The Long-Term Distributional and Welfare Effects of Covid-19 School Closures*

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April 15, 2021

Abstract

Using a structural life-cycle model, we quantify the heterogeneous impact of school closures during the Corona crisis on children affected at different ages and coming from households with different parental characteristics. In the model, public investment through schooling is combined with parental time and resource investments in the production of child human capital at different stages in the children's development process. We quantitatively characterize the long-term consequences from a Covid-19 induced loss of schooling, and find average losses in the present discounted value of lifetime earnings of the affected children of close to 1%, as well as welfare losses equivalent to about 0.6% of permanent consumption. Due to self-productivity in the human capital production function, skill attainment at a younger stage of the life cycle raises skill attainment at later stages, and thus younger children are hurt more by the school closures than older children. We find that parental reactions reduce the negative impact of the school closures, but do not fully offset it. The negative impact of the crisis on children's welfare is especially severe for those with parents with low educational attainment and low assets. The school closures themselves are primarily responsible for the negative impact of the Covid-19 shock on the long-run welfare of the children, with the pandemic-induced income shock to parents playing a secondary role.

Keywords: Covid-19, school closures, inequality, intergenerational persistence
J.E.L. Codes: D15, D31, E24, I24

*Fuchs-Schündeln gratefully acknowledges financial support by the European Research Council through Consolidator Grant No. 815378, and by the DFG through a Leibnizpreis. Krueger thanks the National Science Foundation for financial support under grant SES-1757084. Fuchs-Schündeln and Ludwig gratefully acknowledge financial support by NORFACE Dynamics of Inequality across the Life-Course (TRISP) grant: 462-16-120. Ludwig also thanks Universitat Autònoma de Barcelona for its hospitality during his sabbatical year 2019/20.

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1 Introduction

Governments worldwide have reacted to the Covid-19 pandemic by closing schools and child care centers. In many countries, including the US, these closures started in mid March 2020 and extended well into 2021. Whereas the economic consequences of temporary business closures are immediate and drew significant policy and media attention, the economic consequences of school and child care closures emerge in the longer run and are not always easily measured. Given the importance of human capital for individual prosperity and long-term macroeconomic growth, they are however likely substantial (see e.g. Krueger and Lindahl (2001), Manuelli and Seshadri (2014)).

In this paper, we analyze the long-term income-, welfare- and distributional consequences of the school and child care closures on the affected children. To do so, we build a heterogeneous agent partial equilibrium model with a human capital production function at its core that takes time and monetary inputs by parents and governmental investment into schooling as inputs. Parents also leave inter-vivos transfers to their children, which can be used to finance college and consumption. The key dimensions of heterogeneity we focus on are the age of a child in 2020 (when the school closures first occurred), as well as parental socio-economic characteristics, namely financial resources, marital status, and education. We model school and child care closures as a reduction in the governmental investment in children corresponding to six fewer months of schooling. In the model, parents endogenously adjust their investment into children and inter-vivos transfers in response to the drop in governmental inputs, thereby potentially mitigating the adverse consequences of Covid-19 induced school closures. We use our model as a quantitative laboratory to analyze the long-term aggregate and distributional consequences of the Covid school shock on children's acquired human capital, their high-school graduation and college choice, their labor market earnings, and, ultimately, their welfare. In an extended analysis, in addition to the school closures, we also model a negative income shock to parents due to the Covid-induced economic recession.

The key quantitative ingredients for the quantitative analysis are the parameters characterizing the human capital production function, which we either take from the literature or calibrate to data moments on parental investments into children from U.S. household micro data. Once the model is parameterized, we subject children and parents to a one-time unexpected Covid-19 school closure shock and possibly an associated recession-induced income shock, and document the short- and long run economic consequences. On average (across children aged 4 to 14 when the shock occurs), the model implies that the school closures alone lead to an increase in the future share of children without a high school degree of 7% and a reduction of the share of children with a college degree of -3.2%. On average, the present discounted earnings losses at labor market entry induced by reduced human capital accumulation and lower educational attainment amount to -0.95%. To put these losses into a macroeconomic perspective, if we discount these losses to the beginning of 2020 and aggregate them across all school children impacted by the Covid-19 school closures, they amount to ca. 1.4% of 2019 US GDP.

These effects materialize despite a significant endogenous adjustment of parental investments into their children: time inputs rise by 7.3% and monetary inputs by 14.7% on impact. Measured as consumption-equivalent variation, the average welfare loss of children from the Covid-induced school closures amounts to -0.55%. Given the temporary nature of the shock, assumed to last only half a year, we view these numbers as quite large. Adding the income recession to the model leaves the welfare loss of the children almost unchanged; it only increases very slightly in absolute terms to -0.56%. Thus, from the children's perspective, the welfare losses of school closures are substantial, but the additional losses caused by the income recession affecting their parents negligible. The main reason for this lies in the fact that the reduced parental income is mainly caused by a reduction in hours worked, which frees up time to invest into the children. However, even if the income recession is modelled purely as a productivity shock, 80% of the overall welfare loss of the children is caused by school closures alone.

These average welfare losses mask substantial heterogeneity by the age and parental socio-economic characteristics of the children at the time of the crisis. Turning first to the age of the child, the adverse impact is most pronounced for younger children of school age (i.e. children of ages 6-10). The welfare losses of children aged 6 at the time of the crisis amount to -0.71% in terms of consumption-equivalent variation. Even though parents respond strongly to the closure of schools by increasing their time and resource inputs into the child human capital production function, they do not quite fully offset the reduction in public inputs due to schooling. This implies that children arrive at older ages with less human capital due to the Covid crisis, and due to the self-productivity of human capital the effect is stronger for younger children. Additionally, since the human capital production function features dynamic complementarities, the marginal productivity of private investments at future ages is also reduced. Optimizing parents respond to this by investing less into their children at older ages (relative to the pre-Covid scenario). Combined, these effects lead to lower human capital at age 16, adverse outcomes on high-school completion and college attendance, future wages and, consequently, welfare. Older children at the time of the Covid crisis, instead, have already accumulated most of their human capital, and therefore the adverse future effects due to self-productivity and lower incentives for parental human capital investment due to Covid school closures are less severe.

Apart from the age of the child, parental background matters for the negative impact of the Covid shock on human capital accumulation, wages, and welfare. Broadly speaking, children with poorer parents suffer more. There are two reasons for this. First, even without any parental adjustments in investments, children from lower income households suffer more from the school closures, since for them a larger part of educational investment comes from the government. Second, as a reaction to the school closures, rich parents increase their investment into children by more than poor parents. They have more financial resources to do so, and their children have on average higher human capital. Given that the human capital production function features dynamic complementarity, rich parents thus have higher incentives to compensate the reduction in government investment than poor parents. Focusing on each parental characteristic alone, we find that children from single parents, parents from the lowest asset quintile, or high school dropout parents have around 30% higher welfare losses than children from married parents, parents from the highest asset quintile, or college educated parents. However, these three parental characteristics are positively correlated, and thus losses along a single characteristic compound each other. Children from the most disadvantaged households then have four times larger welfare losses than children from the most privileged households, and the differences become even larger if the length of effective school closures correlates negatively with parental characteristics, and thus children from privileged backgrounds miss less school than poor children.

1.1 Related Literature

This paper ties into the literature on schooling and human capital formation. Our human capital production function relies on Cunha et al. (2006), Cunha and Heckman (2007) and Cunha et al. (2010), especially on the feature of self-productivity, i.e., higher human capital in one period leads to higher human capital in the next period, and dynamic complementarity, i.e., human capital investment pays out more the higher the human capital.[1] This feature implies that early-childhood education is a crucial determinant of future income (Cunha and Heckman (2007) and Caucutt and Lochner (2020)). Consequently, public schooling is a driver of intergenerational mobility. Relying on quantitative models, Kotera and Seshadri (2017) show that differences in intergenerational mobility across US states can be explained by differences in public school finances. Related, Lee and Seshadri (2019) find that education subsidies can significantly increase intergenerational mobility.[2] Agostinelli et al. (2020) also use a structural model of human capital formation to evaluate the consequences of Covid-19 related school closure, but zoom in on the high-school years of teenagers, and emphasize the loss of peer interactions as an important driver of losses

[1] Our human capital production function does not feature innate ability, only innate human capital, and therefore by construction does not include complementarity between ability and human capital investment.

[2] Yum (2020) allows for parental time and monetary investments, as we do, and analyzes specifically the importance of parental time investment for intergenerational mobility. Caucutt et al. (2020) provide estimates of the complementarity of different parental inputs and between parental inputs and market-based child care.

in educational attainment. Jang and Yum (2021) build a general equilibrium model and focus on the effects of the school closures on aggregate outcomes and intergenerational mobility.

Whereas the quantitative literature focuses on the effects of public schooling investment on children's outcomes and intergenerational mobility, there exists an empirical literature that analyzes specifically the link between school instruction time and outcomes of children. Lavy (2015) exploits international differences in school instruction time, caused by differences in the length of an average school day and usual school weeks, and finds that school instruction time in core subjects significantly affects testing outcomes of children. Similarly, Carlsson et al. (2015) exploit exogenous variation in testing dates in Sweden and report that extra 10 days of school instruction raise scores on intelligence tests by 1% of a standard deviation.[3] There are few studies investigating longer-term outcomes of school instruction time on children. Cortes et al. (2015) find a positive effect of math instruction time on the probability of attending college for low-performing students. Pischke (2007) exploits short school years associated with a shift in the school starting date in Germany in the 1960s, and finds no significant effects on employment and earnings of affected children. Jaume and Willén (2019) find that half a year less instruction time during primary school caused by school strikes in Argentina lowers the long-term earnings by 3.2% for men and 1.9% for women.

