios but do not study scenarios by income group. They also use data on access, not effectiveness, and focus on the effects of school closures in poorer economies whereas we show that higher-income economies are disproportionately impacted due to their larger schooling stock and higher returns to experience.

[7] It would be valuable to be able to make distributional statements. However, this would require information about the joint distribution of non-employment, schooling and experience, both in steady state and over the progress of the pandemic, information that is not globally available.

[8] For structural change, see Schoellman and Hobijn (2017), Porzio and Santangelo (2017), Buera et al. (2020), Kugler et al. (2020) and Porzio et al. (2021). For downturns, see Ljungqvist and Sargent (1998), Kahn (2010) and Davis and Von Wachter (2011). For economic transitions, see Dauth et al. (2019).

[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

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 causes 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 U.S., 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, across countries at different levels of development.

Furthermore, we focus on understanding the global and long-lasting effects pandemics might have on incomes for men and women through disruptions to human capital accumulation – and thus on *female relative income*. We achieve this by estimating the returns to education and experience separately for women and men.[12] The impact of the COVID-19 pandemic on men and women turns out to be similar, even after accounting for cohort effects, the impact of motherhood, selection into the workforce, and measurement error due to self-employment varying by gender.

Since we employ the development accounting framework in Jedwab et al. (2022), we spell out how this paper differs. First, we extend the framework in that paper (which focuses on steady states and fundamental differences in human capital stocks) to allow for shocks, specifically shocks to the accumulation of human capital due to pandemics. Second, we do this separately for men and women. Third, in order to differentiate by gender, we provide new estimates of the returns to schooling and experience for men and women separately. Lastly, we consider how the returns to education and experience vary between college graduates and other workers as it is particularly important for our

biased upwards in richer nations if there is more learning there. See Jedwab et al. (2022) 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]Note that we are not the first to study how returns to education and experience vary across dimensions globally. In that, we stand on the shoulders of "giants" who have significantly contributed to this literature (e.g., Psacharopoulos, 1972, 1981, 1994; Psacharopoulos and Patrinos, 2004, 2018a).

estimation in this paper given that the COVID-19 shock disproportionately impacted pre-college education and non-college workers differently across income groups.

Finally, one caveat about our study is that we abstract from physical capital. It is worth considering how our results would be affected by its inclusion. First, Gollin (2002) finds that the capital share of income is around one third across economies at all levels of development. If we assume that all the physical capital continues operating at normal capacity during pandemic shocks, their impact decreases by a third. On the other hand, if we assume that physical capital is complementary to human capital then pandemic-induced losses are as reported. In either case, the order of magnitude of the losses is the same. Interestingly, Krusell et al. (2000) find that physical capital is complementary to high-skilled labor and a substitute for low-skilled labor. To the extent that high-skilled labor is more common in developed economies, this suggests that considering physical capital would exacerbate the differences in losses between HICs and other countries.

The paper is structured as follows. Section 1. describes our development accounting framework with pandemics. Section 2. explains the calibration of the pandemic shock. Section 3. describes the impact of pandemic shocks under different scenarios that affect countries symmetrically. Section 4. discusses scenarios that are relevant for specific groups of countries over the COVID-19 shock specifically. Section 5. provides estimates of the return to schooling and experience for men and women, and studies the impact of the COVID-19 shock on male and female workers. Section 6. concludes.

1. Development Accounting Framework with Pandemics

Our analysis requires 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. (2022), as it allows us to match a variety of statistics required for our exercise, including the distribution of schooling and the rate at which different forms of human capital are accumulated over the life cycle.[13] First, we describe the framework and describe its steady state: this scenario will serve both as the initial condition before the pandemic shock, and as a counterfactual. Then, we introduce the pandemic shock.

[13] Jedwab et al. (2022) use their framework to quantify the global contribution of work experience to human capital accumulation and economic development. As such, they focus on "normal" (i.e., pre-pandemic) conditions. Note that one of the working versions of Jedwab et al. (2022) (available upon request) contained some exploratory results on the economic impact of the COVID-19 shock. The published version of Jedwab et al. (2022) does not contain those results as they merited a dedicated and significantly more extensive study of the impact of the COVID-19 shock, presented herein.

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 year 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.[14]

1.2. Steady State

Regardless of m_0, 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

[14] 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.

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 at each date). 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. 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.[15]

In what follows, 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 retired.

1.3. Modeling Pandemics

We model pandemics as a temporary disruption to the accumulation of human capital through schooling and to employment. In the case of schooling, $r_s(s_{it})$ declines for a period, which could be interpreted as the impact of a partial or complete school shutdown, or as a mode of schooling (e.g., online or hybrid schooling) that is not 100 percent effective. In our benchmark experiments, 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.

The disruption to experience involves a temporary decrease in $r_e(s_{it}, p_{it})$. Broadly, we will assume an initial spike in non-employment due to a pandemic (including unemployment, inactivity and reduced hours), which will decline over a transition period until it returns to normal. However, since our focus is on human capital losses, we will maintain constant values of $\pi_e(\cdot)$. Thus, the spike in non-employment is reflected in less experience being accumulated - not an actual decline in employment, since this would not reflect only the loss of human capital. Thus, the reported losses will

[15]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

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

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

be net of the direct impact of the change in non-employment.

Even though disruptions to $r_s(s_{it})$ and $r_s(s_{it})$ 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.

2. Pre-Pandemic Calibration and Pandemic Scenarios

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.[16]

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 $a \geq 100$.[17]

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 as to exactly match the schooling distribution for the relevant country group, based on data from the World Bank database of more than 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

[16]Country-specific estimates are available upon request – that said, while we are confident of our estimates for country groups, country-specific estimates of the shocks, returns and effects may not be that useful for policy as the potential for measurement error in small samples is greater. For example, while it is possible to gauge the size of the exact education and employment shocks by country groups, doing so for all individual countries is infeasible given the lack of data for many required parameters.

[17]See Web Appx. Fig. $A.1$ and Data Appx. A for these distributions and for details of their calculation.

they retire at age $R = 65$. We assume unemployment and participation are equal across schooling groups in steady state.[18] 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., 2022). If $\underline{r}_e < \bar{r}_e$, then the returns embody a college premium.

This implies that we only compare workers with and without college education.[19]

2.2. Returns Parameters

We follow the methodology of Lagakos et al. (2018b) and Jedwab et al. (2022) 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. I2D2 consists of a large number of household and labor force surveys and censuses. The data was initially compiled by the World Bank's *World Development Report* unit between 2005 and 2011. The database has since been expanded.[20]

[18]The detailed distribution of non-employment does not matter for aggregate welfare. It would affect the distributional impact of the shock, however, that would require information of the joint distribution of age, schooling and non-employment both on average and during the pandemic.

[19]While we could estimate returns by detailed school levels and use this in our calibration, this would bias our sample, as we would lose many country-level observations, thus increasing measurement error. As explained below, we omit less representative samples without at least 10 observations in each experience-education bin. Since we use surveys that are large but not censuses, considering several school levels would make us omit many developed economies where few workers have only primary education as well as many developing economies where few workers have a graduate degree.

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

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 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.[21]

Data are available on the monthly wage. For a substantial subsample, information is available for the hourly wage and the number of hours worked. Next, 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, experience before age 18 is inconsequential and experience equals age minus 18.

Profiles. For individual i and sample t, we 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 and female workers *separately*:

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

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 varying by gender.[22] Finally, we omit samples without at least 10 observations in each bin (results hold with higher cut-offs).

The coefficients help construct wage-experience profiles for LIC, MIC and HIC economies. In the HICs, a worker with 30 years of experience earns 80% more than a worker with zero experience (Fig. 1). For MICs and LICs, the difference is 50%. Differences in the profiles for females and males are 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. 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

[21]We abstract from changes in the returns pre-pandemic that may have continued without the pandemic, thus focusing on level differences that capture more fundamental human capital conditions.

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

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. For the returns to education, we consider the coefficient of the number of years of education.

By College Status. To obtain the returns by college status, we estimate eq. 3 for workers without any college education and workers with some college education *separately*.[23] We then proceed similarly for female workers only, and then male workers only. Again, we omit samples without at least 10 observations in each experience-education bin.

Figure 2 shows higher returns to education for college educated ("college+") workers than for other ("pre-college") workers. The figure also shows the inverted-U shaped 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 populations c. 2018 as weights for the quadratic fit). For college+ workers, the relationship is U-shaped.[24]

Table 1 summarizes the resulting parameters for each country group. The returns to pre-college schooling are lowest in LICs, possibly due to the fact that there is higher demand for human capital in MIC and HIC countries, given their sectoral structure. Returns to college education are higher in the LICs, perhaps due to the scarcity of college education, and the HICs, plausibly due to the higher demand for college education there. Average years of schooling in the LICs is 6, compared to 8 in the MICs and 13 in the HICs. This suggests that disruptions to schooling will be the most consequential in the HICs, as both the quantity of and returns to schooling are high. Finally, 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 that the returns to experience are also overall higher for college+ workers than for pre-college workers, except in the most developed countries. Figure 3 also shows the U-shaped relationship between both returns to experience and income.

Returns to experience are higher in the HICs than in the MICs and LICs, which are more similar (see Table 1 for the resulting parameters). For a pandemic shock to disrupt the economy of a MIC or LIC as much as that of a HIC, some aspect of the shock would

[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]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.

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

2.3. Modeling the Pandemic Shock

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 in the modern era.[25] Thus, both the spread of the pandemic through the community and the required mitigation measures would likely be similar.[26]

We first analyze pandemic shocks as though they affect countries *symmetrically*, 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 on the stock of human capital, as it was low compared to the population and mostly affected the non-working population (see Web Appx. Section B for details).

2.4. Schooling Shock

Incidence. For primary and secondary students, the shock lowers the human capital accumulated via schooling by some share $\nu \in [0, 1]$ during the period of impact. During the shock eq. (1) becomes: $h_{it} = h_{i,t-1} + (1 - \nu) r_s (s_{it})$. $\nu > 0$ due to school closures, imperfectly effective online education, temporary voluntary withdrawal from school, and a lack of remediation post-pandemic. This does not affect the probability of proceeding to the following year $\pi_e (\cdot)$, but slows human capital accumulation.

As a benchmark, we assume that the accumulation of human capital in college is not disrupted. The evidence suggests that the main disruption was to pre-college education rather than college education (Web Appx. Section C). Were college education disrupted, it would increase the relative magnitude of the shock in richer nations where college education is disproportionately important. Our findings that high-income economies are overall more impacted by the pandemic would thus be *reinforced*. For robustness,

[25] 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 https://www.cdc.gov/flu/pandemic-resources/basics/past-pandemics.html, 10/28/2021.

[26] 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).

we will perform additional experiments that allow the quality of college education and college enrollments to be disrupted as well, finding that results are generally similar.

Severity. We explore all possibilities between no disruption and total disruption for 2 years. We consider scenarios whereby primary/secondary schooling is disrupted, i.e. all values of $\nu \in [0, 1]$ over two years. Later we discuss likely values for each country group.

2.5. 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.

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,[27] 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

[27] The OECD data are the broadest set of countries with the relevant information. The OECD data set includes five large developing economies. Patterns are similar for both OECD and non-OECD countries.

deviation from steady state GDP ($0.7143^{10} \approx 0.03$).[28] 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.

Of course, one could argue that a pandemic shock is not a typical employment shock as the removal of restrictions post-pandemic leads to employment recovery. However, employment quickly recovered after the initial shock only in some developed economies with significant fiscal capacity, and in these economies even now the long-run effects such as the impact of supply chain disruptions continue to be felt. The COVID-19 shock increasingly looks like a *typical* recession (OECD, 2022). For robustness, we will consider that the employment shock lasts five years or two years.

3. Quantitative Impact of Pandemic Shocks

3.1. Impact on Output

We first explore output dynamics when a pandemic has the *maximal* impact considered. 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 impact of human capital loss on GDP is gradual, as the lost experience continues to accumulate until the recovery is complete, and the lost schooling does not manifest itself until the students concerned enter the workforce.

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.[29]

Figure 4(b) displays what happens when there is a schooling shock but no experience shock. The impact of the schooling shock is delayed. It is also highly persistent. The impact of the schooling shock on the LIC is smaller, with maximum loss around 19 years out at 2.4 percent of steady state GDP. The maximum loss in the MIC is after 31 years (3.6 percent), while in the HIC the maximum loss is after 39 years (4.1 percent).[30]

[28] 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.

[29] 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.

[30] 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.

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. The schooling distribution and shock magnitude explain the greater delay in richer nations.

Figure 4(c) displays what happens when there is only an experience shock. In the HIC, after 21 years GDP remains 1.1 percent down, recovering slowly as the affected workers retire. In the MIC output remains down 0.37 percent after 18 years, again recovering slowly. In the LIC, output is still down 0.45 after 11 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 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 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 in the first place, and since the returns to experience are greater. These conclusions are, for the time being, drawn from striking countries with the *same* education and employment shocks.

3.2. Potential Impact on Welfare of the Most Severe Scenario

To compute the potential 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.[31]

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

[31]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 a utilitarian social welfare criterion (Harsanyi, 1955).

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

Web Appx. Section E discusses the choice of the discount factor (4 percent). Later, we will also discuss the results when using other discount rates (3 and 1.5 percent).

In the most severe scenario, welfare decreases in the LICs by 1.6 percent in perpetuity, 2.2 percent in the MIC and 2.6 percent in the HICs (see Figure 4(d)). This is equivalent to a one-time loss of 40 percent, 55 percent and 65 percent of GDP respectively. This adds up to about 61 percent of World GDP (or about $\$51$ trillion).

Interestingly, in year 10, once the employment shock is over, ongoing welfare losses as measured using Δ are even higher, amounting to 2.0 percent in the LIC, 3.0 percent in the MIC and 3.4 percent in the HICs. This is larger than the initial impact because the impact of the missing human capital accumulates gradually.

If the shock is to schooling only, then welfare decreases by 1.3 percent in the LICs, 1.9 percent in the MICs and 1.8 percent in the HICs (top-left corner in Fig. 5). In contrast, the experience shock reduces welfare by 0.3 percent in the LICs and the MICs, and 0.8 percent in the HICs (bottom-right corner). 19 percent of the impact on the LICs is from the experience shock, whereas it is 14 and 30 percent in the MICs and HICs respectively. The schooling shock is potentially more severe than the experience shock.

4. Potential Welfare Impact for Different Scenarios

So far we examined the welfare impact of the most severe pandemic scenario, to get a sense of how different factors would impact economies at different income levels through human capital losses. In this section, a range of other scenarios is considered.

4.1. Range of 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 initial 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 slightly closer in the HIC (Fig. 5(a)) than in the MIC (Fig. 5(b)), and much closer 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 wealthier countries than in poorer countries. The potential impact goes from 0 to 2.6 in HIC and 2.2 in the LIC vs. 1.6 in the LIC. Furthermore, the slopes differ. In the HIC the contour lines are steeper than in the MIC and LIC. We call this the "slope" effect. A steeper slope indicates that lost experience has a relatively greater impact on welfare relative to lost schooling.