The remainder of this paper unfolds as follows. Section 2 presents the model, and Section 3 its calibration. Sections 4, 5, and 6 then discuss the results, first in terms of aggregate effects, then in terms of its distribution, before inspecting the mechanisms that give rise to them. Last, section 7 concludes, and the Appendix contains additional quantitative results.

2 A Quantitative Model of Education During the Epidemic

We now describe the quantitative life cycle model that we will use to quantify the long-run consequences of school closures during the COVID-19 pandemic. After setting out the fundamentals of the economy (demographics, time, risk, endowments, preferences and government policy) we immediately focus on the recursive formulation of the model, since this is the representation we will compute.

[3] Other papers studying the link between school instruction time and test scores are Rivkin and Schimann (2015) and Fitzpatrick et al. (2011).

2.1 Individual State Variables, Risk, and Economic Decisions

Time in the model is discrete and the current period is denoted by t. We model the life cycle of one adult and one children generation in partial equilibrium. The timing and events of this life cycle are summarized in Figure 1 below.

Agents are heterogeneous with respect to the generation they belong to $k \in \{ch, pa\}$, either being part of the child or parental generation, and they differ by their marital status $m \in \{si, ma\}$ for single and married, their age $j \in \{0, \ldots, J < \infty\}$, their asset position a, their current human capital h, their education level $s \in \{no, hs, co\}$ for no higher education (no high school completion), $h$igh $s$chool attendance and completion, college attendance and completion, and idiosyncratic productivity risk modeled as a two state Markov process with state vector $\eta \in \{\eta_l, \eta_h\}$, where η_l is low and η_h is high labor productivity, and transition matrix $\pi(\eta' \mid \eta)$ and a transitory shock $\varepsilon \in \{\varepsilon_1, \ldots, \varepsilon_n\}$. The individual state variables and the range of values they can take are summarized in Table 1.

Table 1: State Variables

State Var.	Values	Interpretation
k	$k \in \{ch, pa\}$	Generation
m	$m \in \{si, ma\}$	Marital Status
j	$j \in \{0, 1, \ldots, J\}$	Model Age
a	$a \geq -\underline{a}(j, s, k)$	Assets
h	$h > 0$	Human Capital
s	$s \in \{no, hi, co\}$	Education
η	$\eta \in \{\eta_l, \eta_h\}$	Persistent Productivity Shock
ε	$\varepsilon \in \{\varepsilon_1, \ldots, \varepsilon_n\}$	Transitory Productivity Shock

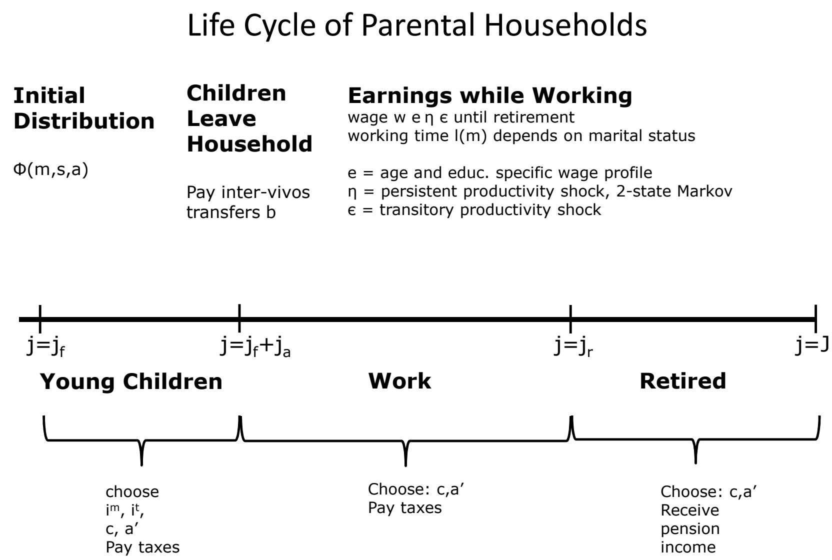
Notes: List of state variables of the economic model.

We assume that parents give birth to children at the age of j_f and denote the fertility rate of households by $\xi(m, s)$, which differs by marital status and education groups. Notice that $\xi(m, s)$ is also the number of children per household. There is no survival risk and all households live until age J and thus the cohort size within each generation is constant (and normalized to 1). We now describe in detail how life unfolds for parents, and then for children, as summarized in Figure 1 below.

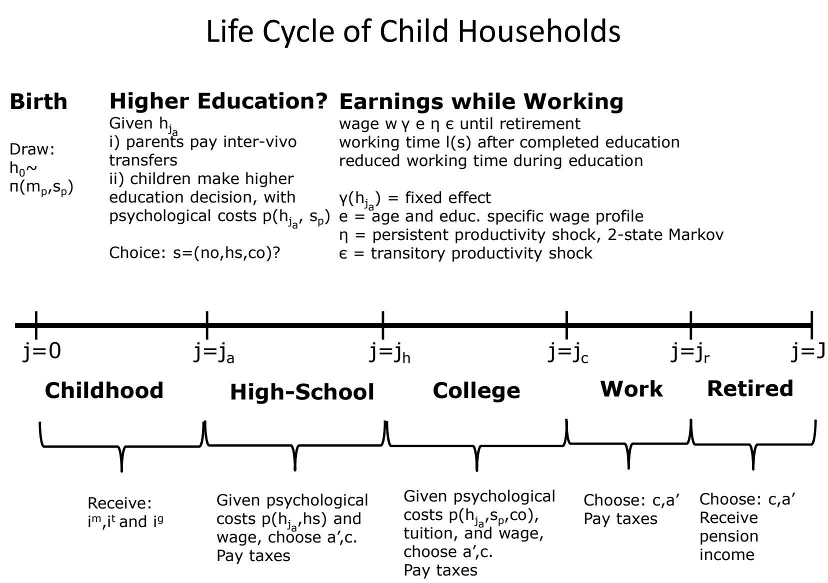
2.1.1 Life of the Parental Generation

Parental households become economically active at age j_f just before their children are born. They start their economic life in marital status m and with education level s, an initial idiosyncratic productivity state η and initial assets a. These initial states are exogenously given to

Figure 1: Life-Cycle of Child and Parental Households



(a)



(b)

the household, and drawn from the population distribution $\Phi(s, m, \eta, a)$ which will be informed directly by the data.

Parents then observe the innate ability (initial human capital) $h = h_0$ of their children which is drawn from an initial distribution $\Psi(h_0|s, m)$ that depends on parental education s and marital status m. Children live with their parents until age j_a (parental age $(j_f + j_a)$), at which point they leave the parental household to form their own household.

During the parental part of the life cycle in which children live with parents (parental age $j \in \{j_f, ..., j_f + j_a\}$), parents invest money i^m and time i^t into the accumulation of human capital h of their children, taking as given public investment into schooling i^g. As a result, the human capital of the child evolves according to

$$h' = g\left(j, h, i^m, i^t, i^g\right), \tag{1}$$

where g is a function of the child's age (to reflect differences in the relative weights of education inputs at different ages), and depends positively on the three inputs (parental time, parental resources and public education).

When children leave the household at parental age $j_f + j_a$, parents may transfer additional monetary resources as inter-vivos transfers b to their children. After this transfer parents and children separate and there are no further interactions between the two generations.

Throughout the work life parental households spend an exogenous amount of time $\ell(m) > 0$ on market work which differs by marital status. Labor productivity and thus individual wages are determined by an exogenous productivity profile $\epsilon(j, s, m)$ that depends on household age, education and marital status, as well as by a persistent stochastic shock η and a transitory stochastic shock ε. The persistent shock η follows a first-order Markov chain with state space $\{\eta_l, \eta_h\}$, transition matrix $\pi\left(\eta' \mid \eta\right)$ and initial distribution Π. Current labor income of parents with characteristics j, s, m is then given by

$$y = w \cdot \epsilon(j, s, m) \cdot \eta \cdot \varepsilon \cdot \ell(m). \tag{2}$$

Parents work until retirement at age j_r, when they receive earnings history dependent per period retirement benefits $b^p > 0$ and live until age J. In addition to making human capital investment decisions for their children when these are present in the household, parents in each period make a standard consumption-saving choice, where household asset choices are subject to a potentially binding borrowing constraint $a' \geq -\underline{a}(j, s, m, pa)$, which will be parameterized such that the model replicates well household debt at the age at which households have children j_f. The borrowing limit is assumed to decline linearly to zero over the life cycle towards the last period of work at age $j_r - 1$. Table 2 summarizes the choices of parents (and children, as described in the next subsection).

Table 2: Per Period Decision Variables

State Var.	Values	Decision Period	Interpretation
c	$c > 0$	$j \geq j_a$	Consumption
a'	$a' \geq -\underline{a}(j, s, k)$	$j \geq j_a$	Asset Accumulation
i^t	$i^t \geq 0$	$j \in \{j_f, ..., j_f + j_a\}$	Time Investments
i^m	$i^m \geq 0$	$j \in \{j_f, ..., j_f + j_a\}$	Monetary Investments
b	$b \geq 0$	$j = j_f + j_a$	Monetary Inter-vivos Transfer
s	$s \in \{no, hi, co\}$	$j = j_a$	(Higher) Education

Notes: List of decision variables of the economic model.

2.1.2 Life of the Children Generation

Children are born at age $j = 0$, but for the first $j_a - 1$ periods of their life do not make economic decisions. Their human capital during these periods evolves as the outcome of parental investment decisions (i^m, i^t) described above and governmental schooling input (i^g). At the beginning of age j_a, and based on both the level of human capital as well as the financial transfer b from their parents (which determines their initial wealth $a = b$), children make a discrete higher education decision $s \in \{no, hs, co\}$, where $s = no$ stands in for the choice not to complete high school, hs for high school completion, and co for college completion, respectively. For simplicity, children are stand-in bachelor households through their entire life-cycle.

Acquiring a high school or college degree comes at a psychological cost $p(s, s_p, h)$, which is decreasing in the child's acquired human capital h and also depends on parental education s_p. In addition, college education requires a monetary cost $\iota \geq 0$. Children may finance some of their college expenses by borrowing, subject to a credit limit given by $-\underline{a}(j, s, ch)$, which is zero for $s \in \{no, hs\}$, i.e. for individuals not going to college. As was the case for parents, this limit decreases linearly with age and converges to zero at the age of retirement j_r, requiring the children generation to pay off their student loans prior to their retirement.

Youngsters who decide not to complete high school, $s = no$, enter the labor market immediately at age $j_w(s = no) = j_a$. Those who decide to complete high school, but not to attend college, do so at age $j_w(s = hs) = j_h > j_a$. While at high school, $\{j_a, ..., j_h - 1\}$, they work part-time at wages of education group $s = no$. Youngsters who decide to attend college enter the labor market at $j_w(s = co) = j_c$ and also work part-time at wages of education group $s = no$ during their high-school and college years $\{j_a, j_c - 1\}$.

At time of labor market entry, $j_w(s)$, the acquired human capital of a worker is mapped into an idiosyncratic permanent productivity state $\gamma(s,h)$. When starting to work, children also draw stochastic persistent productivity η, which follows the same first-order Markov chain as for the parental generation, and stochastic transitory productivity $\varepsilon \sim \Psi(\varepsilon)$. Labor income of children during the working period is then given by

$$w \cdot \gamma(s,h) \cdot \epsilon(j,s,si) \cdot \eta \cdot \varepsilon \cdot \ell(si).$$

Since the children generation does not have any offspring of their own, the remaining decision problem of the child generation amounts to a simple life-cycle consumption-saving problem.

2.2 Decision Problems

Since we focus on a single parent and children generation, we can solve the model backward, starting from the dynamic programming problem of the children.

2.2.1 Children

The children generation makes their first meaningful economic decision at age j_a, when it leaves the parental household with the receipt of inter-vivos transfers, which constitute initial assets a, as well as with human capital h.

The Education Decision At age j_a, based on their initial asset position a, their acquired human capital h and the education of their parents s_p children make an education decision $s \in \{no, hs, co\}$. Children who decide to drop out of high school, $s = no$, realize after this decision their labor productivity through the fixed effect $\gamma(s = no, h)$, the stochastic persistent income shock η and the stochastic transitory income shock ε. Since these shocks only realize at labor market entry, the choice $s = no$-specific state variables prior to labor market entry are thus $(j_a, s = no; a, h)$ and the according value function is $V(j_a, s = no; a, h)$. Children who decide to continue in high school but to thereafter not attend college, $s = hs$, or who decide in addition to attend college after high-school completion, $s = co$, instead work during their education at a non-stochastic wage process. The problem of these children is thus fully deterministic and the decisions of these youngsters on $s \in \{hs, co\}$ are therefore also time consistent. During high school or college these children additionally experience utility (or psychological) costs that depend on the education of their parents, s_p. Therefore, the choice $s \in \{hs, co\}$-specific state variables are $(j_a, s \in \{hc, co\}, s_p; a, h)$ and the value functions are $V(j_a, s \in \{hs, co\}, s_p, ; a, h)$.

We thus obtain as post-education decision skill state

$$s = \begin{cases} no & \text{if } V(j_a, s=no; a,h) \geq \max\{V(j_a, s=hs, s_p; a,h), V(j_a, s=co, s_p; a,h)\} \\ hs & \text{if } V(j_a, s=hs, s_p; a,h) \geq \max\{V(j_a, s=no; a,h), V(j_a, s=co, s_p, a,h)\} \\ co & \text{if } V(j_a, s=co; s_p, a,h) \geq \max\{V(j_a, s=no; a,h), V(j_a, s=hs, s_p; a,h)\}, \end{cases} \tag{3}$$

where the education decision $s \in \{no, hs, co\}$ determines the children's permanent productivity in the labor market $\gamma(s,h)$. The pre-education decision value function is given as

$$V(j_a, s_p; a, h) = \max_{s \in \{no,hs,co\}} \{V(j_a, s=no; a,h), V(j_a, s=hs, s_p; a,h), V(j_a, s=co, s_p; a,h)\}. \tag{4}$$

In the computational implementation, we additionally apply Extreme Value Type I (Gumbel) distributed taste shocks to smooth the decision problem.[4] Accordingly, decisions for the three education alternatives are probabilistic and governed by the choice probabilities $\pi(j_a, s=no; a,h)$ and $\pi(j_a, s \in \{hs, co\}, s_p, a, h)$.

Choices During Working Life After having made the education decision $s \in \{no, hs, co\}$ which determines their permanent productivity in the labor market $\gamma(s,h)$ children who decided $s = no$ draw the stochastic components of their labor productivity, the persistent shock $\eta \sim \Pi(\eta)$ which then evolves according to the Markov transition matrix $\pi(\eta' \mid \eta)$ and the transitory shock $\varepsilon \sim \Psi(\varepsilon)$. The state variables of the newly formed household of type $s = no$ consequently are $(j, s=no, \eta, \varepsilon; a, h)$ and the continuation value functions $V(j, s=no, \eta, \varepsilon; a, h)$ are determined by a simple life-cycle consumption-saving problem during working ages $j \in \{j_a, ..., j_r - 1\}$

$$V(j, no, \eta, \varepsilon; a, h) = \max_{c,a'} \left\{ u(c) - v(\ell(si)) + \beta \sum_{\eta'} \pi(\eta' \mid \eta) \sum_{\varepsilon'} \psi(\varepsilon') V(j+1, no, \eta', \varepsilon'; a', h) \right\}$$

subject to

$$\begin{aligned} a' + c(1+\tau^c) &= a(1 + r(1-\tau^k)) + y(1-\tau^p) - T(y(1-0.5\tau^p)) \\ y &= w\gamma(no,h)\epsilon(no,j,si)\eta\varepsilon\ell(si) \\ a' &\geq 0 \end{aligned}$$

[4] Given this structure, the set of individuals exactly indifferent between two education choices is of measure zero and thus it is inconsequential how we break the indifference.

where the per period utility function $u(\cdot)$ with household consumption c as its argument satisfies standard properties. Since labor supply is exogenous, the disutility of work $v(\cdot)$ does not affect optimal choices of children, but impacts the child value functions which enter the parental transfer decision problem. In the budget constraint, recall that $\gamma(s,h)$ is permanent labor productivity which depends on acquired human capital and the chosen level of education $s = no$. The function $T(\cdot)$ represents a progressive labor income tax code and $(1-0.5\tau^p)y$ is taxable labor income, where τ^p is the social security contribution rate (and employer contributions to social security are non-taxable income). Accordingly, we can write the education-specific expected value function $V(j_a, s = no; a, h)$ in (3) as

$$V(j_a, s = no; a, h) = \sum_{\eta} \Pi(\eta) \sum_{\varepsilon} \Psi(\varepsilon) V(j_a, s = no, \eta, \varepsilon; a, h).$$

Children who continue in high school but do not attend or complete college, i.e., education group $s = hs$, may work during high school at a deterministic wage and draw after high-school completion stochastic labor productivity $\eta \sim \Pi(\eta)$, $\varepsilon \sim \Psi(\epsilon)$ and accordingly solve the following decision problem at age $j = j_a$

$$\begin{aligned} V(j_a, hs, s_p; a, h) = \max_{c,a'} \Big\{ & u(c) - v(\chi(hs)\ell(si)) - p(s, s_p, h) + \\ & \beta \sum_{\eta'} \Pi(\eta') \sum_{\varepsilon'} \psi(\varepsilon') V(j+1, hs, \eta', \varepsilon'; a', h) \Big\} \end{aligned}$$

subject to

$$\begin{aligned} a' + c(1+\tau^c) &= a(1 + r(1-\tau^k)) + y(1-\tau^p) - T(y(1-0.5\tau^p)) \\ y &= w\gamma(no, h)\epsilon(no, j, si)\chi(hs)\ell(si) \\ a' &\geq 0. \end{aligned}$$

That is, high-school students work for high-school dropout wages $w\gamma(no,h)$ for a fraction $\chi(hs)$ of their time $\ell(si)$. The term $p(s, s_p, h)$ represents a utility cost associated with attending high school which is decreasing in the amount of human capital h previously acquired by the student. They have to form expectations over their stochastic labor market productivity upon graduating in the subsequent period. Upon graduating, for their remaining working life-cycle $j \in \{j_h, ..., j_r - 1\}$ these individuals solve a dynamic problem analogous to the one of high-school dropouts described above, but with earnings process $w\gamma(hs,h)\epsilon(hs,j,si)\eta\varepsilon\ell(si)$.

Finally, children who decide, at age j_a, to attend (and by assumption, to complete) college have education indicator $s = co$, and solve, during ages $\{j_a, ..., j_{h-1}\}$ the same problem as group $s = hs$, with the modification that the continuation value differs at age j_{h-1} through the value function $V(j_h, co, s_p; a, h)$. For ages $j \in \{j_h, ..., j_c - 2\}$ they solve

$$V(j, co, s_p; a, h) = \max_{c,a'} \{u(c) - v(\chi(co)\ell(si)) - p(co, s_p, h) + \beta V(j+1, co, s_p; a', h)\}$$

subject to

$$\begin{aligned} a' + c(1+\tau^c) &= a(1 + r(1-\tau^k)) + y(1-\tau^p) - T(y(1-0.5\tau^p)) - \iota \\ y &= w\gamma(hs, h)\epsilon(hs, j, si)\chi(co)\ell(si) \\ a' &\geq -\underline{a}(j, co, ch). \end{aligned}$$

where ι is the per-period (net) tuition cost.