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 $(75, 25)$. These (respectively) represent a shock that mainly impacts schooling, a shock that impacts both schooling and experience accumulation, and a point where the main disruption is to experience. The middle point B $(50, 50)$ has a welfare impact of $\Delta = 0.8$ in the LIC, compared to 1.1 in the MIC, and 1.3 in the HIC economy. As before, a symmetric shock causes a greater welfare loss in richer nations.

Point A $(25, 75)$, where schooling is mainly disrupted, has an impact of 1.0 in the LIC, 1.5 in the MIC and 1.6 in the HIC. In contrast, C $(75, 25)$, where the main disruption is to experience, leads to an impact of 0.5 in the LIC, 0.7 in the MIC and a much larger 1.0 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 and returns to experience being higher relative to returns to education in the HIC.

4.2. Parametrization for the COVID-19 Shock

We now use our framework to identify specifically for the case of COVID-19 which education and employment scenario is most appropriate for each income group.

4.2.1. Schooling and Employment Shocks

One possibility for estimating learning losses in schools would be to use estimates from the literature. Researchers attempted to measure these losses starting early in the pandemic, reflecting their policy importance - see for instance Hanushek and Woessmann (2020), who base their assessment on historical estimates of the link between the schooling stock and economic growth rates, as well as assumptions about the extent of schooling disruption. Meta-analyses such as Patrinos and Carter-Rau (2022) and Betthäuser et al. (2023) identify the most reliable studies that provide quantitative estimates of learning losses around the World. Patrinos and Carter-Rau (2022) examine 35 studies from 20 countries, finding learning losses of 0.17 standard deviations on average, which they find to be equivalent to about a third of a school year based on the correspondence between standard deviations and test scores. Betthäuser et al. (2023) examine 42 studies from 15 countries, finding learning losses of 0.14 standard deviations on average. However, for our purposes, these studies cannot be used to directly measure learning losses. One reason is that almost all the studies included in the meta-analyses focus on HICs. There are few MICs (4 in Betthäuser et al. (2023) and 4 in Patrinos and Carter-Rau (2022)) and no LICs, as the few studies available for those countries were excluded from the final analysis for not delivering a quantitative assessment of losses or for being deemed "low quality".[32]

That said, one finding that stands out from both studies is that learning losses in the MICs appear worse. Among studies in HIC, the median loss across the two meta-studies is about 0.14 standard deviations (so about a third of a school year based on Patrinos and Carter-Rau (2022), or about 17% over two years), compared to 0.29 for MICs (about 34% over two years). Thus, while the specific estimates in these studies are not suitable for measuring learning losses for our country groups, they do point to overall learning losses of around a third of a school year - the baseline scenario in Hanushek and Woessmann (2020)[33] - and to higher losses in MICs than HICs. Information for LICs is less clear because of the paucity of studies.[34] That said, UNESCO (2021) notes that the number of days of school closures was higher in MICs than in HICs and LICs, and also report that many LICs responded to school closures by extending the school year, suggesting that the schooling shock was likely most severe in the MICs.

Since we wish for a consistent approach to measuring schooling losses across country groups, we proceed as follows. Note that we find two-year education shocks of 21% for HICs and 33% for MICs. These estimates are strikingly similar to the ones derived from the meta-studies (17% and 34%, respectively). For LICs, we find 28%.

The size of the schooling shock amounts to an estimate of the value of the parameter

[32]Across the two meta-studies, only 6 MICs are included in total. They are all upper middle-income economies and one of them is Russia, considered a developed economy for most of the 2010s.

[33]The calibration in Agostinelli et al. (2022) has a loss in the productivity of human capital production of a half due to school shut-downs, but it is difficult to map this into our parameters of interest as there are also grade-specific factors of human capital accumulation.

[34]There exist some studies of lower middle-income economies such as Adeniran et al. (2022) (Nigeria), Angrist et al. (2022) (Botswana) and Singh et al. (2022) (Tamil Nadu), and a few studies of LICs such as Hassan et al. (2021) (Bangladesh) and Crawfurd et al. (2021) (Sierra Leone), and one might consider applying their estimates to LICs. However, these studies focus on the impact of remediation technologies. Since they were performed in areas where active remediation measures were adopted, their loss estimates are difficult to generalize, even if the findings concerning remediation technologies are valuable.

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 (see Figure 6 for a probability tree diagram of the various inputs considered). 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 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. When schools are closed but children have access to distance learning, they offset its ineffectiveness $(1-e)$ thanks to school remediation efforts by schools and/or parents. The share of lost knowledge that is regained is $r1$. When schools are closed but children do *not* have access to distance learning, they make up a share $r2$ of their learning loss thanks to school remediation efforts. Thus, $\nu = s \times (c \times (1-e) \times (1-r1) + (1-c) \times (1-r2))$. Absent remediation, $\nu = s \times (1-ce)$.

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.[35] 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. 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). Using these measures, we obtain for HICs the effective closure rates of 40% in year 1 and 50% in year (45% on average). MICs had higher effective closure rates of 63.5% and 37.5% (50.5% on average). India notoriously closed its schools for two years. The closure rate was also high in year 1 in LICs (53%). However, most schools had

[35]The last version of the data is from March 2022. Were we to update the results using information up to March 2022, we believe that results would be similar, as most schools had reopened by early 2022.

fully reopened the second year (closure rate of 18%; average of 35.5% over two years).

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 HICs and MICs), *take-home packages* (HICs, MICs), *television* (MICs, LICs), and *radio* (LICs) (Web 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 LICs and MICs than in HICs (Web 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).[36]

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).

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 the 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 range (take-home packages were used less often), $c \times e$ could be 75%.
2. In the LICs, given the low reach of online platforms, the radio and the television are used the most. Reach $\times$ effectiveness is about 22-23% for both. [37]
3. In the 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%

[36] 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."

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

for take-home packages. We could roughly assume $c \times e$ = 50% on average.[38]

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 the HICs and absent remediation, ν = 0.44 (1-0.42) = 0.26, or a loss of 26%. Likewise, McKinsey explains that pre-college students were two months behind by November 2020, suggesting a 29% loss. Were we to use the ministries' estimate, we would have 0.44 (1-0.75) = 0.11, hence a 11% loss only. Thus, we assume reach $\times$ effectiveness = 40% in year 1 and 50% in year 2, allowing for improvement over time.

For the 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 the LICs we have reach*effectiveness = 22-23% based on the ministries' data. Since we use 40-50% for HICs, 35% for MICs, and since the Ministries' estimate of 22-23% in LICs is possibly biased upwards, we assume 20% for LICs. While there could be better data for some countries, we believe that it is important in our framework to use data that is as global as possible, even if imperfect. However, to our knowledge, there does not exist (yet) for enough countries consistent data on these dimensions.

Remediation. We assume no school remediation effect because no such policies have been implemented beyond a few schools and/or families in a few countries. The NAEP long-term trend (LTT) assessments results for age 9 U.S. students that were released on 09-01-2022 indicate that for mathematics and reading the average score decreased to

[38] UNESCO (2020b) relies on survey data up to October 2020. Since our initial analysis of the data, UNESCO (2022b) has released information available up to October 2021. We thus verify for each income group that: (i) the ranking of the modalities is unchanged; and (ii) any change in the usage rate of one modality should be inconsequential. For example, fewer MICs and HICs now report relying on the radio, which does not affect our estimates since the radio was already for them a marginal technology in 2020.

levels last seen c. 2000.[39] Even for students at the 90th percentile scores decreased to their c. 2008 level, suggesting limited remediation. Likewise, for age 13 U.S. students, the very recent 2023 assessment suggests that for reading the average score decreased to levels last seen in 2004. For mathematics, one must go as back far as 1990.[40]

Therefore, the evidence suggests that remediation was on average limited in the U.S. If that is the case in one of the most developed and technologically advanced economies, school remediation is even less likely in developing economies. If $r1 \approx r2 \approx 0$ in the three income groups, then ν simplifies to $\nu \approx s \times (1 - ce)$. Nonetheless, in Section 4.3. below we discuss how altering values of $r1$ and $r2$ could change the results.[41]

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

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).

Note that this assumes that workers do not work more hours post-pandemic than pre-pandemic, thus potentially "catching up" on the experience lost.

4.2.2. Baseline Results

The welfare impact equals 1.01 percent of steady state income in perpetuity in the HICs, compared to 0.91 percent in the MICs and 0.56 percent in the LICs (see the black dot in Figures 5(a)-5(c); results summarized in row A of Table 4). This is equivalent to a one-off hit of 25, 23 and 14 percent of income respectively.[42] However, recall that the

[39] See URL: https://www.nationsreportcard.gov/highlights/ltt/2022/ (last accessed 09-11-2022).

[40] See URL: https://www.nationsreportcard.gov/highlights/ltt/2023/ (last accessed 11-04-2023).

[41] UNESCO (2022a) shows that 39% of countries increased instructional time in 2021-22, which tapered to 34% in 2022-23. UNESCO (2022a) only reports data on the extensive margin, not the intensive margin, i.e., the number of extra hours of instructional time per year and how efficient these hours are. The report also explains that there are high rates of teacher resignations globally, reducing school quality and limiting remediation. In contrast, Werner and Woessmann (2023) finds that German parents increased their efforts to assist students with school from about half an hour a day to over an hour, for Spring 2020 and Fall 2021. However, it is difficult to use this information without information on how effective that time is.

[42] This amounts to 24 percent of global GDP ($\approx \$20$ trillion) given the high contribution of HICs (68%).

damage to output from the missing human capital increases gradually over time as impacted students enter the workforce and as experience continues to be lost during the recovery. 10 years after the shock begins, ongoing forward-looking welfare losses equal 1.1 percent in the HICs, compared to 1.1 percent in the MICs and 0.6 percent in the LICs. LICs are the *least* impacted group in both absolute and relative terms. However, given the vulnerabilities in LICs, such an impact could have far reaching effects.

The impact through schooling is highest for the MICs. The impact from the schooling shock equals 0.66 percent of steady state income in perpetuity in the MICs, compared to 0.40 percent in the HICs and 0.37 percent in the LICs (Figures 5(a)-5(c) and row A1 of Table 4). Indeed, the disruption to schooling is more severe in the MICs (33%) than the HICs (21%), even though the quantity of schooling is higher in the HICs.

Lost experience has a bigger impact for the HICs. The impact from the experience shock equals 0.61 percent of steady state income in perpetuity in the HICs, compared to 0.24 percent in the MICs and 0.20 percent in the LICs (Figures 5(a)-5(c) and row A2 of Table 4). Indeed, employment losses are relatively similar across countries but the HICs have much higher returns to experience.

Finally, in addition to the magnitudes, it is interesting to observe that the contribution of schooling and experience to these losses also varies by level of development. Experience accounts for 60 percent of the losses in the HIC (row A3), due to the higher returns to experience. In contrast, experience accounts for 26 percent of the losses in the MIC, as the returns to experience are lower. In addition, experience accounts for 36 percent of the losses in the LIC, since both returns to schooling and experience are low. Globally, experience accounts for exactly half of the losses.

4.3. Robustness Checks

Overall, the global economic impact of COVID-19 is mainly felt by the HICs, due to their higher initial stock of education and also their higher returns to experience. The MICs are also strongly impacted due to their relatively large education shock. Overall, the shock to experience is significant across the three income groups. We now discuss how sensitive these results are to changing some of the assumptions of the model.

a. Remediation. We assume, based on U.S. evidence, that the lost human capital was not made up for later, hence that early and late human capital investments are essentially complements. Of course, any hypothesis 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, as well as an indication of how much expenditure on remediation would "pay for itself".

In particular, we can use Figures 5(a)-5(c) to see how the welfare impact decreases as we raise the remediation rates $r1$ – for families with access to the alternative education technology – and $r2$ –for families without such access. If we assume that technological access is a broader proxy for the availability of parental remediation inputs and that remediation is four times more difficult for families without the technology than for families with it ($r2 = r1/4$), then a 50% remediation rate for families with the technology ($r1$=0.5) implies an education shock of 13% (21% before). Based on Fig. 5(a), the welfare impact in HICs decreases from 1.0 percent to 0.8 percent of steady state income in perpetuity. Thus, remediation would have to be considerable to alter the results.

Still, it is worth exploring to what extent the literature suggests lost human capital might be recovered later without explicit policy intervention. First, is there evidence that disruptions to human capital accumulation are compensated for later (or not)? Second, if not, does this have a long term impact on earnings?

There is evidence that schooling disruptions are *not* in general made up for later (see Hanushek and Woessmann (2020, Annex A) for a survey of the literature). Andrabi et al. (2021) find that children displaced by the 2005 Pakistan earthquake performed worse on tests years later: factors other than just schooling could be at work, but important relief programs were put in place to mitigate such factors. Marcotte and Hemelt (2008) find that students perform worse in standardized tests due to weather-related school closures. Deming and Dynarski (2008) find that students who enroll in school later for one reason or another spend fewer years in school than their peers of equal age. Kuhfeld (2019) finds that learning discontinuities due to summer break are associated with learning losses. Meyers and Thomasson (2020) find that students whose education was disrupted by the 1916 polio pandemic obtained less schooling than prior cohorts.

The literature also indicates that disruptions to schooling have a significant long-term impact on earnings. Deming and Dynarski (2008) find that students who enroll in school late accumulate less schooling and have lower lifetime income. Ichino and Winter-Ebmer (2004) study outcomes among students who missed school in post-war Germany and Austria, showing that their income remains measurably reduced after 40 years. Chetty et al. (2016) find that assigning disadvantaged students to better schools has a measurable impact on future income. But the analogy between school quality and time spent in school, in this case months or years away from school, may be imperfect. Likewise, Schoellman (2016) finds that adult outcomes of refugees are independent of age at arrival to the United States up to age six. In other words, initial human capital losses from being born in developing economies are later recovered. However, age six is precisely when children start going to primary school. After age six, early and late schooling and other human capital investments are more likely to be complements.[43]

As for COVID-19, either students would need to spend more time in school, spend extra time with tutors to catch up, or the production of educational services would have to become more efficient and intensive. During the crisis and recovery phases of the pandemic, such remedial education was unlikely as most countries saw their fiscal capacity eroded by the pandemic. There was no sign of widespread remedial schooling policies, and private remediation is heavily dependent on wealth. 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 between parental and formal instruction, are key to mitigating schooling losses, finding that parental wealth and education are essential for any such substitution to occur.[44] The point is that any attempt at remediation depends on the ability – and willingness – of parents to step in. Indeed, Fuchs-Schündeln et al. (2020) emphasize *dynamic complementarities*, whereby learning is more effective if there has been greater prior learning, so that COVID-19 may in fact lead the typical household to find it optimal to invest in *less* education rather than more. Their study is also for the United States: if remedial action is difficult in developed economies, then in developing economies it should be even more limited.

In fact, there are reasons why the disruption to schooling could 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 there has been some degree of drop-out (see below). Second, to the extent that knowledge is cumulative, having missed certain topics or not learned them properly hampers progress in future years. For example, Card and Krueger (1992) find that men who are in better schools tend to have a higher

[43]The last two studies consider shocks to individuals rather than shocks to whole communities.
[44]We already factor this in as our estimates are based on assessments of schooling loss over the period.

return to subsequent schooling – a scenario more severe than that contemplated in our framework where there are no compounding effects of disruption. As an example, Hernandez (2011) finds that students who do not read properly by the end of the 3^{rd} grade struggle with subsequent learning. Thus, we think our study provides a useful benchmark that is not too far from reality even if there is recovery among some students.

So far this discussion has focused on schooling disruptions. However, a substantial part of the human capital lost over the pandemic is experience. Clearly, a year of lost experience can only be "made up for" later by future experience, which is precisely the mechanism in this paper that leads to a slow recovery from the employment shock. We assume that experience human capital does not decay during periods of unemployment: this is a conservative assumption, see for example Ljungqvist and Sargent (1998) where the depreciation of experience is a key factor driving aggregate labor market outcomes. In fact, Casey (2020) notes the likelihood that the structure of the economy after COVID-19 might be different from before, which would imply some depreciation of experience to the extent that people are rehired into new occupations. As such, the "Great Reset" may lead to a decrease in the aggregate stock of experience. Having said that, the better matches allowed by the "Reset" could lead, at least for some individuals, to faster experience human capital accumulation in the future. However, "Resets" likely only occurred in developed economies with significant unemployment benefits, hence less than 15% of the world's population. We also do not have data on what the "Reset" may entail in the longer run. We thus abstract from this question.[45]

b. Pre-College Dropouts. Another factor we abstracted from that might increase the long-run impact of the COVID pandemic in developing countries is the possibility of students dropping out of school altogether. However, we suspect that this would not be a quantitatively important factor. To see this, note that data from UNESCO (2020a) suggest that in LICs (MICs) 0.7% (0.3%) of primary students and 1.8% (1.4%) of secondary students were "at risk" of dropping out due to the pandemic (see Web Appx. Table A.5 for the full details). Suppose 2% of students drop out of school due to the pandemic and, to be conservative, assume that they drop out randomly. Average

[45] One way in which experience could be rebuilt could be through retraining. Whether retraining programs exist or are effective varies significantly from place to place: for example, Heinrich et al. (2008) find that the Workforce Investment Act which reinforced retraining programs in the US had little or no impact on the incomes of participants. Therefore, while there may be effective retraining programs in some places, the presence of such a program is no guarantee that human capital can be rebuilt.

schooling in the LICs (MICs) is 6 (8) years, so random dropouts imply an additional $6 \times 0.02 = 12\%$ $(8 \times 0.02 = 16\%)$ of schooling lost, or 6% (8%) if we spread it over the 2 years of the pandemic. For LICs, this moves the magnitude of the schooling shock from 0.28 to 0.34. Figure 5(c) shows that this would increase the welfare cost of the COVID pandemic in the LIC from 0.56 to about 0.65 percent, still below the 1.0 percent in the HICs and the 0.9 percent in the MIC. For MICs, the schooling shock would increase from 0.33 to 0.41 and the welfare cost would increase from 0.9 to 1.0 percent (Figure 5(b)).

Likewise, the data from UNESCO (Web Appx. Table A.5) suggest that dropouts are likely to be similar between males and females across the three income groups.

Given that the number of at-risk students exceeds the number of likely dropouts, and that at-risk students were likely not random but rather among a pool of students most likely to leave schooling relatively early, the impact of dropouts is likely smaller than implied by these calculations. This suggests that including drop-outs in our model would increase the complexity of our framework without affecting the results.

c. College Shock. We assumed as a benchmark that the schooling shock does not affect college education. In row B of Table 4, we assume that the effectiveness of college decreases by one third of the decrease of other forms of education. Hence, with a pre-college education shock of 21% for LICs, 33% for MICs, and 28% for HICs (Table 2), the college education shock is 7%, 11% and 9%, respectively. This essentially assumes that college is somewhat (but less) disrupted than other forms of education.

In row C, we instead assume that 10% of the high school students who would have gone to college do not go to college and instead join the workforce. For example, if, say, 20% of high school graduates normally go to college and this share decreases by 10% in the first two years after COVID, only 18% do in year 1 and year 2.

Results are essentially the same. If anything, these scenarios slightly increase the overall welfare loss, especially for HICs relative to MICs and MICs relative to LICs.

One could argue that the disruption to college might be lower in the HIC than in other countries due to better communications infrastructure, allowing the delivery of more effective college education while universities are closed. In Table 5 panel A, we explore alternative scenarios where the effectiveness of college in the HIC and the MIC+LIC declines by $1/3$, $2/3$ or $3/3$ (i.e., 100%) of the general decline in education separately. Considering $1/3$ in the HIC and $3/3$ in the LIC+MIC, the loss disproportionately increases in the LIC+MIC. However, the results are similar to the baseline results with $0/3$ for each group. Conversely, if we assume that universities in developing economies remained mostly open during COVID ($1/3$) but that universities in developed economies failed to adjust to COVID conditions ($3/3$), then the loss disproportionately increases in the HIC. Yet, the results are similar to before.

Similarly, in panel B, we allow college enrollment rates to decline by 10%, 20% or 30%. As can be seen, the combinations of different scenarios nonetheless yield broadly similar results. That is true whether we consider the case where, due to increased poverty, enrolment decreases the most in the LIC+MIC ($3/3$ vs. $1/3$ for the HIC), or the case where enrolment decreases the most in the HIC ($3/3$ vs. $1/3$ for the LIC+MIC) as labor shortages raise wages, hence the opportunity cost of college education.

d. Employment Recovery. As a benchmark, we have assumed that the employment recovery is complete after 10 years. We verify that the resulting employment patterns are consistent with what can be observed in the data. Total working hours lost due to the COVID-19 crisis (including unemployment, inactivity and reduced hours) in 2020 were 6.7% in the LIC, 9.5% in the MIC, and 8.3% in the HIC. In the ILO (2023) data for the year 2023, we get similar values to our constructed shock after three years: 2.1% vs. 1.7% for the LIC, 1.6% vs. 2.4% for the MIC, and 1.6% vs. 2.1% for the HIC.

We explore other possibilities in Table 4. We assume that the recovery is complete within 5 years (row D). We also contemplate a scenario where the recovery is complete within 2 years (row E). Naturally the welfare impact in such scenarios is smaller, but it is still significant (the impact decreases by one-fourth of a percentage point with just 2 years). The only difference is that whereas in the benchmark we find that the impact on the HIC is a little larger than on the MIC, in these cases the impact on the MIC is slightly larger, because the employment shock was larger to begin with. In both cases, the impact on the LIC is around 60% of the impact in the MIC and HIC. Indeed, with the experience shock being smaller, a larger share of the shock comes from the education shock, which was larger in MICs than in HICs. As a result, the loss decreases more in HICs than in MICs, to the point that the impact is now higher in MICs.[46]

[46] If anything, we may slightly over-estimate the speed of employment recovery in the LIC and slightly under-estimate the speed of employment recovery in the MIC and the HIC. That should reinforce our main result that more developed nations are more impacted by the shock. Likewise, using 10 years for the LIC and 5 years for the MIC and the HIC, we still find much higher effects in more developed nations.

e. Youth Unemployment. Returns to experience are higher among younger workers (Figure 1). This could be important since employment was more severely disrupted by COVID-19 among younger workers (Section 4.2.1.). We repeat the simulation distinguishing between returns to experience in the 0-5 bin and the 10-25 bin. The returns and quantitative findings are similar (Web Appx. Tables A.6 and A.7).

f. Child Labor. We assume that agents start accumulating experience from age 18 at the earliest. Thus, even if agents were to work before 18, the associated experience is irrelevant later on. We thus repeat the quantitative exercise assuming experience is accumulated from age 15, 13 or even 6. The returns are similar (Web Appx. Table A.6) and, as a result, so are the quantitative findings (Web Appx. Table A.7).

Indeed, pandemics may increase child labor. However, in Web Appx. Section G we discuss how substitution effects due to worsening labor market conditions might compensate for income effects leading to reduced school enrollment, thus precluding any effects of COVID-19 on child labor. Note that the ILO and UNICEF (2021) also argue that child labor may have not increased overall as a result of the COVID-19 pandemic.

In addition, even if child labor increases 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 the HICs, MICs and LICs, respectively. Children who work few hours and for low wages (Jedwab et al., 2021). 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.

g. Human Capital Spillovers. Our baseline scenario assumes that the human capital of individual workers does not create spillovers for other workers. Still, there is a literature that argues that spillovers from human capital might be a factor of aggregate productivity (Bils and Klenow, 2000). Rows F-G of Table 4 examine the possibility that, if an agent has human capital h_t, then the contribution to aggregate income is $h_t(1+\beta)$ for $\beta > 0$%. Bils and Klenow (2000) and Jedwab et al. (2022) estimate a spillover parameter β of 0.77 and 0.89, respectively. In both cases, the welfare impact is larger, although not significantly so. Furthermore, since more human capital is lost in the HIC than the MIC and LIC, the increased loss mainly impacts the HIC when there are spillovers.

h. 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 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 of different income levels.

i. Cohort Effects. One cannot include schooling, experience, age, time fixed effects and cohort fixed effects in the same estimation (Heckman and Robb, 1985). Since we cannot include year of birth fixed effects, we instead 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 implemented by Jedwab et al. (2022).[47]

More precisely, we include *decadal* cohort fixed effects (FE) or cohort FE based on important *historical events* specific to each country. 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

[47] However, this approach does not fully solve the experience-time-cohort problem since there may still be yearly cohort effects. Our returns to experience and results should be taken with this in mind.

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.[48] The cohort FE are then tailored to the country's history. The returns and the quantitative findings are similar (see Web Appx. Tables A.6-A.7).

j. Measurement and Selection. We exclude self-employed individuals, as there could be issues with how self-employed individuals calculate and self-report the amount of salary taken from the business. 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 are 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. The returns are similar (Web Appx. Table A.6) and, as a result, so are the quantitative findings (Web Appx. Table A.7).[49]

Note that the returns to education are not causal. They are nonetheless consistent with causal studies (see Jedwab et al. (2020a) for a discussion). Furthermore, if returns are over-estimated because better able individuals study longer, the causal returns would mean a lower relative contribution of the education shock to the overall shock than what we obtain, reinforcing our result that experience significantly matters.[50]

k. Impact in HICs vs. LICs. We find that lost learning over the pandemic has a larger impact on HICs than LICs. This finding considers differences in rates of return to human

[48]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). Wikipedia-BBC includes events that might not be important for workers. However, it is better if we follow their selection rather than picking the events ourselves.

[49]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 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.

[50]Web Appx. Table A.6 shows that the estimated returns to education decrease but remain high if we add industry fixed effects and also control for the relationship to the household head, marital status, urban residence and self-employment. As explained below for the gender analysis, we cannot include too many possibly *endogenous* controls. That is for example why we do not add occupation fixed effects.

capital across countries, as well as differences in the extent of disruption. However, one might ask whether small variations in the assumptions might overturn this finding.

For example, this finding could be sensitive to an overestimation in the schooling losses in HICs. Note that the reach-effectiveness combination of learning methods adopted during the pandemic in HICs is far higher than in LICs, due to the low reach and relative ineffectiveness of the available remote learning forms in LICs (radio and television) compared to HICs (virtual instruction). As a result, our assumptions on the effectiveness of remote learning (based on surveys) bias our results *against* this key finding. Recall that in a *symmetric* scenario HICs suffer more than LICs: this result is robust even to significant *asymmetry* in the disruption to education in favor of HICs.

An alternative would be to have *underestimated* the losses in the LICs. If we assume a total learning loss in the LICs among non-presential students, this raises the schooling shock to 35 percent (28 percent before), which increases the losses to about 0.65 percent per year (Fig. 5(c)). This is still well below the 1.0 percent figure for the HIC.

There is another question about how much this finding might be sensitive to the ability of parents, schools or other institutions to remedy ex-post for lost schooling. Fuchs-Schündeln et al. (2020) find that, even in the U.S., remediation measures during the pandemic are concentrated among wealthier households, suggesting this is unlikely to have much impact on *overall* differences in human capital lost. However, this also suggests remediation is more likely in the wealthier HIC than the LIC, suggesting that it is worth asking how much remediation in the HIC might close the gap with the LIC. Regarding remediation during the pandemic, however, it is important to note that we already assume that remote schooling technologies are better in the HIC.

Alternatively, even if remediation efforts were to *entirely erase* the impact of the pandemic on lost schooling (education loss = 0%), the impact of COVID in the HIC would be about 0.62 percent (Fig. 5(a)), still higher than in the LIC (0.56 percent; Fig. 5(c)). In other words, any reversal of this key finding would require us to significantly overestimate lost *experience* in the HIC. Hence, one would need remediation rates of 100% including for poorer families *without* technological access.[51]

Next, the education loss could raises returns to education because of the lower relative supply of skilled workers. Since the education shock is larger in LICs than in

[51] Section 4.2.1. suggests remediation rates of 2% for families *with* technological access.

HICs (28% vs 21%), this should if anything mitigate the overall losses more in LICs than in HICs, reinforcing our main takeaways that: (i) the experience shock significantly matters as well as the education shock; and (ii) HICs are more impacted than LICs.

The lost experience has then two components: the employment shock and the returns to experience. Regarding the former, we find a larger employment shock in the HIC than in the LIC (8.3% vs. 6.7%). However, if the size of the employment shock were lowered to equal that in the LIC, Figure 5(a) shows a decline in the impact in the HIC from 1.0 to 0.6 percent, still higher than in the LIC (0.56 percent).

Regarding returns to experience, differences in the returns across groups are robust to a number of estimation specifications, so we are confident in the existence of a gap in the returns to lost experience. Note from Fig. 5(a) that the employment/experience disruption would have to be more than one third the size of that in the LIC for the overall impact to be equal in both economies (or, alternatively, we would have to overestimate the return to experience in the HIC by at least triple the correct numbers).

There is a further question about how much this finding is sensitive to how much agents might be able to increase their hours later on to try to remedy for lost experience. This is unlikely for several reasons. First, short- and medium-term variation in working hours is small (Bick et al., 2022). Thus, remediation would likely require a post-pandemic increase in employment along the extensive margin above pre-pandemic trends. Second, there is no such increase in employment relative to trend in the US.

l. Discount Rates. The choice of discount rate could matter for two reasons. First the related literature tends to use a lower discount rate of 3 percent (e.g., Hanushek and Woessmann, 2011). In Table 4 row H, we repeat our experiments assuming such a discount rate. The impact of human capital losses is much greater. However, the loss is still higher in the HIC than in the MIC, and in the MIC relative to the LIC.

Second, since according to macroeconomic theory the discount rate is the rate of time preference minus the rate of economic growth (e.g., King et al., 1988; Hanushek and Woessmann, 2011), the possibility of convergence dynamics might suggest that the appropriate discount rate is smaller for developing economies. Row I reports results assuming the discount rate equals 1.5. In this case, the welfare impact in the HIC and MIC are comparable (but still much higher than in the LIC).[52] However, our welfare

[52] As can be seen when comparing rows H and I, the welfare impact in the HIC and the MIC remains higher than the impact in the LIC when considering 3% for the former and 1.5% for the latter.

measure is such that the rate of time preference is all that matters, not the rate of economic growth. The reason is that, with $\log$ utility, the growth trend is netted out so that all that matters are changes in the detrended consumption stream. This will be so even if the trend growth rate varies across groups (see Web Appx. Section E for details).

5. Application to Gender

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

5.1. Estimating the Returns by Gender

As described in Section 2.2., for each country at a time we estimate eq. (3) for female workers and male workers *separately*, and use the estimated coefficients to construct wage-experience profiles for developing (G) and developed (D) countries.