At age $j = j_c - 1$ their continuation value (but not their budget set) changes to reflect entry into the labor market in the subsequent period, taking expectations over the stochastic component of productivity η' and ε' next period:

$$V(j, s, s_p; a, h) = \max_{c,a'} \Big\{u(c) - v(\chi(co)\ell(si)) - p(s, s_p, h) + \\ \beta \sum_{\eta'} \Pi(\eta') \sum_{\varepsilon'} \psi(\varepsilon') \cdot V(j+1, co, \eta'; a', h)\Big\}.$$

For the remaining working phase of the life-cycle $j \in \{j_c, ..., j_r - 1\}$ these individuals solve a dynamic problem analogous to the one of high-school dropouts described above, but with earnings process $w\gamma(co, h)\epsilon(co, j, si)\eta\varepsilon\ell(si)$.

The Retirement Phase During retirement, at ages $\{j_r, ..., J\}$, all three education groups of the children generation solve a standard consumption-saving problem of the form:

$$V(j, s, \eta; a) = \max_{c,a'} \{u(c) + \beta V(j+1, s, \eta; a')\}$$

subject to

$$\begin{aligned} a' + c(1+\tau^c) &= a(1 + r(1-\tau^k)) + y - T(y) \\ y &= pen(s, si, \eta_{j_r-1}, h) \\ a' &\geq -0 \\ \eta &= \eta_{j_r-1}, \end{aligned}$$

where $pen(s, si, \eta_{j_r-1}, h)$ is retirement income, whose dependence on η_{j_r-1}, s and h serves to proxy for the progressive nature of the social security system.

2.2.2 Parents

Given the focus of the paper, we model parental households as becoming economically active at the beginning of age $j_f > j_a$ when they give birth to children. Parents are endowed with initial assets a, education s, an initial idiosyncratic productivity state η, an initial transitory income shock ε, and are distinguished by their marital status m. Children live with adult households until they form their own households as described above. Thus, for parental ages $\{j_f, ..., j_f + j_a - 1\}$ children are present in the parental household. Parents derive utility from per capita consumption of all household members and leisure. During the age bracket $\{j_f, j_f + j_a - 1\}$ they solve the dynamic problem

$$\begin{aligned} V(j, s, m, \eta, \varepsilon; a, h) = \max_{c, i^m, i^t, a', h'} \Bigg\{ & u\left(\frac{c}{1 + \zeta_c \xi(m, s) + \mathbf{1}_{m=ma}\zeta_a}\right) \\ & -v\left(\frac{\ell(m) + \kappa \cdot \xi(m, s) \cdot i^t}{1 + \mathbf{1}_{m=ma}}\right) + \beta \sum_{\eta'} \pi(\eta'|\eta) \sum_{\varepsilon'} \psi(\varepsilon') V(j, s, m, \eta', \varepsilon'; a', h') \Bigg\} \end{aligned}$$

subject to

$$\begin{aligned} a' + c(1 + \tau^c) + \xi(m, s) i^m &= a(1 + r(1 - \tau^k)) + y(1 - \tau^p) - T(y(1 - 0.5\tau^p)) \\ y &= w\epsilon(s, j, m)\eta\varepsilon\ell(m) \\ a' &\geq -\underline{a}(j, s, k) \\ h' &= g(j, h, i(i^m, i^t, i^g)) \end{aligned}$$

where h is the human capital of the number $\xi(m, s)$ of children in the household characterized by parental education s and marital status m. We express monetary investments i^m and time investments i^t on a per-child basis. Notice that the sum of hours worked and weighted time investment in children in the disutility function $v(\cdot)$ is divided by the number of working household members. Parameter κ is a weight on time investments into children, and reflects the possibility that reading to children carries a different disutility of time than answering emails at work.

At parental age $j_f + j_a$ children form own adult households and this is the only period in which parents can make inter-vivos transfers b. These transfers immediately (that is, within the period) become assets of their children, and thus generate utility for their parents.[5] The dynamic

[5] Note that since assets in the value function enter the budget constraint as being multiplied by the gross, after-tax interest rate $1 + r(1 - \tau^k)$, and since inter-vivos transfers are received in the same period in which

program then reads as

$$V(j_a+j_f,s,m,\eta;a,h)=\max_{c,b,a'}\left\{u\left(\frac{c}{1+\mathbf{1}_{m=ma}\zeta_a}\right)-v\left(\frac{\ell(m)}{1+\mathbf{1}_{m=ma}}\right)\right.$$
$$\left.+\beta\sum_{\eta'}\pi(\eta'|\eta)\sum_{\varepsilon'}\pi(\varepsilon')V(j_a+j_f+1,s,m,\eta',\varepsilon';a')+\nu V\left(j_a,s_p;\frac{b}{1+r(1-\tau^k)},h\right)\right\},$$

where $V\left(j_a,s_p;\frac{b}{1+r(1-\tau^k)},h\right)$ is the pre-education decision value function of their children, cf. equation (4). Maximization is subject to

$$\begin{aligned}a'+c(1+\tau^c)+\xi(m,s)b&=a(1+r(1-\tau^k))+y(1-\tau^p)-T(y(1-\tau^p))\\ y&=w\epsilon(s,j,m)\eta\varepsilon\ell(m)\\ a'&\geq 0.\end{aligned}$$

After children have left the household, the parent generation solves, at age $j\in\{j_a+j_f+1,...,j_r-1\}$

$$\begin{aligned}V(j,s,m,\eta,\varepsilon,a)=\max_{c,a'}&\left\{u\left(\frac{c}{1+\mathbf{1}_{m=ma}\zeta_a}\right)\right.\\ &\left.-v\left(\frac{\ell(m)}{1+\mathbf{1}_{m=ma}}\right)+\beta\sum_{\eta'}\pi(\eta'|\eta)\sum_{\varepsilon'}\psi(\varepsilon')V(j+1,s,m,\eta',\varepsilon',a')\right\}\end{aligned}$$

subject to

$$\begin{aligned}a'+c(1+\tau^c)&=a(1+r(1-\tau^k))+y(1-\tau^p)-T(y(1-\tau^p))\\ y&=w\epsilon(s,j,m)\eta\varepsilon\ell(m)\\ a'&\geq 0\end{aligned}$$

Finally, in retirement ages $j\in\{j_r,...,J\}$, all three education groups of parents solve a standard consumption-saving problem analogous to the one of the children generation described in the previous section.

they are made and thus do not accrue interest, these transfers b have to be divided by $1+r(1-\tau^k)$ in the Bellman equation of the parent.

2.3 Government

The government runs a pension system with a balanced budget. It also finances exogenous government spending, expressed as a share of aggregate output G/Y, and aggregate education subsidies (of pre-tertiary and tertiary education) through consumption taxes, capital income taxes and a progressive labor income tax code. In the initial scenario without the COVID-19 shock and the ensuing recession, the government budget clears by adjustment of the average labor income tax rate. In the thought experiments we hold all tax parameters constant, therefore implicitly assuming that the shortfalls or surpluses generated by a change in the environment are absorbed by government debt serviced by future generations.

2.4 Thought Experiment

We compute an initial stationary partial equilibrium with exogenous wages and returns prior to model period $t = 0$. In period $t = 0$, the COVID-19 shock unexpectedly occurs, and from that point on unfolds deterministically. That is, factor prices and fiscal policies are fixed, and households get surprised once by the shock, after which they have perfect foresight with respect to aggregate economic conditions. The COVID-19 crisis impacts the economy through two channels:

1. An education crisis: the government closes schools, represented in the model by a temporary (6 month) reduction in public investment i^g into child human capital production.

2. An aggregate income recession: a decline in parental incomes induced by an assumed decline of hours worked and an increase in the probability of drawing a low labor productivity $\pi(\eta' = \eta_l \mid \eta \in \{\eta_l, \eta_h\})$, which also increases the probability weight on η_l in the stationary invariant distribution $\Pi(\eta)$.

We then trace out the impact of these temporary shocks on parental human capital inputs (both time and money) and intergenerational transfer decisions, as well as on the education choices, future labor market outcomes, and welfare of the children generation, both in terms of its aggregates as well as in terms of its distribution. Since children differ by age at the time of the shock (as well as in terms of parental characteristics), so will the long-run impact on educational attainment, future wages, and welfare. We will place special emphasis on this heterogeneity.

3 Calibration

A subset of parameters is calibrated exogenously not using the model. These first stage parameters are summarized in Table 3. The second stage parameters are those that are calibrated endogenously by matching moments in the data and are summarized in Table 4. We next describe in detail our choice and sources of first stage parameters and the moments we match to calibrate the second stage parameters.

3.1 Data

In the first stage of calibration we use PSID data to estimate the deterministic age wage profiles and to construct the initial distribution of parents. Furthermore, we use NSLY79 data to estimate education-specific human capital gradients of the non-age related wage component. Finally, in the second stage of the calibration we use the Child Development Supplement (CDS) of the PSID, surveys I-III, to obtain empirical moments related to the child human capital and parental investments into children.

PSID. The initial distribution of parents by marital status, education, number of children and assets is constructed based on the four most recent PSID waves: 2011, 2013, 2015 and 2017. We use the PSID family files and keep only parents in the sample (i.e., only observations where children are present in the household). We keep only observations with positive hours and labor income of the household head. This leaves us with 7591 observations. Labor earnings and wealth are inflated to 2010 dollars using the CPI . Deterministic age wage profiles are estimated using a PSID sample from 1967 to 2013[6] based on observations from both households with and without children.

NLSY79. We use the NLSY79 dataset provided in the replication files of Abbott et al. (2019). Following their approach, we approximate adult human capital by the test scores taken from the Armed Forces Qualification Test AFQT89.

PSID CDS. To obtain child related statistics by parental characteristics, we merge the CDS data files with the PSID family files of the respective waves. As children of married couples, we consider children for whom both caregivers correspond to the household head and the spouse in a PSID household,[7] and for whom at least one of the caregivers is the biological parent. This leaves us with 4393 observations (2419 children) for the three waves of the survey.

[6] We thank Chris Busch for helping us with the data.
[7] In case of singles, only the household head is the primary caregiver.

Table 3: First Stage Calibration Parameters

Parameter	Interpretation	Value	Source (data/lit)
	Population		
$j=0$	Age at economic birth (age 4)	0	
j_a	Age at beginning of econ life (age 16)	6	
j_h	Age at finishing HS (age 18)	7	
j_c	Age at finishing CL (age 22)	9	
j_f	Fertility Age (age 32)	14	
j_r	Retirement Age (age 66)	31	
J	Max. Lifetime (age 80)	38	
$\xi(m,s)$	Fertility rates	see main text	PSID 2011-2017
$\Phi(j_f,m,s)$	Distribution of parents by martial status and education, age j_f	see main text	PSID 2011-2017
	Preferences		
θ	Relative risk aversion parameter	1	
φ	Curvature of labor disutility	0.5	
	Labor Productivity		
$\{\epsilon(j,s,m)\}$	Age Profile	see main text	PSID 1968-2012
$[\varepsilon_l,\varepsilon_h]$	Realizations of Transitory Shock	$[0.881, 1.119]$	PSID 1968-2012
$[\eta_l,\eta_h]$	States of Markov process	[0.8226, 1.1774]	PSID 1968-2012
π_{hl}	Transition probability of Markov process	0.0431	PSID 1968-2012
$\pi^r_{hl}(s)$	Transition probability of Markov process after lockdown	[0.0493,0.0486,0.0456]	see main text
$\pi^r_{ll}(s)$	Transition probability of Markov process after lockdown	[0.9630,0.9624,0.9594]	see main text
χ^s	Hours worked for students, as a fraction of full time (HS and CL)	$\{0.2, 0.5\}$	see main text
$\gamma(s,h)$	Ability gradient of earnings	see main text	NLSY79
	Endowments		
r	(Annual) interest rate	4.0%	Siegel (2002)
$l(m)$	Average hours worked by marital status (annual)	$\{1868, 3810\}$	PSID 2011-2017
$\Phi(a\|j_f,m,s)$	Asset distr-n of parents by martial status and education, age j_f	see main text	PSID 2011-2017
$\underline{a}(j_f,m,s,pa)$	Borrowing limit for parents at age j_f	see main text	PSID 2011-2017
$rp(m=si,s,pa)$	Education-specific repayment amount for parents: singles	see section 3.5.4	$\{0.006, 0.083, 0.151\}$
$rp(m=ma,s,pa)$	Education-specific repayment amount for parents: couples	see section 3.5.4	$\{0.048, 0.129, 0.110\}$
	Ability/Human Capital and Education		
ι	College tuition costs (annual, net of grans and subsidies)	14756$	Krueger and Ludwig (2016)
$\underline{a}(j\in[j_h,j_c-1],co,ch)$	College borrowing limit	45000$	Krueger and Ludwig (2016)
$rp(ch)$	Repayment amount for children who choose college	0.049	see section 3.8
σ^h	Elast of subst b/w human capital and CES inv. aggr.	1	Cunha et al. (2010)
σ^g	Elast of subst b/w public inv. and CES aggr. of private inv.	2.43	Kotera and Seshadri (2017)
σ^m	Elast of subst b/w monetary and time inv.	1	Lee and Seshadri (2019)
κ^m_3	CES share parameter of monetary and time inv. (age bin 6-8)	0.5	normalization
$\kappa^g_j=\bar{\kappa}^g, j>0$	Share of government input for ages 6 and older	0.676	Kotera and Seshadri (2017)
$\Phi(h(j=0)\|s_p,y_p,a_p)$	Innate ability dist-n of children by parental char-s	see main text	PSID CDS I
$\underline{h}_0$	Normalization parameter of initial dist-n of initial ability	0.1248	PSID CDS I-III
	Government policy		
ξ	Public CL education subsidy	38.8%	Krueger and Ludwig (2016)
i^g_j	Public early education spending by age	$\approx 5000$$	UNESCO (1999-2005)
τ_c	Consumption Tax Rate	5.0%	legislation
$\tilde{\tau}_k$	Capital Income Tax Rate	20%	legislation
τ^p	Soc Sec Payroll Tax	12.4%	legislation
G/Y	Government consumption to GDP	13.8%	current value

Notes: First stage parameters calibrated exogenously by reference to other studies and data.

Table 4: Second Stage Calibration Parameters

Parameter	Interpretation	Value
	Preferences	
β	Time discount rate (target: asset to income ratio, age 25-60)	0.9808
ν	Altruism parameter (target: average IVT transfer per child)	0.8380
	Labor Productivity	
$\rho_0(s)$	Normalization parameter (target: $\mathbb{E}\gamma(s,h)=1$)	$[0.1890, 0.0034, -0.2015]$
	Human Capital and Education	
κ	Utility weight on time inv. (target: average time inv.)	0.7310
κ_j^h	Share of human capital (target: average monetary inv. & slope of time inv.)	cf. Figure 2
κ_j^m	Share of monetary input (target: slope of money inv.)	cf. Figure 2
κ_0^g	Share of government input for age bin 4-6 (target: average time inv. age bin 4-6)	0.4437
$\bar{A}$	Investment scale parameter (target: average HK at age j_a)	1.1989
$\tilde{A}$	Investment scale parameter in HS (target: average HK at age j_{a+1})	1.0739
ϕ	psychological costs $s=hs$ (target: fraction of group $s=hs$)	0.0561
$\tilde{\varrho}(s^p=no)=\tilde{\varrho}(s^p=hs)$	psychological costs $s=co, s^p=no \wedge s^p=hs$ (target: fraction of group $s=co$)	1.2120
$\tilde{\varrho}(s^p=co)$	psychological costs $s=co, s^p=co$ (target: conditional fraction of group $s=co$)	0.1707
	Government policy	
λ	Level parameter of HSV tax function (balance gvt budget)	0.8880
ρ^p	Pension replacement rate (balance socsec budget)	0.1893

Notes: Second stage parameters calibrated endogenously by targeting selected data moments.

3.2 Age Brackets

The model is calibrated at a biannual frequency. We initialize the parental economic life-cycle when their children are of age 4, which is model age $j=0$. The reason for this initialization age is the calibration of the initial human capital endowment $h(j=0)$, which is informed by data on test score measures at child biological ages 3 to 5, as described below. Thus, children are irrelevant to the economic model for the first 3 years of their biological lives. Parental age at the economic "birth" of children is $j_f=14$, which we also refer to as "fertility" age. This corresponds to a biological age of 32, when children are of biological age 4.[8] Children make the higher eduction decision at biological age 16, model age $j_a=6$. Children who complete high school stay in school for one additional model period, thus high school is completed at $j_h=7$. Children who attend college stay in college for two model periods, thus college is completed at $j_c=9$. Retirement is at the exogenous age $j_r=31$, corresponding to biological age 66. Households live at most with certainty until age $J=38$, biological age 80.

[8] Thus, children are biologically born at parental age 28.

3.3 Prices

We normalize wages to $w = 1$ and directly parameterize the income process. The interest rate is set to an annual rate of 4% based on Siegel (2002).

3.4 Preferences

The per period subutility function $u(x)$ is of the standard iso-elastic power form

$$u(x) = \frac{1}{1-\theta}\left(x^{1-\theta} - 1\right).$$

We set $\theta = 1$ (logarithmic utility), and consequently child and adult equivalence scale parameters are irrelevant for the problem. In the parental household's problem, the per period subutility function $v(x)$ is

$$v(x) = x^{1+\frac{1}{\varphi}}$$

so that if $x = \ell$, parameter φ can be interpreted as a Frisch elasticity of labor supply. In our model of exogenous labor supply this interpretation of course seizes to be relevant, but it provides us with a direct way of calibrating the power term of the utility function. We set $\varphi = 0.5$ based on standard estimates of the Frisch elasticity.

When children live in the parental household, we have $x = \frac{\ell(m)+\kappa\cdot\xi(m,s)\cdot i^t}{1+\mathbf{1}_{m=ma}}$. $\ell(m)$ are hours worked by marital status, which we estimate from the data, giving annual hours of $\ell(si) = 1868$ and $\ell(ma) = 3810$. The time cost parameter κ is calibrated to match average time investments by parents into the education of children, giving $\kappa = 0.74$ (with further details described below as part of the calibration of the human capital technology).

When children attend high school or college, they experience psychological costs for $s \in \{hs, co\}$ according to the cost function

$$p(s, s^p; h) = \phi(1 + \varrho(s^p)\mathbf{1}_{j\in[h_h,j_c-1]}\mathbf{1}_{s=co}) + \frac{1}{h}$$

and thus psychological costs (or utility costs) of obtaining a high-school degree are equal to $\phi + \frac{1}{h}$, irrespective of parental education, and are thus monotonically decreasing and convex in the acquired human capital h. Psychological costs for obtaining a college degree depend on parental education and are equal to, $\tilde{\varrho}(s^p) + \frac{1}{h} \equiv \phi(1 + \varrho(s^p)) + \frac{1}{h}$. If children choose to drop out of high school, psychological costs are zero.