As shown in Fig. 1, in HICs, 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 the other countries, the profiles are flatter and corresponding differentials are 50% and 40-50% respectively. While women fare better in HICs (70% vs. 40-50% in MICs and LICs), the absolute gap is bigger in HICs (30 vs. 0-10 in MICs and LICs). In economies where experience is more valuable, factors causing differences across gender are more consequential in absolute terms. Thus, even if there is less gender discrimination in HICs, 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 8.2% and 9.4%, respectively. While women show lower returns to experience, they have higher returns to education. While there are some contexts where women have lower returns in both dimensions, there are indeed many 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 corroborated by Fig. 7 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. In most countries, a negative gap for experience is compensated by a positive gap for education.[53]

[53] Trostel et al. (2002) and Dougherty (2005) also find higher returns to education for women in selected economies, and Psacharopoulos and Patrinos (2018b) find similar patterns when reviewing the literature.

Likewise, Figure 8 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.[54] Figure 9 then displays the same relationship for the returns to education. The gap in the returns to education is overall lower in richer nations.

The aggregate returns for each income group are reported in Panel A of Table 3. Across the three groups we find consistently higher returns to education for females than for males (the male - female difference ranges from -1.1 to -1.7 percentage points per year of education). This is especially true in the HICs (-1.7), then the LICs (-1.4), then the MICs (-1.1). Also, we find systematically higher returns to experience for males than for females, especially in richer nations (1.1 in the HICs per year of experience vs. 0.4 for the MICs and 0.1 for the LICs).

Finally, we 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. Across most subcategories, the returns to education remain higher for women than for men, and the returns to experience remain higher for men than for women.

5.2. Robustness Checks for the Analysis by Gender

Before discussing the calibration, we provide some important robustness checks regarding our estimates of the overall returns to experience by gender.

The gender-specific 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.

Table 6 shows that gender differences in the returns to education (see col. (3) of Panel A) are mostly preserved if we include *decadal* cohort FE (row 2) or cohort FE based on important *historical events* specific to each country (row 3). Since we run separate regressions for female and male workers, the cohort FE are gender-specific, which is important to control for selection issues that could arise from social change. Focusing

[54] There are plausible reasons why men have higher returns to experience than women. It could be that women have jobs that generate less human capital 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, thus allowing for the characteristics underlying the gaps to matter (via the returns).

on work experience (Panel B), the returns for men are now even higher compared to the returns for women in the MICs and the LICs, which should also diminish the influence of the large employment shock for women. See Web Appx. Section I for details.

Differences in the returns to experience (Panel B) are preserved if we include 10 industry FE (row 4 of col. (3)), 10 occupation FE (row 5), or both types of FE at the same time (row 6).[55] For the returns to education (Panel A), the occupation FE disproportionately reduce the returns for women in the HICs and the MICs (rows 5-6), which might indicate selection of more educated women into better occupations. However, the ability to enter better (i.e., higher-return) occupations is part of the returns to education, so the occupation FE may lead to over-controlling. In addition, overall patterns in the returns remain, and our simulation results should be largely unaffected.

A related concern is whether there are differences in self-employment across genders. In the I2D2 data, we find that women are globally less self-employed: The self-employment rate is 36, 18 and 6% for women in the 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. However, the returns are similar when excluding the self-employed (see rows 7 of col. (3)).

Since women are more likely to be selected in contexts where they work less, row 8 of col. (3) 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 in the sample (54%).[56] Alternatively, we drop samples where the non-employment rate is much higher for women than for men, in particular samples with rates above the median (22%) in the sample (row 9).

Finally, we also 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 (rows 10-11 of col. (3)). 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.[57]

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

[56] 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.

[57] 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.

Lastly, the returns in terms of monthly wages are driven by hourly wages (not shown). Of course, all the estimated returns should be taken with caution, especially given how difficult it is to reliably estimate returns to education and experience for female workers.

5.3. 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.

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.

5.4. 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 HICs, MICs and LICs, 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.

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 H 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 experience 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 observed by looking at changes over time in *relative* income, and by decomposing it based on the two 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 10. The relative log-income of women does not deviate much from that of men over the entire period of the shock (the patterns for *Overall* differ little from 0). In the HICs and the MICs, relative income *rises* by about 0.25 percent, slowly returning to zero after 50 years, whereas in the LICs there is close to no change.

If we apply only the schooling shock we see that the changes are even smaller, indicating that it is the experience shock that is responsible for any differences. That female relative income actually increases slightly indicates that the larger experience loss of women is offset by the fact that the returns to experience for men are higher.

In addition, even though there are differences in the returns to schooling across gender, as well as differences in the quantity of schooling, these differences appear too small to have any significant impact on relative losses. Indeed, the returns to education for women are within 1.7 percentage points of the returns for men, so that a given period of disrupted schooling is similar as a share of the human capital stocks by gender.

In any case, there is close to no asymmetric impact by gender through the channel of human capital accumulation. In contrast, Figure 11 repeats the experiment in Figure 10, except that it allows for employment (not just experience) to decline during the pandemic. As such, it combines both the impact of human capital differences after the experience and schooling losses and the *direct* employment shock. Here we see that the relative income of men and women *do* now diverge by several percentage points, with female relative income declining. However, the divergence is almost entirely driven by the fact that women experience a more severe employment shock. Differences in human capital play little role in the divergent experiences of men and women.[58]

To sum up, while the more severe employment shock for women will lead to an increase in the number of single-income households with employed men, which would lead to changes in intra-household bargaining dynamics, on average we find that income differences are relatively small and do not persist beyond the pandemic itself.

6. 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. Despite the lower losses relative to HICs and MICs, LICs are still heavily and durably impacted by the pandemic shock given preexisting vulnerabilities. Richer nations are *less* likely to be insulated from pandemic 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. Even decades later, the world economy will still continue to suffer significant losses due to lost experience in richer nations. This emphasizes the role of experience in the global learning losses due to COVID-19.

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. This turns out to be because differences across genders in returns to human capital are too small to make much difference in transition dynamics.

[58] With the *schooling shock* only, there is almost no change in relative income. This again indicates that almost all of the differential impact of the pandemic shock is due to the employment/experience shock.

Our analysis has several policy implications. First, the huge losses that we estimated highlighted the urgency of fully reopening schools in all countries. Alternatively, governments and schools need to be prepared for future pandemics. Second, our results show the importance of bridging the digital divide between and within countries. Third, recovery from the pandemic may require investments in remedial education. Fourth, payment protection programs may be 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 future infections.[59] Alternatively, retraining programs may be useful.

Our analysis also has limitations. We do not model the impact of pandemics on human capital through deteriorating (physical and/or mental) health of survivors.[60]

We also do not model the impact of pandemics on mortality. However, in the case of COVID-19, mortality among working-age individuals, although non-zero, was low,[61] 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.[62]

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.[63]

Finally, we only consider first-order effects, for example ignoring the effects of the pandemic on adolescent pregnancy or fertility more generally, as well as the impact of female education on female labor force participation or child outcomes.[64] We also assume a closed economy framework in that there are no economic or human capital spillovers from the HICs to MICs and LICs. To the extent that LICs and MICs rely on demand from HICs for exports, the economic damage to HICs could spill over to less

[59] If we know the impact of payment protection programs on infection rates and school closures, one can use our model to balance the human capital gains and losses in terms of education and experience.

[60] There is now clear evidence that some COVID-19 patients may have long-term health effects. See, for example, https://www.nature.com/articles/d41586-021-01693-6, last checked 10/25/2021.

[61] 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.

[62] 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).

[63] 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.

[64] Evidence on adolescent pregnancy and fertility is mixed (e.g., Aassve et al., 2020, 2021; Marquez-Padilla and Saavedra, 2022; Alon et al., 2022). While dropping out of school might lead to pregnancy among adolescent girls, school closures and lockdowns also reduced (sexual) contacts between students.

developed economies. Conversely, restrictions in LICs and MICs can also impact HICs due to supply-side chain issues. The resulting higher global prices and goods shortages lower the value of savings, limiting possibilities for consumption smoothing that might alleviate some of the welfare losses from the employment and education shocks. Lastly, we ignore the indirect effects of human capital on social cohesion. Integrating all of this in our framework could be a challenging but valuable endeavor.

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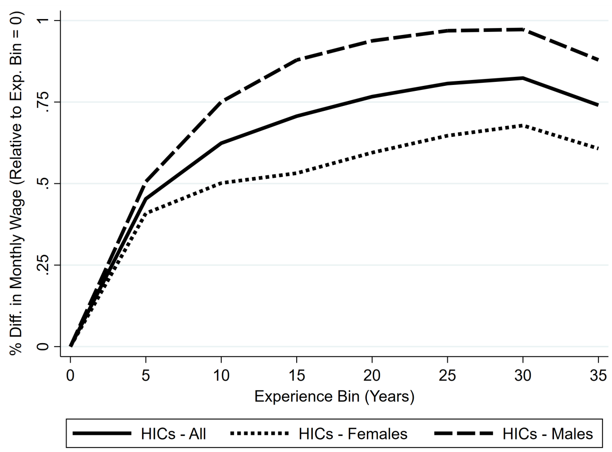
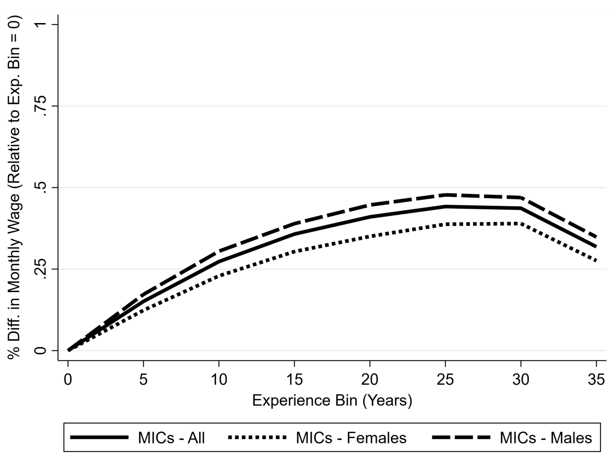
Figure 1: Wage-Experience Profiles by Development Status and Gender

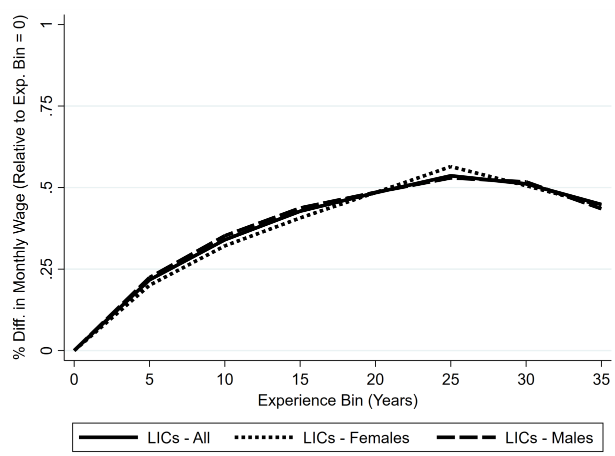
(a) High-Income Economies (HICs) Only



(b) Middle-Income Economies (MICs) Only

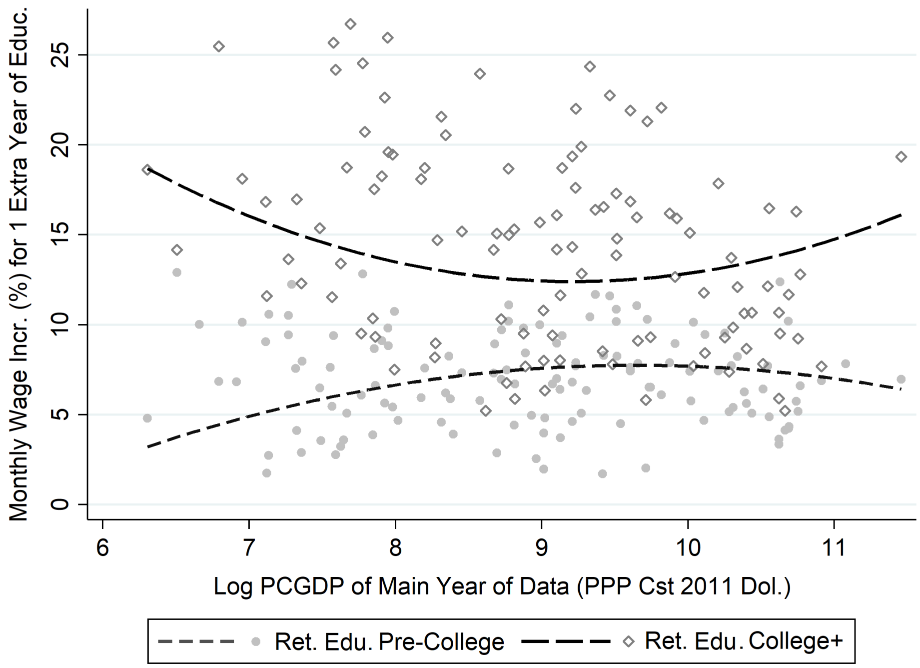


(c) Low-Income Economies (LICs) Only



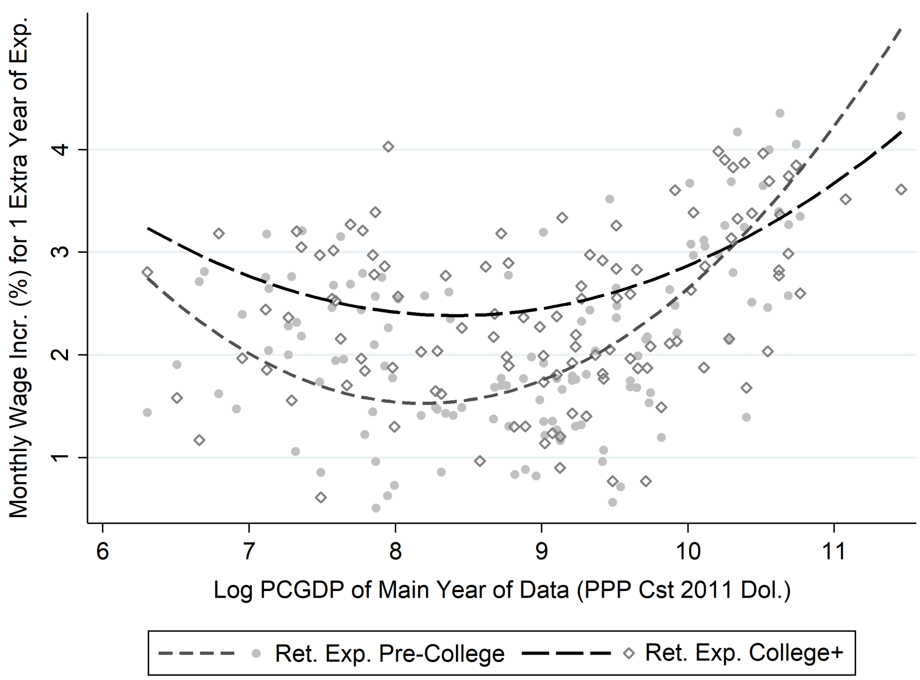
Notes: This figure shows the average wage differential for the seven experience bins for all, male and female workers in low-income economies, middle-income economies, and high-income economies (using pop. ca. 2018 as weights). The 0 bin is the omitted group. Samples from 1990 to 2016 are used.

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



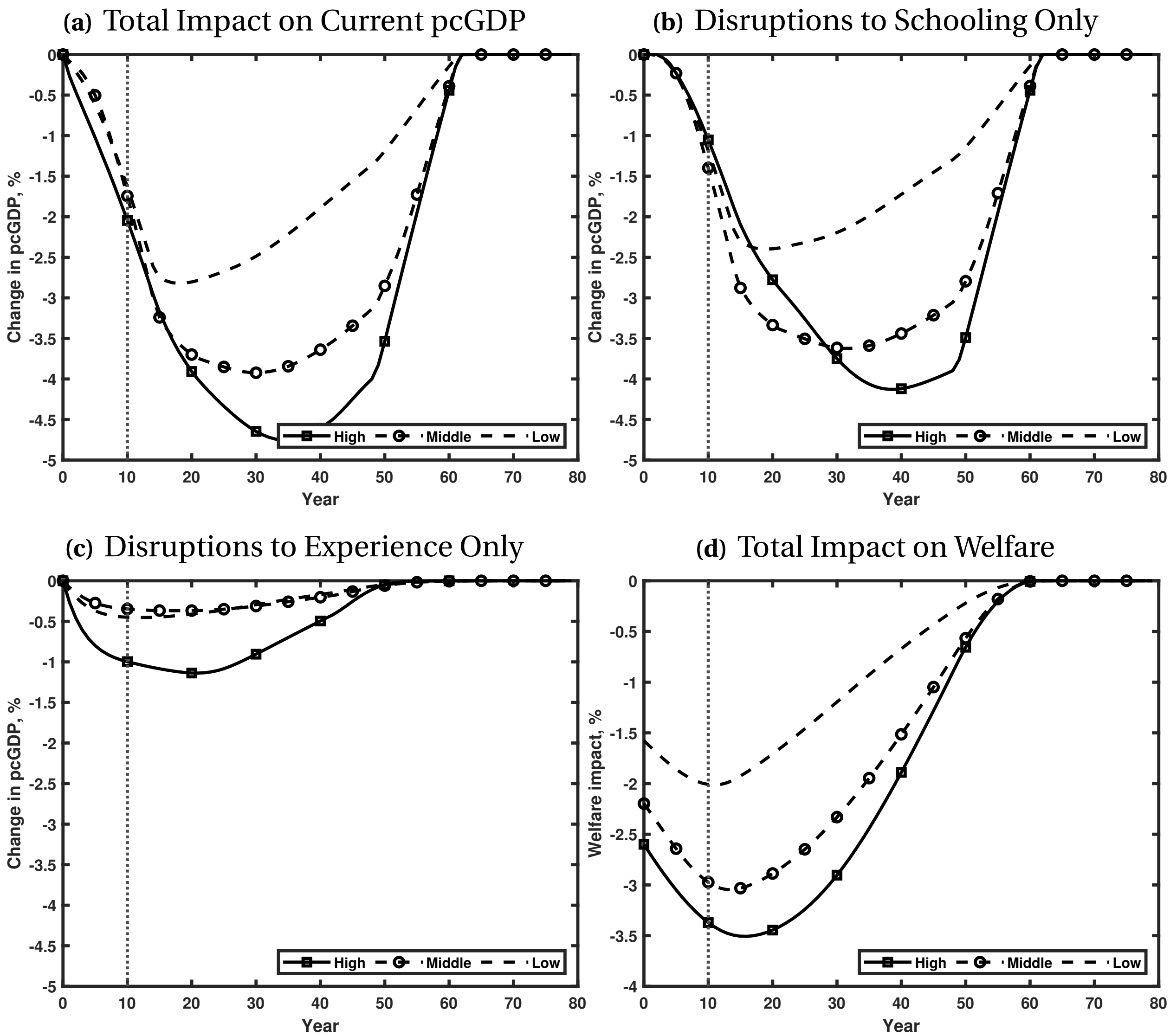
Notes: This figure shows the correlation between the estimated returns to education for pre-college vs. college+ workers (estimated using data for the period 1990-2016 depending on the country) and log per capita GDP (PPP; cst 2011 USD; for the mean year in the data for each country) (using pop. c. 2018 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



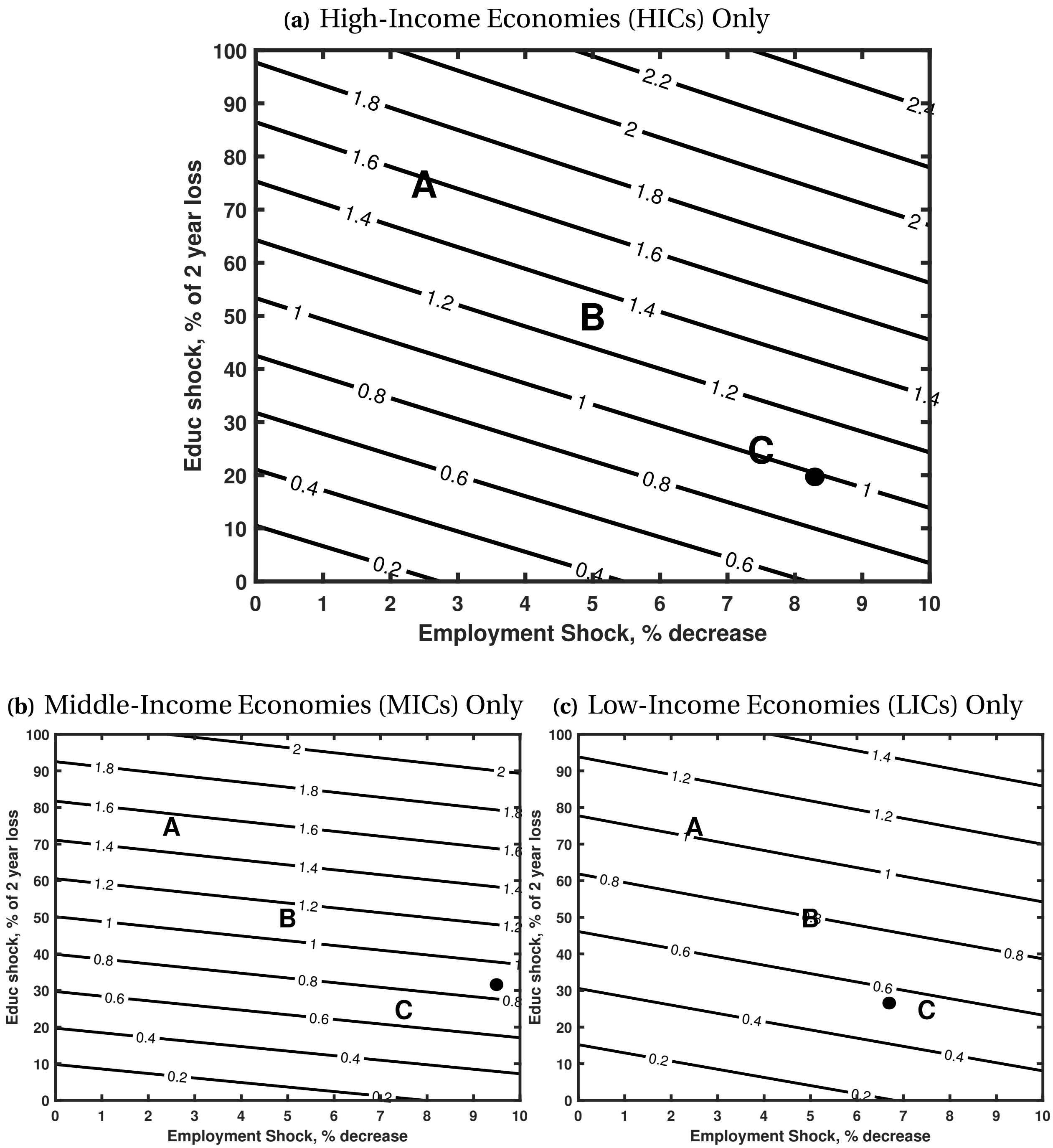
Notes: Figure 4(a): The pandemic shock is assumed to disrupt both schooling and experience. Figure 4(b): The pandemic shock is assumed to disrupt only schooling. Figure 4(c): The pandemic shock is assumed to disrupt only experience. Figure 4(d): The welfare measure is the percent of GDP that would have 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 experience. Note that we never include the direct effects of the employment shock, thus focusing on human capital accumulation effects.

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

(a) High-Income Economies (HICs) Only

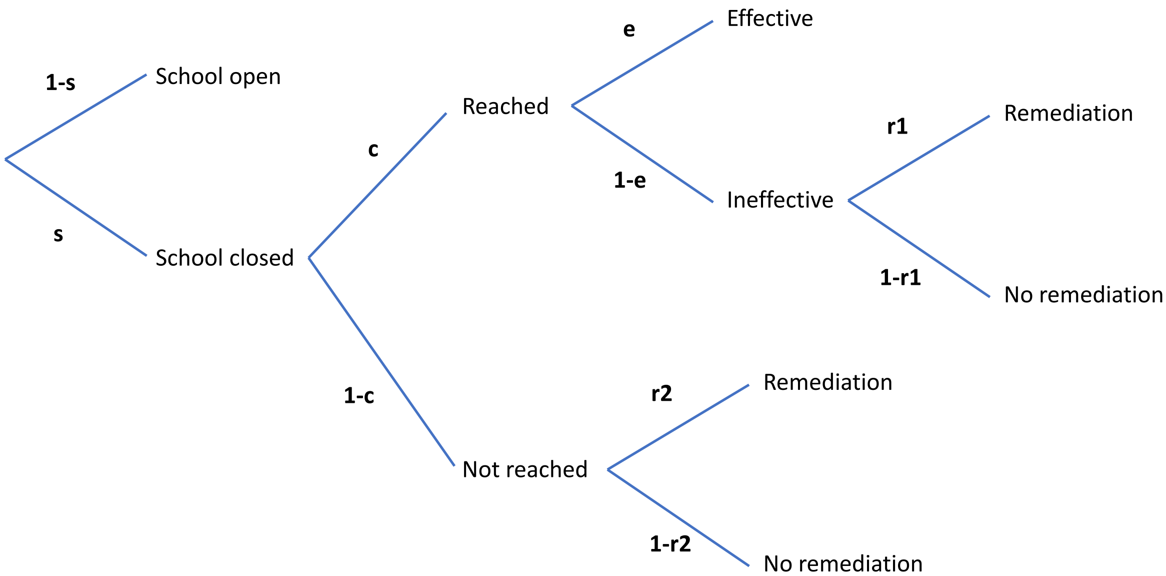
(b) Middle-Income Economies (MICs) Only

(c) Low-Income Economies (LICs) Only



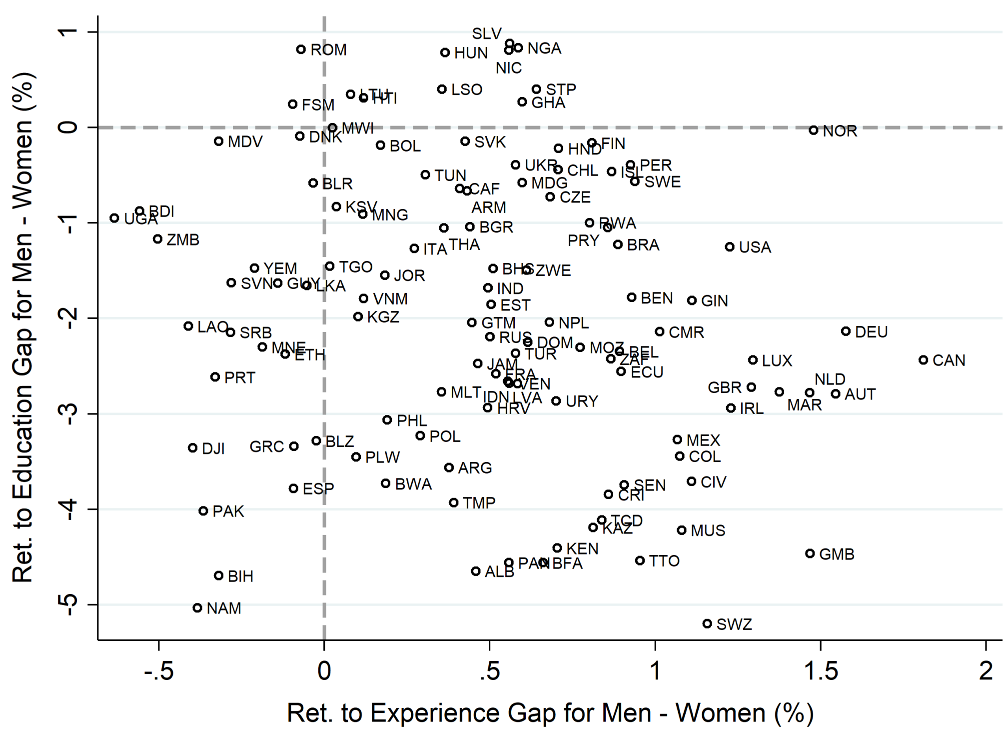
Notes: The horizontal axis measures the unemployment shock of between 0 and 10 percentage points. The vertical axis describes the extent between 0% and 100% of our maximal shock to schooling, a total disruption for two years. The dot represents the most likely scenario in each group of countries. Note that the COVID-19 education shock for HICs, MICs and LICs is 21%, 33% and 28%, respectively (see Table 2). The COVID-19 employment/experience shock is 8.3%, 10.9% and 7.7%, respectively (see Table 2). We do not include the direct effects of the employment shock, thus focusing on human capital accumulation.

Figure 6: Probability Tree for the Schooling Shock



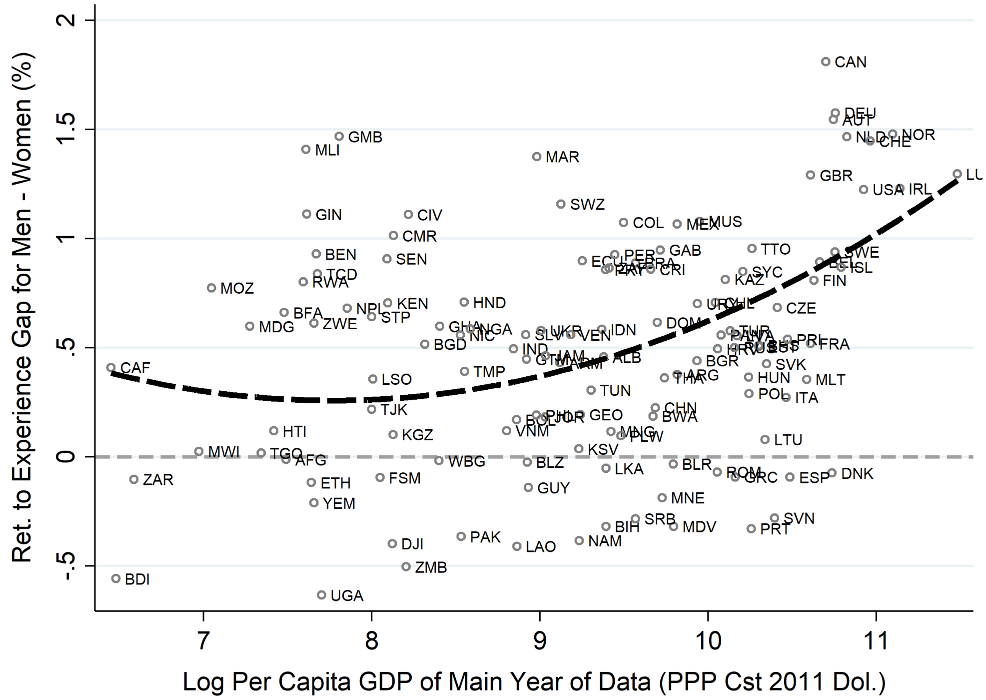
Notes: This figure shows the probability tree for the schooling shock. s is the school closure rate. c is the share of students that are reached by the alternative education technology when schools are closed. e is the effectiveness rate of the technology, i.e., the extent to which the learning loss due to the school closures is made up for. $r1$ is the school remediation rate for the students who have access to an ineffective alternative education technology. $r2$ is the school remediation rate for the students who do not have access to the technology. Presumably, the students facing $r2$ are poorer than the students facing $r1$.