We calibrate the parameters of the cost function to match education shares in the data for the three groups $s \in \{no, hs, co\}$. We measure these shares for adults older than age 22—which is the labor market entry age of all education groups in the model—and younger than age 38 based on the PSID waves 2011, 2013, 2015 and 2017.[9] Parameter ϕ is calibrated to match the fraction of children without a high school degree of 12.16%, giving $\phi = 0.06$. With regard to the additional utility costs during the college period we restrict $\tilde{\varrho}(no) = \tilde{\varrho}(hs)$ and calibrate it to match the fraction of children with a college degree of 33.21% giving $\tilde{\varrho}(no) = \tilde{\varrho}(hs) = 1.21$. Finally, parameter $\tilde{\varrho}(s^p = co)$ is calibrated to match the fraction of children in college conditional on parents having a college degree of 63.3%, cf. Krueger and Ludwig (2016), giving $\tilde{\varrho}(co) = 0.17$.

Households discount utility at rate β. We follow Busch and Ludwig (2020) and calibrate it to match the assets to income ratio in the PSID for ages 25 to 60 giving an annual discount factor of $\beta = 0.98$.

Utility of future generations is additionally discounted at rate ν. Parameter ν is chosen so that average per child inter-vivoss transfer is ca. 61,200$, as implied by the Rosters and Transfers supplement to the PSID (based on monetary transfers from parents to children until age 26, see Daruich (2020)). This gives $\nu = 0.84$.

3.5 Initial Distribution of Parents

For the initial distributions of parents at the fertility age, we restrict the sample to parents aged 25-35, leaving us with 3,024 observations.[10]

3.5.1 Marital Status

Marital status is measured by the legal status of parents. This gives a share of singles of 51.7% and a share of married households of 48.3%.

3.5.2 Education Categories

We group the data by years of education of household heads older than age 22. Less than high school, $s = no$, is for less than 12 years of formal education. High school completion (but no college) is for more than 12 but less than 16 years of education. College is at least 16 years of education. The population shares of parents in the three education categories by their marital status are summarized in Table 5.[11]

[9] Observe that we do not impose that children have the same education shares as parents.

[10] For education, which is not changing much with age, we keep parents aged 22 or above.

[11] The educational distribution is consistent with many other studies based on the PSID, cf., e.g., Heathcote et al. (2010).

Table 5: Fraction of Households by Education for each Marital Status

Education s/Marital Status m	si	ma
no	0.2194	0.1621
hs	0.6064	0.5577
co	0.1742	0.2802

Notes: Fraction with education $s \in \{no, hs, co\}$ by marital status.

3.5.3 Demographics

The number of children by marital status and education of parents $\xi(m,s)$ is computed as the average number of children living in households with household heads aged 25-35. It is summarized in Table 6.

Table 6: Number of Children by Marital Status and Education

Education s/Marital Status m	si	ma
no	2.36	2.33
hs	1.86	2.15
co	1.77	1.96

Notes: Number of children by marital status and education.

3.5.4 Assets

Conditional on the initial distribution of parents by marital status and education, we measure the distribution of assets according to asset quintiles, which gives the initial distribution $\Phi(a \mid j_f, m, s)$. We set the borrowing constraint of parents as follows. First, we calculate average assets (debt) of the lowest asset quintile at age j_f from the data and set it equal to $\underline{a}(j_f, m, s, pa)$, the initial debt of parents in the lowest asset quintile in the model. The result is summarized in Table 7.

For all ages $j > j_f$ we then compute the borrowing limit recursively as:

$$\underline{a}(j, m, s, pa) = \underline{a}(j-1, m, s, pa)(1+r) - rp(m, s, pa) \tag{5}$$

where $rp(m, s, pa)$ is chosen such that the terminal condition $\underline{a}(j_r, m, s, pa) = 0$ is met.

Table 7: Lower Asset Limit by Marital Status and Education

Education s | Marital Status m	si	ma
no	-2,380	-18,931
hs	-33,065	-51,332
co	-60,037	-43,629

Notes: Lower asset limit for parents at model age j_f, by marital status and education, expressed in 2010 dollars.

3.5.5 Income

We draw initial income shocks assuming independence of the asset position according to the stationary invariant distribution of the 2-state Markov process, thus $\Pi(\eta_h) = 0.5$.

3.6 Productivity

We use PSID data to regress by education of the household head log wages measured at the household level on a cubic in age of the household head, time dummies, family size, a dummy for marital status, and person fixed effects. Predicting the age polynomial (and shifting it by marital status) gives our estimates of $\epsilon(m, s, j)$. We next compute log residuals and estimate moments of the earnings process by GMM and pool those across education categories and marital status.[12] We assume a standard process of the log residuals according to a permanent and transitory shock specification, i.e., we decompose log residual wages $\ln(\mathrm{y}_t)$ as

$$\ln(\mathrm{y}_t) = \ln(\mathrm{z_t}) + \ln(\varepsilon_t)$$
$$\ln(\mathrm{z_t}) = \rho \ln(\mathrm{z_{t-1}}) + \ln(\nu_t)$$

where $\varepsilon_t \sim_{i.i.d} \mathcal{D}_\varepsilon(0, \sigma_\varepsilon^2)$, $\nu_t \sim_{i.i.d} \mathcal{D}_\nu(0, \sigma_\nu^2)$ for density functions $\mathcal{D}$, and estimate this process pooled across education and marital status. To approximate the persistent component in our model, we translate it into a 2-state Markov process targeting the conditional variance of $\mathrm{z_t}$, conditional on $\mathrm{z_{t-2}}$, $(1+\rho^2)\sigma_\nu^2$ (accounting for the two year frequency of the model). The transitory component is in turn approximated in the model by two realizations with equal probability with the spread chosen to match the respective variance σ_ε^2. The estimates and the moments of the approximation are reported in Table 8.

We set the fraction of time working during high school to $\chi(hs) = 0.2$, which can be interpreted as a maximum time of work of one day of a regular work week. In college, students may work for longer hours and we accordingly set $\chi(co) = 0.5$.

[12] We thank Zhao Jin for sharing her code with us.

Table 8: Stochastic Wage Process

	Estimates			Markov Chain		Transitory Shock
Parameter	ρ	σ_ν^2	σ_ε^2	$\pi_{hh} = \pi_{ll}$	$[\eta_l, \eta_h]$	$[\varepsilon_l, \varepsilon_h]$
Estimate	0.9559	0.0168	0.0566	0.9569	$[0.8226, 1.1774]$	$[0.881, 1.119]$

Notes: Estimated moments of residual log wage process.

The mapping of acquired human capital into earnings according to $\gamma(s,h)$ is based on Abbott et al. (2019). We use their data—the NLSY79, which includes both wages and test scores of the Armed Forces Qualification Test (AFQT)—to measure residual wages $\omega(s)$ of education group s (after controlling for an education specific age polynomial) and run the regression

$$\ln(\omega(s)) = \rho_1(s) \cdot \ln\left(\frac{e}{\bar{e}}\right) + v(s),$$

where $v(s)$ is an education group specific error term and $\bar{e}$ are average test scores. We denote the education group specific coefficient estimate by $\hat{\rho}_1(s)$, see Table 9. The estimated ability gradient is increasing in education reflecting complementarity between ability and education. In the model, we correspondingly let

$$\ln(\gamma(s,h)) = \rho_0(s) + \hat{\rho}_1(s) \cdot \ln\left(\frac{h}{\bar{h}}\right),$$

where $\bar{h}$ is average acquired human capital at $j = j_a$ (biological age 16) and $\rho_0(s)$ is an education group s specific normalization parameter, chosen such that

$$\int \exp\left(\rho_0(s) + \hat{\rho}_1(s) \cdot \ln\left(\frac{h}{\bar{h}}\right)\right) \Phi(dh, s) = 1.$$

The normalization—which gives $\rho_0(s) = 0.19, 0.00, -0.20$, for $s \in \{no, hs, co\}$, respectively—implies that the average education premia are all reflected in $\epsilon(s, j, ma)$, which in turn are directly estimated on PSID data.

3.7 Human Capital Production Function

At birth at age $j = 0$, children draw their innate ability (initial human capital) $h = h_0$ conditional on the distribution of parents by parental characteristics s_p, m_p, thus $h_0 \sim \Psi(h(j=0) \mid s_p, m_p)$. We calibrate the distribution from the Letter Word test score distribution in the PSID Child Development Supplement (CDS) surveys I-III, and match it to parental characteristics by merging the survey waves with the PSID. Table 10 reports the joint distribution of average test scores

Table 9: Ability Gradient by Education Level

Education Level	Ability Gradient
HS-	0.351 (0.0407)
(HS & CL-)	0.564 (0.0233)
(CL & CL+)	0.793 (0.0731)

Notes: Estimated ability gradient $\hat{\rho}_1(s)$, using NLSY79 as provided in replication files for Abbott et al. (2019). Standard errors in parentheses.

of the children by parental education and marital status. We use this test score distribution as a proxy for the initial human capital distribution of children conditional on parental education and marital status.[13] We base the calibration of the initial ability distribution of children on this data by drawing six different types of children depending on the combination of marital status (2) and parental education (3). Children's initial human capital is normalized as the test score of that m^p, s^p-group relative to the average test score. We further scale the resulting number by the calibration parameter $\bar{h}_0$ and, thus, initial human capital of the children is a multiple of $\bar{h}_0$. Parameter $\bar{h}_0$ is calibrated exogenously to match the ratio of mean test scores at ages 3-5 to mean test scores at ages 16-17, which gives $\bar{h}_0 = 0.125$. Initial abilities relative to average abilities and the corresponding multiples of $\bar{h}_0$ for the six types are contained in Table 10.