Figure 7: Returns to Education Gap vs. Returns to Experience Gap



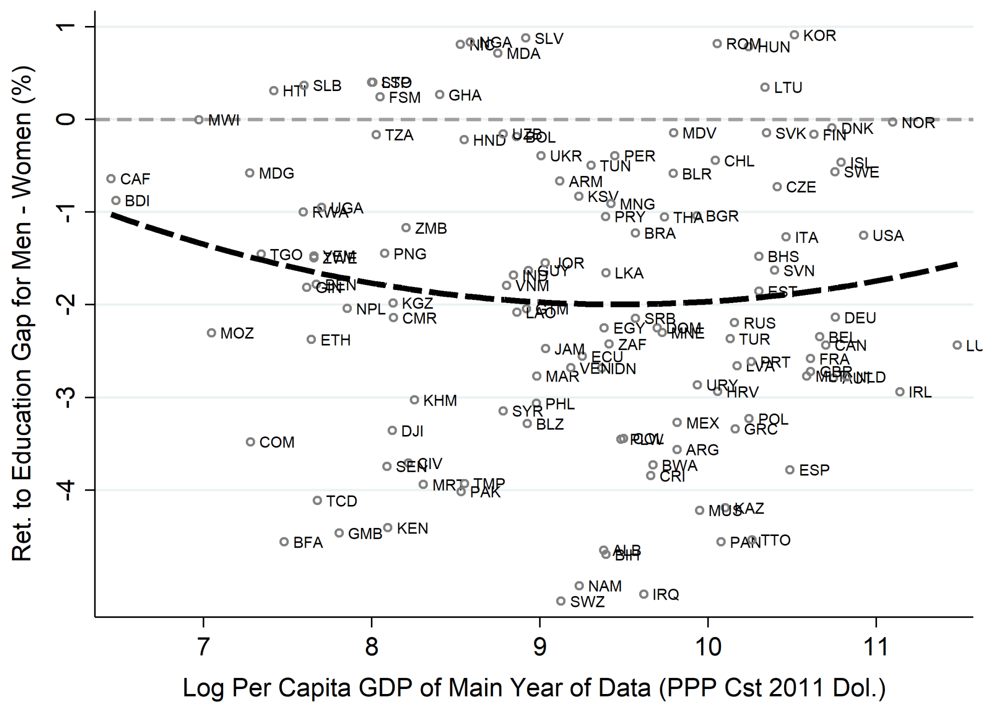
Notes: This figure shows the correlation between the absolute difference between the estimated returns to education for male workers and the estimated returns to education for female workers (a positive value indicates higher returns for men) and the absolute difference between the estimated returns 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 8: 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 9: 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 10: Relative Log Income of Women Compared to Men After the COVID-19 Shock, and Decomposition by Schooling and Experience Shocks.

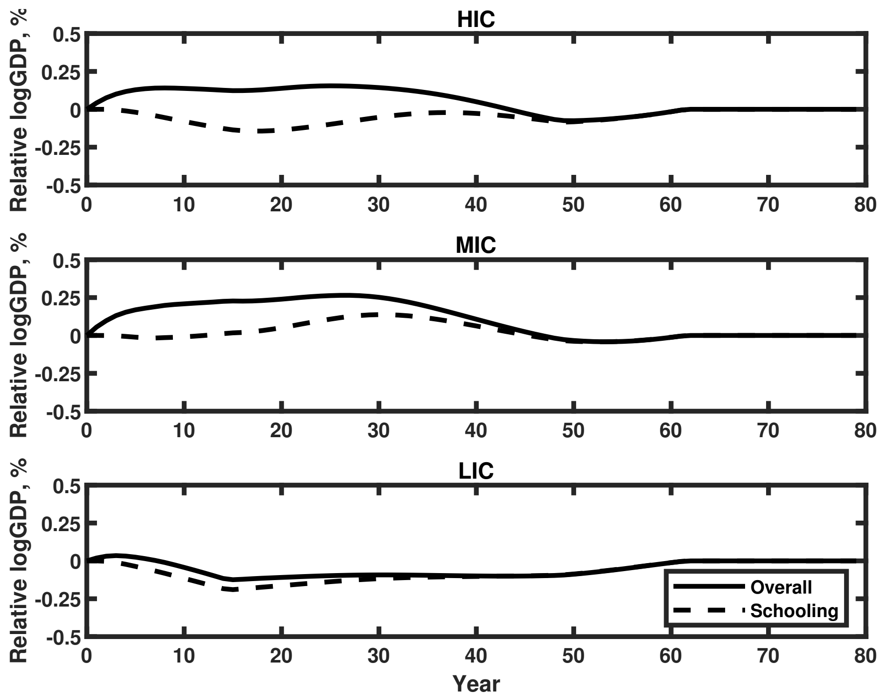


Figure 11: Relative Log Income of Women Compared to Men After the COVID-19 Shock, Taking the Direct Effect of the Employment Shock into Account.

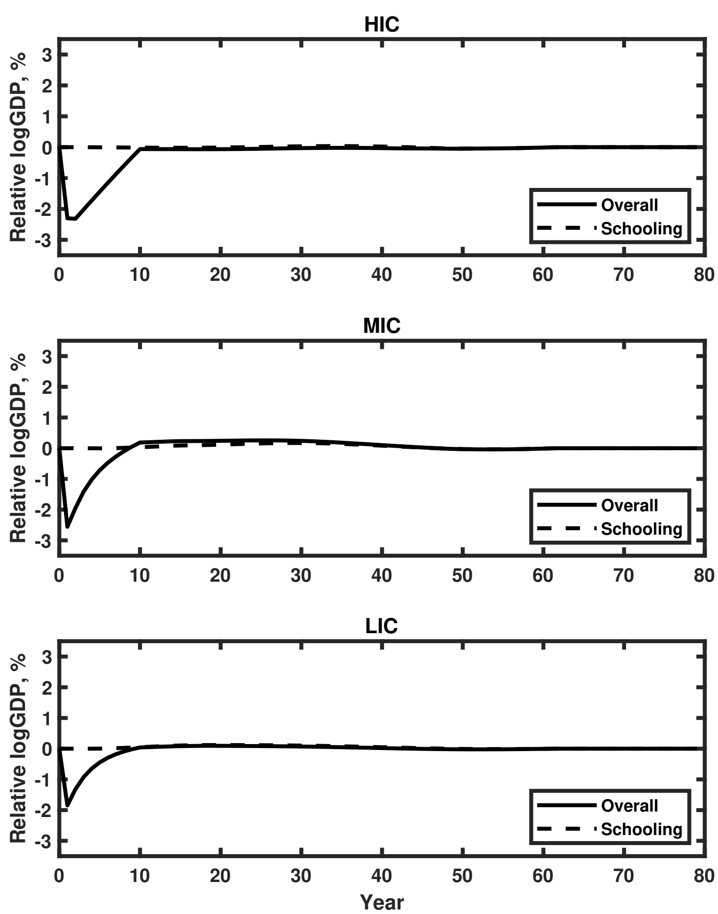


Table 1: Calibration Statistics: Aggregate Analysis

A. Control Parameters	Parameter	High (HIC)	Middle (MIC)	Low (LIC)
Population growth rate	g_b	0.2%	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 (s)	Reach (c) × Effectiv. (e)	Remediation ($r1$, $r2$)	Lost Educ. (ν)	Avg Educ. Shock %	Employment Shock % All	Male	Female
HIC	1	44.0	40	0, 0	26.4	21	8.3	7.2	9.5
HIC	2	32.5	50	0, 0	16.3				
MIC	1	63.5	35	0, 0	41.3	33	9.5	8.8	10.9
MIC	2	37.5	35	0, 0	24.4				
LIC	1	53.0	20	0, 0	42.4	28	6.7	6.2	7.7
LIC	2	18.0	20	0, 0	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 × 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.

Table 4: Welfare Cost of COVID through Human Capital Disruptions: Robustness

	Welfare (annual)				Welfare (one-off)				Comparisons		
Group	HIC	MIC	LIC	World	HIC	MIC	LIC	World	L/H	M/H	L/M
A. Baseline	1.01	0.91	0.56	0.98	25.3	22.6	14.1	24.4	0.56	0.90	0.62
A1. Baseline-School Only	0.40	0.66	0.37	0.48	10.09	16.50	9.28	12.07	0.93	1.65	0.56
A2. Baseline-Experience Only	0.61	0.24	0.20	0.49	20.33	8.00	6.67	16.36	0.33	0.39	0.83
A3. Experience Only/Baseline	0.60	0.26	0.36	0.50	0.80	0.35	0.47	0.67	0.59	0.43	1.34
B. College shock (efficiency)	1.06	0.94	0.59	1.02	26.5	23.4	14.7	25.5	0.56	0.88	0.63
C. College shock (entry)	1.05	0.93	0.59	1.01	26.4	23.2	14.8	25.3	0.56	0.88	0.64
D. 5 year empl. shock (10 before)	0.80	0.82	0.49	0.80	20.0	20.5	12.3	20.1	0.62	1.02	0.60
E. 2 year empl. shock (10 before)	0.72	0.78	0.47	0.74	18.0	19.6	11.6	18.5	0.65	1.09	0.59
F. Spillovers Bils & Klenow 2000	1.10	0.93	0.58	1.04	27.5	23.2	14.5	26.1	0.53	0.84	0.63
G. Spillovers Jedwab et al 2022	1.11	0.93	0.58	1.05	27.8	23.2	14.5	26.3	0.52	0.83	0.63
H. Discount rate 3% (4% before)	1.26	1.16	0.70	1.23	42.0	38.6	23.3	40.9	0.55	0.92	0.60
I. Discount rate 1.5% (4% before)	1.81	1.72	0.99	1.78	120.6	114.9	65.7	118.6	0.54	0.95	0.57

Notes: World welfare is based on shares of GDP in 2020. Welfare is defined as the percentage of consumption that would have to be added to agents in each period to make them indifferent between the losses from lost human capital due to the COVID-19 pandemic and the steady state. Row B assumes a drop in college effectiveness of 1/3 compared to other schooling levels in year 1 and year 2. Hence, if the pre-college education shock is 21% for LICs, 33% for MICs, and 28% for HICs, the college education shock is 7%, 11% and 9%, respectively. Row C assumes that 10% of high school students who would have gone to college do not go in year 1 and year 2. Row D (E) assumes that the employment effects of COVID wind down after 5 (2) years. Decay is linear (100% in year 1, 50% in year 2, 0% after that). Rows F-G allow for human capital spillovers (so a loss of human capital lowers the productivity of others too). See the text for details. Rows H-I have different discount rates (the baseline uses 4%).

Table 5: Welfare Cost through Disruptions to College Effectiveness and Attendance

A. Effectiveness (% Pre-College)		LIC + MIC			B. Enrollment Decline (%)		LIC + MIC		
HIC	Country	1/3	2/3	3/3	HIC	Country	10%	20%	30%
	HIC	1.06	1.06	**1.06**		HIC	1.05	1.05	**1.05**
1/3	MIC	0.94	0.96	**0.99**	10%	MIC	0.93	0.95	**0.97**
	LIC	0.59	0.61	**0.64**		LIC	0.59	0.62	**0.65**
	HIC	1.11	1.11	1.11		HIC	1.10	1.10	1.10
2/3	MIC	0.94	0.96	0.99	20%	MIC	0.93	0.95	0.97
	LIC	0.59	0.61	0.64		LIC	0.59	0.62	0.65
	HIC	**1.15**	1.15	1.15		HIC	**1.14**	1.14	1.14
3/3	MIC	**0.94**	0.96	0.99	30%	MIC	**0.93**	0.95	0.97
	LIC	**0.59**	0.61	0.64		LIC	**0.59**	0.62	0.65

Notes: World welfare is based on shares of GDP in 2020. Panel A: We assume that the effectiveness of college declines by X = {1/3, 2/3, 3/3} of the general decline in schooling in year 1 and year 2. Hence, if we select 1/3 for the three groups of countries and the pre-college education shock is 21% for LICs, 33% for MICs, and 28% for HICs ("Avg Educ. Shock %" column from Table 2), the college education shock is 7%, 11% and 9%, respectively. Panel B: We assume that the share of high school graduates going to college declines by X = {10%, 20%, 30%} in year 1 and year 2. For example, if 20% of high school graduates normally go to college and this share decreases by 10% in the first two years after COVID, only 18% do so in year 1 and only 18% do so in year 2.

Table 6: Returns to Experience and Education for Women vs. Men, Robustness

Group:	(1) Male			(2) Female			(3) Male - Female		
***Panel A:* 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% (Med.)	9.5	9.8	8.7	11.2	10.1	9.9	-1.7	-0.3	-1.2
9. Diff Fem - Male Non-Empl $<$ 22% (Med.)	9.6	10.0	9.3	11.4	9.8	10.9	-1.8	0.2	-1.6
10. 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
11. 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
***Panel B:* 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% (Med.)	4.1	2.1	2.2	3.2	1.5	2.0	0.9	0.6	0.2
9. Diff Fem - Male Non-Empl $<$ 22% (Med.)	4.2	2.0	2.3	3.2	1.6	2.2	1.0	0.4	0.1
10. 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
11. 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

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

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.[1] 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 5.1. 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.[2] 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).

Bauer et al. (2021) examine a sample of European countries as well as the U.S., and

[1] 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.

[2] "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

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 Figure 4 confirms that COVID-19 mortality rates were relatively low below age 60 in most countries.

C Calibration: Defining the Pandemic: Schooling Shock

College Shock & 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.[3] Additionally, the literature on the effectiveness of online college is mixed. Some studies find that online education can be 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 sometimes less effective than in-person instruction (Donnelly and Patrinos, 2021), 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 learning losses than MICs and LICs.

Effectiveness of Online 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 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,

[3] 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.

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. More generally, Donnelly and Patrinos (2021) explain that seven studies found evidence of student learning loss in developed countries, although developed countries are the countries where distance learning is likely to be the most efficient. We conclude conservatively that online instruction is imperfectly effective.

School Closure Data. UNESCO (2021) classifies 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.[4] 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 non-employment rates in the range of zero to 10 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".[5] While the official

[4]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.

[5]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 losses 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 losses equal to the average over 2020, i.e. 8.3%, 9.5% and 6.7% respectively (ILO, 2020, Fig. 7), and 10% is a reasonable upper bound.

Workers with Sub-College Education and the Young. Based on the COVID-19 experience (ILO, 2020; Kugler et al., 2021), 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).[6] 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 & 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, & 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. We then calculate 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.

[6]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 as 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 its 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 follows. 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 10 percentage points.

E Choice of the Discount Rate and Implications of Ignoring Growth

Discount Rates. For 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 typical 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.

Human Capital Spillovers. In any case, in Table 4, we explore alternative values of 3 percent and 1.5 percent. Naturally these lower discount rates increase the welfare impact of human capital losses due to COVID, almost doubling it. That said, the overall impact on the LIC relative to the MIC and HIC remains the same, around 60%.

Non-Implications of Ignoring Growth. Finally, an argument could be made regarding whether a larger discount rate should be used for MICs and/or LICs, as they might grow faster than HICs due to convergence dynamics, and since in Macroeconomics the discount factor equals the growth factor divided by the factor that reflects time preference. One can use Table 4 to perform such a comparison and, indeed, if we were to assume that the discount rate in the HIC is 4 percent and in the LIC it is 1.5 percent then the welfare losses would be comparable (see the LIC column in row I vs. the HIC column in row A). However, our definition of welfare (which in Macroeconomics is quite standard) only requires knowledge of the rate of time preference and is unaffected by differences in growth trends.

Suppose agents preferences are based on discounted utility from an infinite consumption stream. Suppose there is a discount rate that reflects the rate of time preference r, and a corresponding discount factor $\beta = e^r$. Suppose also that instantaneous utility is the natural logarithm of consumption, as is common in growth theory. Then, if an agent experiences a consumption stream $\{C_t\}_{t=0}^{\infty}$ their discounted utility is

$$\sum_{t=0}^{\infty} \beta^t \log\left(C_t\right)$$

Suppose the country has a counterfactual balanced growth path consumption $\bar{C}_t = e^{gt}\bar{c}$, such that $\bar{c}$ is detrended consumption along the balanced growth path.

Now suppose the country experiences a shock so that consumption is $\{C_t\}_{t=0}^{\infty}$. We can define c_t so that $C_t = e^{gt}c_t$. Then c_t is detrended consumption after the shock. In our case $\lim_{t\to\infty} c_t = \bar{c}$, so it is meaningful to think of c_t as consumption detrended from the balanced growth path.

Our welfare measure is the value of Δ such that the agent is indifferent between having share Δ of their consumption added each period and never having experienced the COVID shock at all, i.e. they are indifferent between $C_t(1+\Delta)$ and $\bar{C}_t$. Thus, we seek the Δ such that:

$$\sum_{t=0}^{\infty} \beta^t \log\left(C_t\left(1+\Delta\right)\right) = \sum_{t=0}^{\infty} \beta^t \log\left(\bar{C}_t\right)$$

Now notice this is equivalent to

$$\sum_{t=0}^{\infty} \beta^t \log\left(e^{gt}\right) + \sum_{t=0}^{\infty} \beta^t \log\left(c_t\left(1+\Delta\right)\right) = \sum_{t=0}^{\infty} \beta^t \log\left(e^{gt}\right) + \sum_{t=0}^{\infty} \beta^t \log\left(\bar{c}\right)$$

which simplifies to:

$$\sum_{t=0}^{\infty} \beta^t \log\left(c_t\left(1+\Delta\right)\right) = \sum_{t=0}^{\infty} \beta^t \log\left(\bar{c}\right)$$

As a result, the value of g does not affect the welfare calculations. Notice that, since the counterfactual is country-specific, this also means that if g is different for countries groups it still does not affect the welfare calculation: all that matters is the rate of time preference.

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 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.

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.

H 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] (Kugler et al. (2021) find similar results).[7] As such, women were $(5.0 \div 3.9 - 1)*100 = 28\%$ more impacted than men and $(5.0 \div 4.3 - 1)*100 = 16\%$ 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.[8] Comparing women to the overall population, we thus find that they 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.

I 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

[7] 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 [...]."

[8] This is the change between the first and second quarter of 2020, which is the shock that we are interested in measuring. Post-support labor income is "labour income that takes into account income support measures". The countries in the analysis are Brazil, Italy, Peru, the UK, the US and Vietnam.

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.[9] We cross-check this information using other sources, e.g. the BBC Profile of each country.[10] 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 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

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

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

occupations; 10 = Armed forces occupations/Other/Unspecified occupations.

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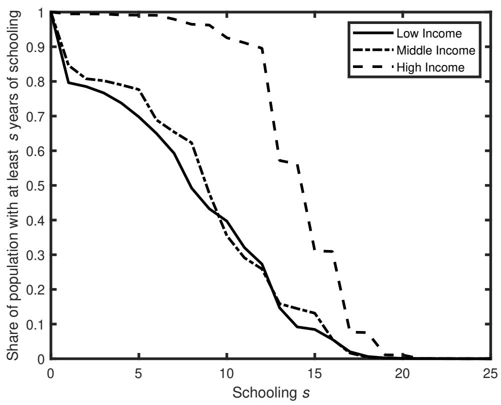
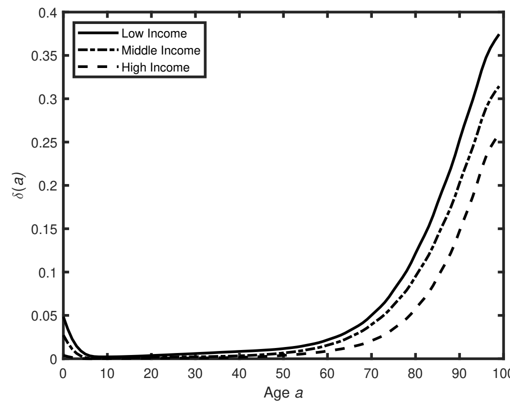
A. Appendix Figures and Tables

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

(a) Distributions of Schooling



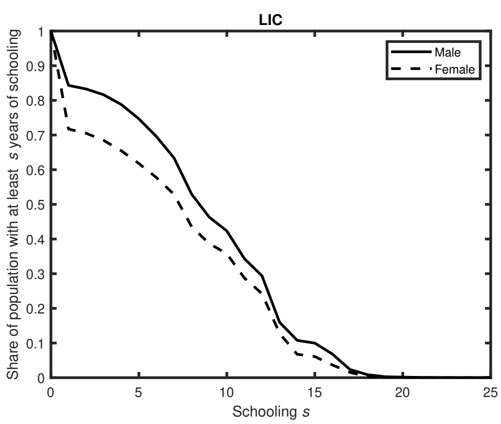
(b) Distributions of Mortality



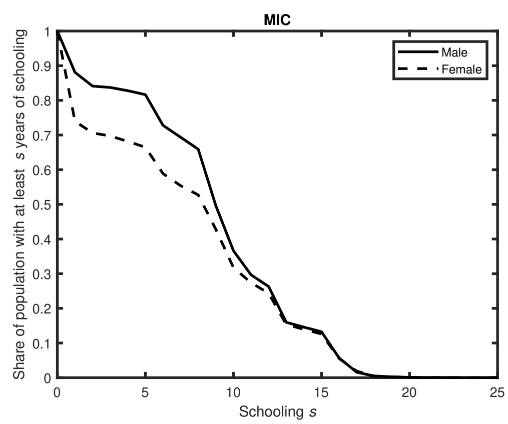
Sources – United Nations (2019), I2D2 database.

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

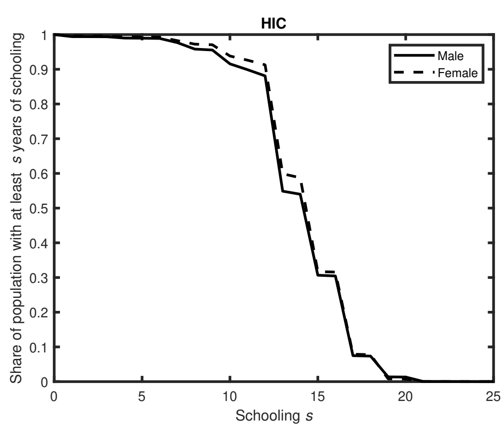
(a) Low-Income Economies



(b) Middle-Income Economies



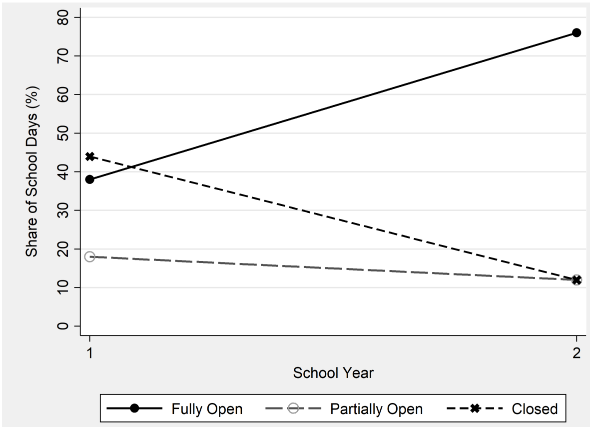
(c) High-Income Economies



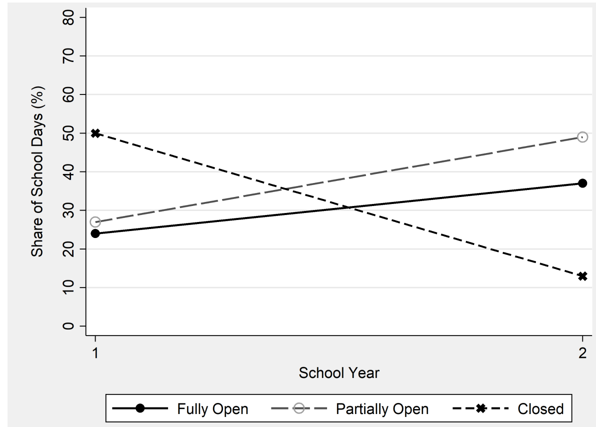
Sources – I2D2 database.

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

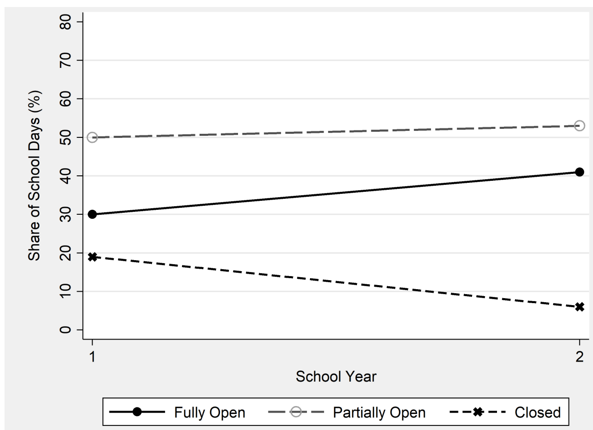
(a) Low-Income Economies



(b) Middle-Income Economies



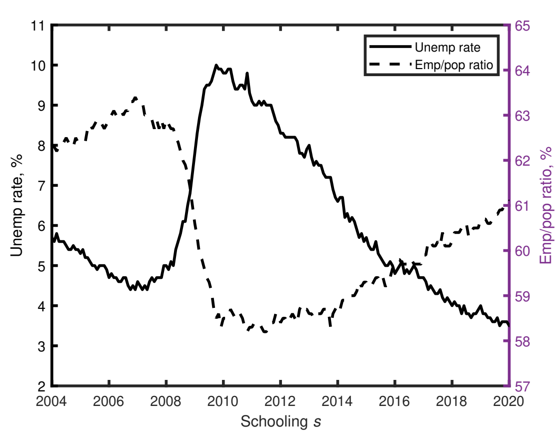
(c) High-Income Economies



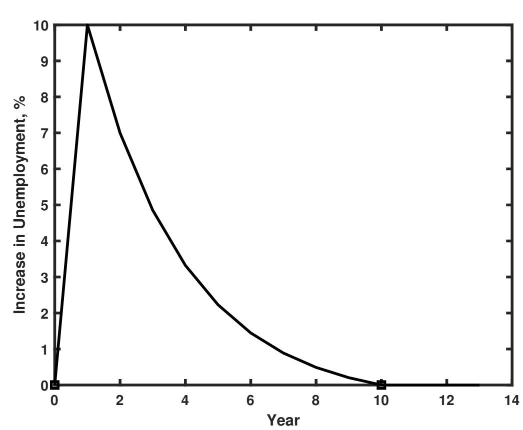
Sources – UNESCO (2021). According to their methodological note, *partially open schools* are schools that are: "*(a) open/closed in certain regions only; and/or (b) open/closed for some grade levels/age groups only; and/or (c) open but with reduced in-person class time, combined with distance learning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

Figure A.4: Duration of the Employment Shock

(a) The Great Recession and Employment

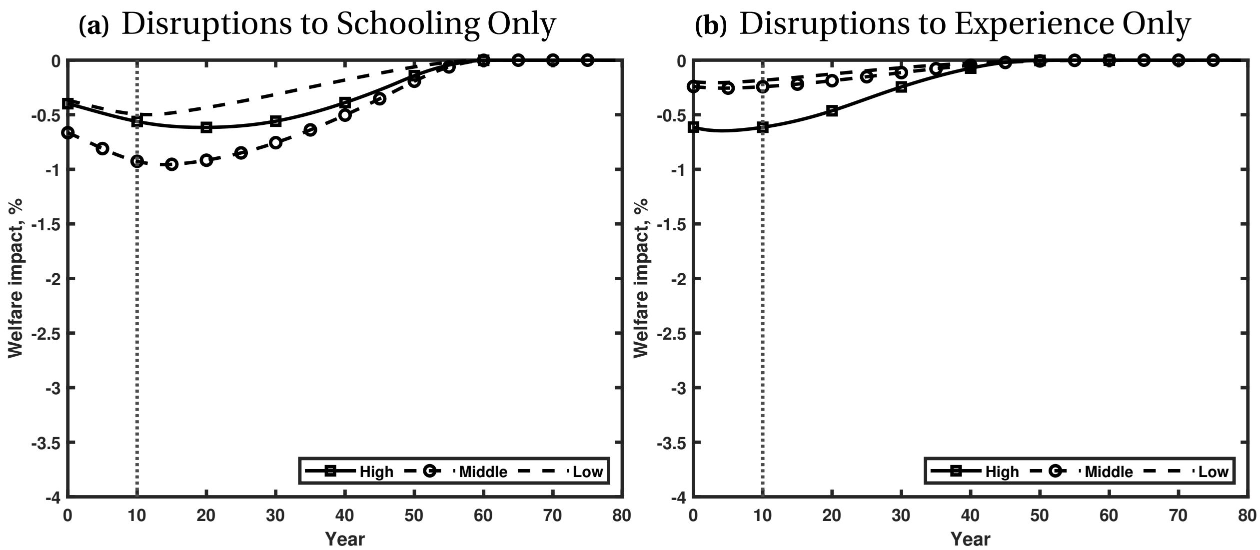


(b) Maximal Employment Shock



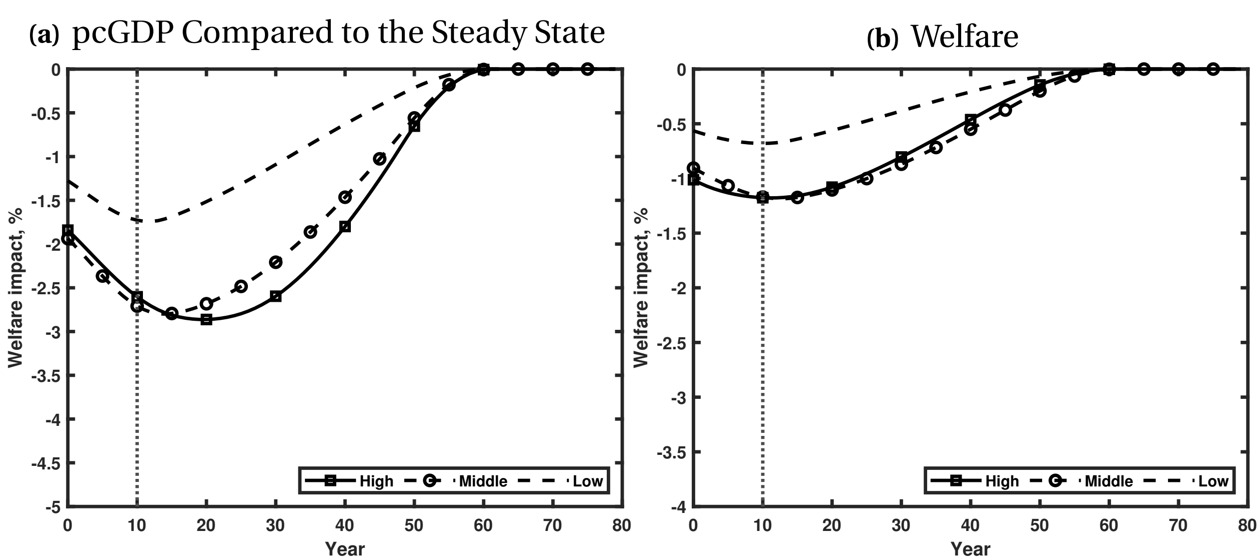
Left figure: Source – Federal Reserve Bank of St. Louis. Right figure: See text for construction details..