Table 10: Initial Ability by Parental Education

Marital Status and Educ of HH Head	Avg. Score	Fraction of $\bar{h}_0$
Single Low	35	0.843
Single Medium	38	0.906
Single High	46	1.107
Married Low	39	0.945
Married Medium	41	0.984
Married High	45	1.085

Notes: Estimated initial ability of children as measured by the letter word test in the Child Development Supplement Surveys 1-3 (years 1997, 2002, 2007) of the PSID.

At ages $j_0, \ldots, j_a - 1$ children receive parents' education investments through money and time $i^m(j), i^t(j)$ and governmental time investments i^g, respectively. Education investments of the government are certain, known by parents, and equal across children. Human capital is

[13] Importantly, by correlating the test score distribution with these parental characteristics, we do not pose a causal link between parental education and children's characteristics. The test scores just give us a convenient way to proxy the initial joint distribution.

acquired given a multi-layer human capital production function

$$h'(j) = \left(\kappa_j^h h^{1-\frac{1}{\sigma^h}} + (1-\kappa_j^h) i(j)^{1-\frac{1}{\sigma^h}}\right)^{\frac{1}{1-\frac{1}{\sigma^h}}} \tag{6a}$$

$$i(j) = \bar{A}\left(\kappa_j^g \left(\frac{i^g}{\bar{i}^g}\right)^{1-\frac{1}{\sigma^g}} + (1-\kappa_j^g)\left(\frac{i^p(j)}{\bar{i}^p}\right)^{1-\frac{1}{\sigma^g}}\right)^{\frac{1}{1-\frac{1}{\sigma^g}}} \tag{6b}$$

$$i^p(j) = \left(\kappa_j^m \left(\frac{i^m(j)}{\bar{i}^{m,d}}\right)^{1-\frac{1}{\sigma^m}} + (1-\kappa_j^m)\left(\frac{i^t(j)}{\bar{i}^{t,d}}\right)^{1-\frac{1}{\sigma^m}}\right)^{\frac{1}{1-\frac{1}{\sigma^m}}}, \tag{6c}$$

which partially features age dependent parameters for calibration purposes. We also divide the exogenous investments by the government i^g and the endogenous age dependent per child monetary and time investments by the parents $i^m(j), i^t(j)$, as well as the CES aggregate of these (normalized) investments, $i^p(j)$, by their respective unconditional means through which we achieve unit independence.

The outermost nest (first nest) augments human capital and total investments according to a CES aggregate with age-specific parameter κ_j^h and age-independent substitution elasticity σ^h. We set $\sigma^h = 1$,[14] and calibrate κ_j^h to match (per child) time investments by age of the child. We model age dependency as

$$\ln\left(\frac{1-\kappa_j^h}{\kappa_j^h}\right) = \alpha_0^{\kappa^h} + \alpha_1^{\kappa^h} \cdot j + \alpha_1^{\kappa^h} \cdot j^2 \tag{7}$$

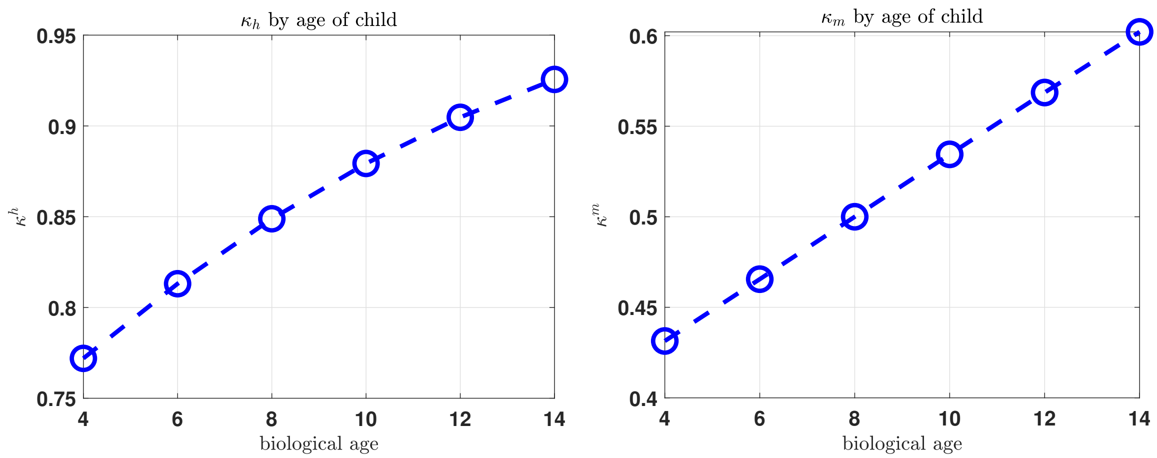
and determine $\alpha_1^{\kappa^h}, \alpha_2^{\kappa^h}$ by an indirect inference approach such that the age pattern of log per child time investments in the data equals the pattern in the model for biological ages 6 to 14 of the child. Recall that we in turn match the average level of time investments at biological ages 6 to 14 by calibrating the utility cost parameter κ. Time investments at biological age 4 are matched differently, with details described below. The intercept term $\alpha_0^{\kappa^h}$ is calibrated to match average monetary investments. Panel (a) of Figure 2 displays the resulting age profile. Consistent with Cunha et al. (2010), we find that the weight on acquired human capital at age j is increasing in j, so that investments become less important in the course of the life-cycle. While our model is not directly comparable to their empirical analysis,[15] also the magnitude of κ_j^h is similar.

In the second nest, division of time investments by the government through its mean implies that in the initial equilibrium $\frac{i^g}{\bar{i}^g} = 1$. We restrict $\kappa_j^g = \bar{\kappa}^g$ for $j > 0$ and calibrate it

[14] That is approximately the mean value of the parameter for young and old children in Cunha et al. (2010)

[15] Total Investments in our model in the first nest include government investments from the second nest, and we do not distinguish explicitly between cognitive and non-cognitive skills.

Figure 2: Age Dependent Parameters κ_j^h, κ_j^m over Child Age



(a) Weight κ_j^h

(b) Weight κ_j^m

Notes: Age-specific weight parameters κ_j^h and κ_j^m calibrated endogenously to match time and money investment profiles.

exogenously according to the estimates for the US by Kotera and Seshadri (2017)—who estimate the parameters of a CES nesting of private and public education investments similar to ours—giving $\bar{\kappa}^g = 0.676$.

At biological age 4 of the child, children are still in kindergarten. To take into account this structural break in the process of education according to the institutional setting, we separately calibrate κ_0^g to match the average time investments by parents into their children at biological age 4 of the child. This gives $\kappa_0^g = 0.44$.

The calibration of the substitution elasticity σ^g is again by reference to Kotera and Seshadri (2017) who estimate an elasticity of substitution between private and government investment of $\sigma^g = 2.43$. Thus, parental and government investments are gross substitutes but substitution across these education inputs is far from perfect.

$\bar{A}$ is a computational normalization parameter which we choose such that average acquired human capital is equal to 1, sufficiently below the maximum human capital gridpoint, giving $\bar{A} = 1.20$.

The third nest augments the endogenous age specific per child monetary and time investments. As in Lee and Seshadri (2019) we restrict $\sigma^m = 1$. The age dependency of κ_j^m is specified as

$$\ln\left(\frac{1-\kappa_j^m}{\kappa_j^m}\right) = \alpha_0^{\kappa^m} + \alpha_1^{\kappa^m} \cdot j.$$

We calibrate $\alpha_0^{\kappa^m}$ to achieve the normalization $\kappa_3^m = 0.5$, and $\alpha_1^{\kappa^m}$ is calibrated to match the monetary investment profile, which is relatively flat in the data. The resulting age profile of κ_j^m is displayed in Panel (b) of Figure 2.

At age j_a the human capital process is extended to the high school period (i.e., for all children with education $s = hs$ and $s = co$). Time and monetary investments by parents in this phase of the life-cycle are zero, because children have already left the parental household and the human capital production function at $j = j_a, s \in \{hs, co\}$ is

$$h'(j) = \tilde{A}\left(\kappa_6^h h^{1-\frac{1}{\sigma^h}} + (1-\kappa_6^h)\left(\frac{i^g}{\bar{i}^g}\right)^{1-\frac{1}{\sigma^h}}\right)^{\frac{1}{1-\frac{1}{\sigma^h}}}. \tag{8}$$

We compute κ_6^h as a predicted value from the above described regression in (7) and calibrate the additional scaling parameter $\tilde{A}$ such that the ratio of average human capital at $j = 6$ (biological age 16) to average human capital at age $j = 5$ is equal to the ratio of test scores of ages $16 - 17$ to age $14 - 15$ of 1.05. This gives $\tilde{A} = 1.07$.

The production function in (8) is an approximation as it ignores parental inputs entirely,[16] reflecting that parental inputs may not be that effective at that age. The specification also ignores that children may invest into the human capital formation themselves, which may be of particular relevance for our main experiment of school closures. We thus regard our model of biological age 16 children as a crude approximation and will accordingly not put a key emphasis on those children when discussing our results. However, it is important for parental decisions at younger child ages that parents do foresee that the human capital process for age 16 children continues when children have left the household, which is our main motivation for extending the human capital accumulation process beyond that age.

3.8 College Tuition Costs & Borrowing Constraint of Children

We base the calibration of college tuition costs and borrowing constraints for college youngsters on Krueger and Ludwig (2016). The net price ι (tuition, fees, room and board net of grants and education subsidies) for one year of college in constant 2005 dollars is 13,213\$. In 2008 dollars, the maximum amount of publicly provided students loans per year is given by $11,250\$$, which is the children's borrowing limit in the model for $s = co$ and $j \in [j_h, j_c - 1]$. For all ages $j \geq j_c$ we let

$$\underline{a}(j, co, ch) = \underline{a}(j-1, co, ch)(1+r) - rp(ch)$$

[16] It would not be possible in our setup to model parental inputs at that age because children have already left the household.

and compute rp such that the terminal condition $\underline{a}(j_r, co, ch) = 0$ is met.