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



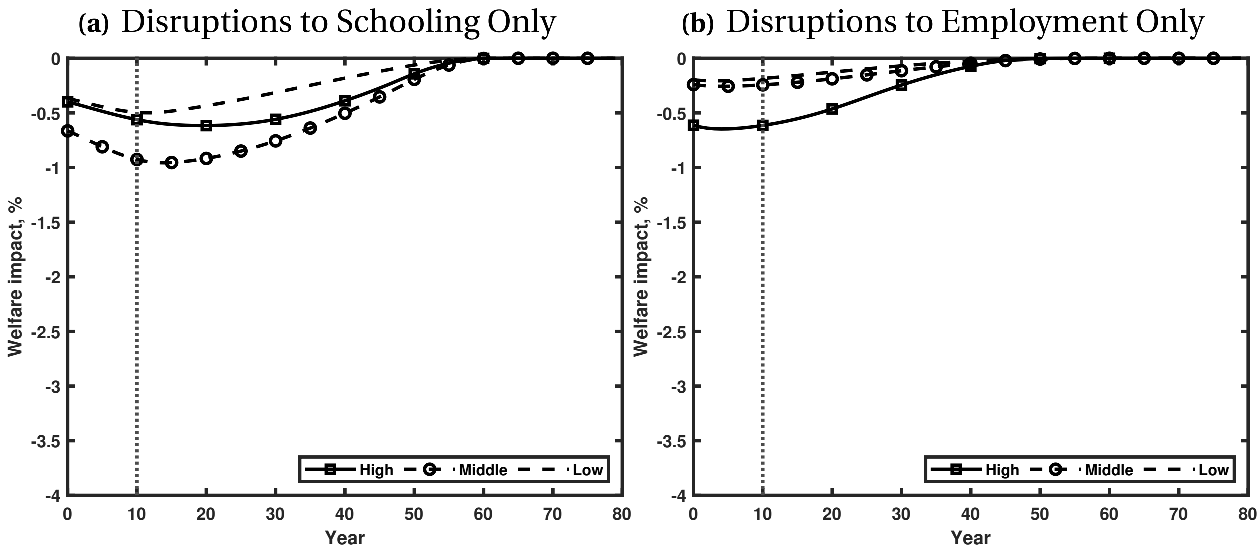
Notes: Welfare measure = the percent of GDP that would have to be added in each period in order to make agents indifferent between the pandemic shock and remaining in the steady state. Left fig.: The shock is assumed to disrupt schooling only. Right fig.: The shock is assumed to disrupt employment only.

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



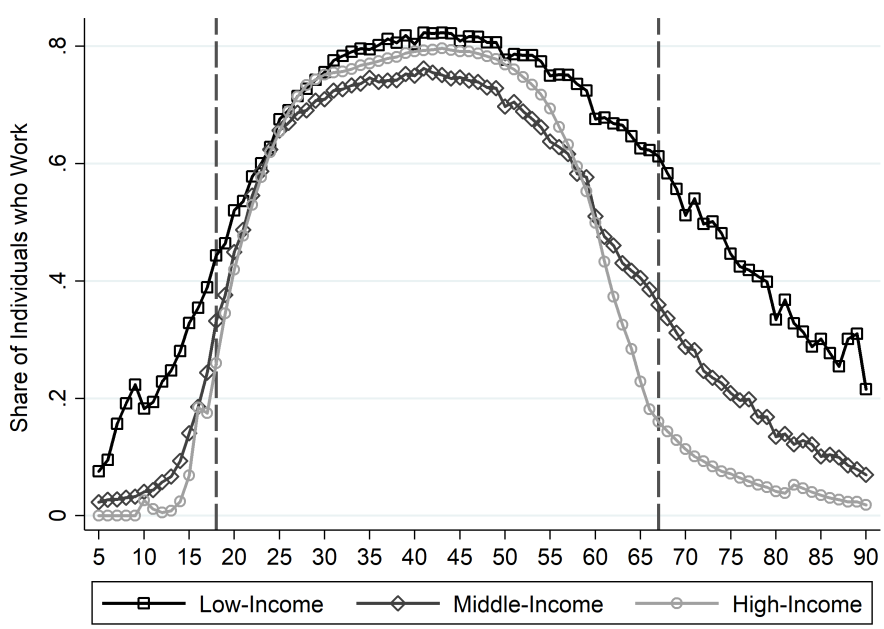
Notes: Left figure: Impact on current per capita GDP of the shock year-by-year compared to the steady state for economies at different levels of development. Right figure: Impact of the shock on welfare in economies at different levels of development. The welfare measure is the percent of GDP that would 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

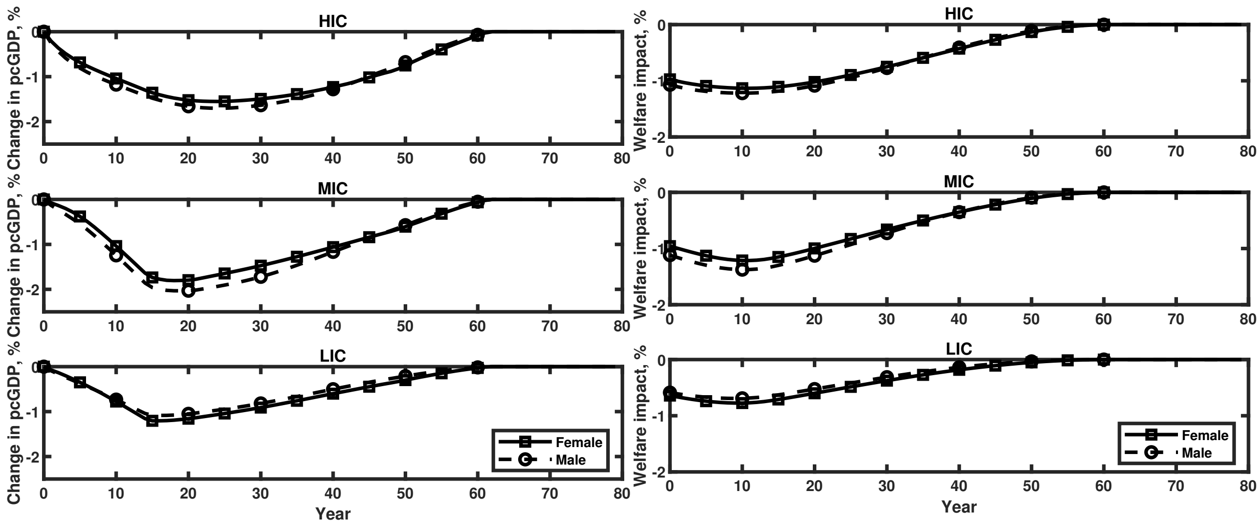


Notes: These figures show for each age from 5 to 90 in LICs, MICs and HICs the share of individuals who work (no matter the number of work hours). These graphs were created using the I2D2 data (1990-2016), only for country-year-samples and ages with available information on employment. We then use the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

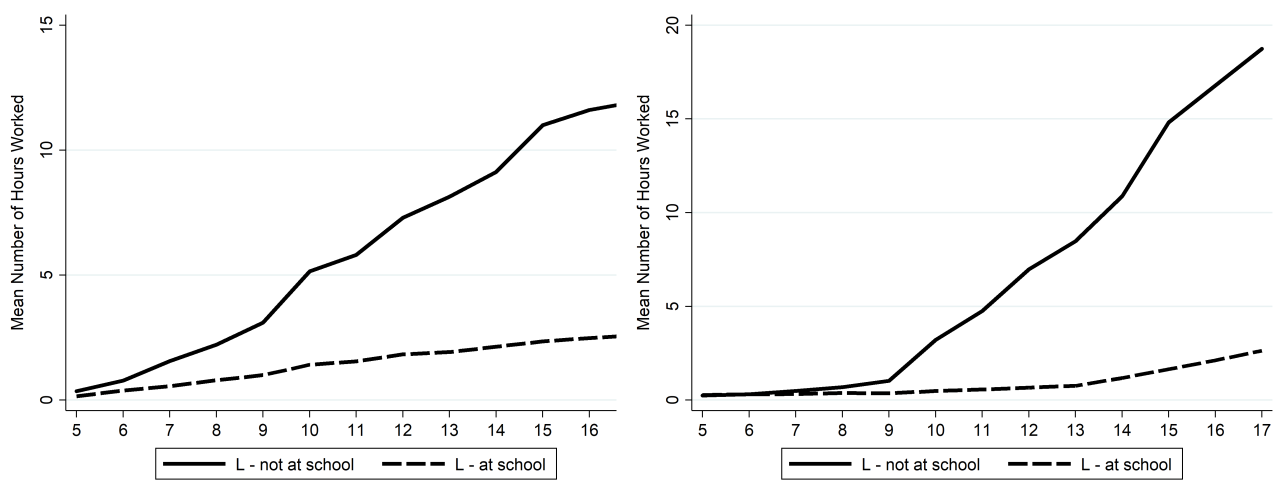


Notes: Left figure: Impact on current per capita GDP year-by-year compared to the steady state for economies at different levels of development and by gender. Right figure: Impact on welfare in economies at different levels of development and by gender. The welfare measure is the percent of GDP that 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 TV (%)	Share with Radio (%)
HIC	86	98	99
MIC	34	69	47
LIC	6	35	35

Notes: Sources - Internet: World Bank (2020) (among 3-17 y.o.); TV & 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). Effectiveness rate = percentage share of *Very Effective* + 0.8 × 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			COVID Deaths as % of	
Age	Deaths	Pop.	Age	Deaths	Pop.
0-17	0.97	0.00	50-64	13.3	0.22
18-29	2.67	0.01	65-74	13.7	0.55
30-39	7.63	0.03	75-84	13.2	1.23
40-49	12.4	0.08	85+	11.4	3.20

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

Table A.5: Projected Dropout Rates due to the COVID-19 Pandemic, UNESCO

	Number of At-Risk Students / Number of Pupils * 100					
	Primary Education			Secondary Education		
	HICs	MICs	LICs	HICs	MICs	LICs
Total (%)	0.0	0.3	0.7	1.9	1.4	1.8
Male (%)	0.0	0.3	0.7	1.8	1.4	1.9
Female (%)	0.0	0.3	0.7	2.0	1.4	1.7

Sources: UNESCO (2020a), World Bank (2022) and authors' calculations

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
10 Industry FE	4.4	6.7	6.0	13.1	10.7	11.1
10 Industry FE + Controls	4.0	4.3	6.0	10.7	8.5	10.5

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. Controls: dummies for the relationship to the head of household (head, spouse, children, parents, other relatives, non-relatives), dummies for the marital status (married, never married, living together, divorced/separated, widowed), dummy if the individual lives in an urban location, and dummy if the individual is self-employed.

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

Scenario	Summing across all years			
	Shock	HIC	MIC	LIC
Baseline	Empl	0.61	0.24	0.20
	School	0.40	0.66	0.37
	Total	1.01	0.91	0.56
Including Child Labor Exp from 15	Empl	0.63	0.26	0.21
	School	0.45	0.70	0.39
	Total	1.09	0.97	0.60
Including Child Labor Exp from 13	Empl	0.63	0.27	0.25
	School	0.46	0.72	0.40
	Total	1.10	0.99	0.65
Including Child Labor Exp from 6	Empl	0.63	0.26	0.23
	School	0.48	0.74	0.46
	Total	1.11	1.00	0.68
Decadal Cohort Fixed Effects	Empl	0.61	0.24	0.20
	School	0.40	0.66	0.36
	Total	1.01	0.91	0.56
Important Events Fixed Effects	Empl	0.55	0.25	0.16
	School	0.40	0.64	0.36
	Total	0.94	0.89	0.52
Excluding Self-employed Individuals	Empl	0.63	0.23	0.19
	School	0.40	0.60	0.31
	Total	1.03	0.83	0.50
Estimated using Males Only	Empl	0.71	0.26	0.21
	School	0.37	0.68	0.34
	Total	1.08	0.94	0.54
Unemployment Rate $< 7\%$ (25p)	Empl	0.59	0.25	0.20
	School	0.38	0.70	0.37
	Total	0.97	0.95	0.56
Unemployment Rate $> 7\%$ (25p)	Empl	0.66	0.25	0.20
	School	0.38	0.56	0.57
	Total	1.04	0.81	0.77
Unemployment $< 10\%$ (50p)	Empl	0.60	0.24	0.20
	School	0.41	0.66	0.37
	Total	1.00	0.90	0.56
Unemployment $< 10\%$ (50p)	Empl	0.62	0.24	0.22
	School	0.43	0.58	0.60
	Total	1.05	0.82	0.82
Non-Labor Force Participation $< 35\%$	Empl	0.60	0.24	0.22
	School	0.39	0.67	0.54
	Total	1.00	0.91	0.76
Non-Labor Force Participation $> 35\%$	Empl	0.59	0.22	0.19+
	School	0.47	0.52	0.32
	Total	1.06	0.74	0.51
Non-Linear Returns to Exp $(0-5$ vs. $10-25)$	Empl	0.71	0.28	0.24
	School	0.41	0.66	0.36
	Total	1.12	0.94	0.61

Table A.8: 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.