3.9 Government

The government side features the budget of the general tax and transfer system and a separate budget of the pension system. In the general budget the revenue side is represented by consumption, capital income and labor income taxes. The consumption tax rate is set to $\tau_c = 5\%$ based on Mendoza et al. (1994), and the capital income tax rate to $\tilde{\tau}_k = 20\%$, which is the current statutory capital income tax rate on long-term capital gains (assets held longer than a year) for households in the highest income tax bracket.

The labor income tax code is approximated by the following two-parameter function, as in, e.g., Benabou (2002) and Heathcote et al. (2017):

$$T(y) = y - \lambda y^{1-\tau},$$

where τ is the progressivity parameter and λ determines the average tax rate. We set $\tau = 0.18$ as suggested by estimates of Heathcote et al. (2017) and calibrate λ endogenously to close the government budget, giving $\lambda = 0.89$.

Exogenous government spending (net of spending on education) is set to $G/Y\% = 13.8\%$. In addition, the government spends on schooling for children and pays the college subsidy for college students. The former we approximate as $5000\$$ per pupil based on UNESCO (1999-2005) data, as for example in Holter (2015). The latter is set to 38.8% of average gross tuition costs, as in Krueger and Ludwig (2016). Assuming, as in Krueger and Ludwig (2016), that the difference between net and gross tuition costs is due to both a public and a private subsidy with the latter not being explicitly modelled in our setup[17] gives an average public subsidy of $\$6,119$ per student.

As for the pension system, the payroll tax τ^p is set to the current legislative level of 12.4% and the pension benefit level relating average pension benefits to average net wages is endogenously chosen such that the benefits of the parent generation equal their contributions, giving a replacement benefit level of $\rho^p = 0.19$.

3.10 Calibrating the Pandemic Induced Recession

The calibration of the average income loss for parental households during the lockdown is based on the aggregate output drop in the US in year 2020, which we measure by relating the quarterly changes of GDP per capita based on data of the Bureau of Labor Statistics to quarter 4/2019.[18]

[17] The private subsidy is set to 16.6% of average gross tuition costs as in Krueger and Ludwig (2016).

[18] We assume a population growth rate of 0.25%, which is half of the population growth rate of 2018 to 2019.

This gives a drop of -4.57% on an annual basis, thus -2.285% in our biannual model.[19] We also measure from the data provided by the Bureau of Labor Statistics a drop of total hours worked per capita in the population relative to quarter 4/2019 of 6.41%, which translates to a drop by 3.205% in our biannual model.[20] Assuming a labor share in aggregate production of two thirds, this implies that $\frac{0.66 \cdot 6.41}{4.57} \cdot 100\% = 92.68\%$ of the aggregate income reduction is due to the drop in hours and 7.32% is due to a drop in productivity. This productivity reduction is calibrated by assuming a one-time percent increase of the probabilities of remaining in the low income state, respectively of transiting from the high to low the income state, in our two stage approximation of the Markov process, π_{ll} and π_{hl}. In turn, the hours drop is calibrated by reducing hours worked of those households who have low labor productivity, $\eta = \eta_l$, during the recession, assuming full recovery of hours in the next period.

To also take into account the heterogenous distribution of this reduction of hours and productivity across education groups we resort to Mahnken (2020), who reports that the unemployment rate of workers with education of less than high school ($s = no$) increased by 14.4 percentage points, for workers with a high school degree but less than college ($s = hs$) it increased by 12.9 percentage points, and for workers with a college degree ($s = co$) only by 5.9 percentage points.[21] We approximate this in our income shock calibration in terms of relative losses of hours and productivity by factor $14.4/5.9 = 2.44$ for education group $s = no$ and by factor $12.9/5.9 = 2.18$ for education group $s = hs$. To account for this heterogeneity across education groups we specify the absolute change of the transition probabilities of the Markov process in the period of the lockdown as education specific and calibrate $\pi^r_{il}(s) = \pi^r(\eta' = \eta_l \mid \eta = \eta_i, s)$, for $i \in \{l, h\}$ where superscript r stands in for $r$ecession, to match the share of 8% of the aggregate income decline and its distribution. For $i \in \{h, l\}$ we accordingly let

$$
\begin{aligned}
\pi^r_{il}(s = co) &= \pi_{il} + \Delta\pi \\
\pi^r_{il}(s = hs) &= \pi_{il} + 2.18 \cdot \Delta\pi \\
\pi^r_{il}(s = no) &= \pi_{il} + 2.44 \cdot \Delta\pi
\end{aligned}
$$

and calibrate $\Delta\pi$ to match the average income per capita reduction of 4.57% taking as given the contribution of aggregate hours per capita reduction (and its distribution) of $0.66 \cdot 6.41\% = 4.23\%$. This gives $\Delta\pi = 0.0025$ implying that $\pi^r_{hl}(s = co) = 0.0456$, $\pi^r_{hl}(s = hs) = 0.0486$ and $\pi^r_{hl}(s =$

[19]Notice that relative to the assumed rate of technological progress of 1.5% annually, by which we deflate the annual interest rate (see above) the total annual drop of per capita GDP relative to trend growth according to our calibration is thus approximately 6.1%, which still ignores population growth.

[20]This corresponds with the survey evidence of Bick and Blandin (2020).

[21]See the figure entitled “Unemployment Rate by Educational Attainment (seasonally adjusted)” from which one can read off these exact numbers.

$no) = 0.0493$, and $\pi^r_{ll}(s = co) = 0.9594$, $\pi^r_{ll}(s = hs) = 0.9624$, and $\pi^r_{ll}(s = no) = 0.9630$. Likewise, we distribute the aggregate hours reduction of 3.205% across the education groups who experience low productivity, $\eta = \eta_l$, in the period of the recession.

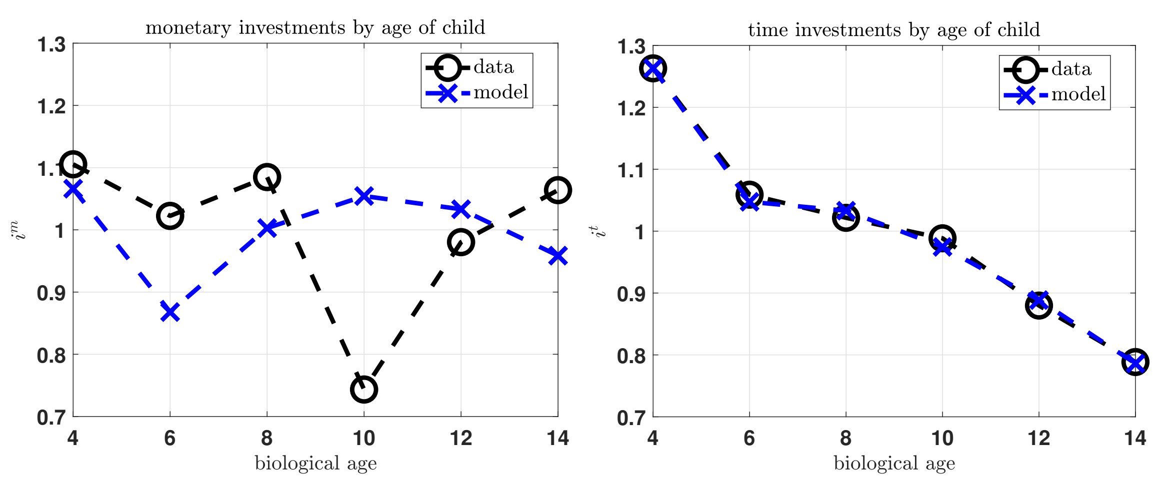
3.11 Evaluating Non-targeted Predictions of the Model

3.11.1 Time and Resource Investments

Figure 3 shows average time and monetary investments in the model and the data by the age of the child. The good match of the model of time investments in Panel (b) is a consequence of calibration since this is a targeted profile through age dependent parameter κ^h_j and parameter κ^g_0. Monetary investments in Panel (a) are slightly downward sloping in the data, and we match the lower slope of monetary investments compared to time investments through the age dependency of κ^m_j.

Figure 4 shows the analogous output by parental education levels, all of which are not targeted in the calibration. The model matches well the positive slope of both types of investment in parental education. Since income and initial wealth of a household is increasing in the household's education it is perhaps not surprising that more highly educated parents invest significantly more resources in each child, especially since these households have fewer children. The same observation (number of children decreasing in household education) is also responsible for the mildly increasing per-child time investment by parental education (see right panel of Figure 4)

Figure 3: Money and Time Investments by Age of Child

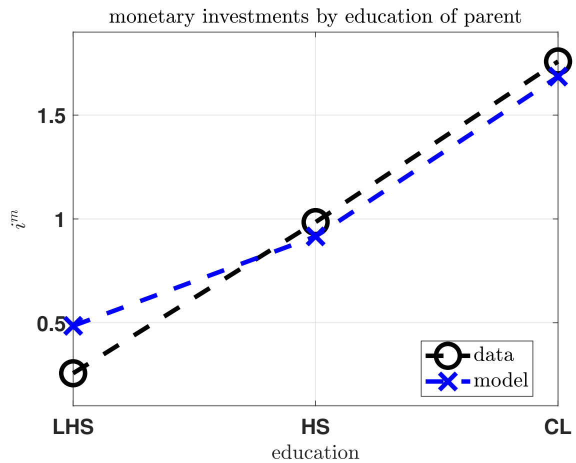


(a) Money Investments

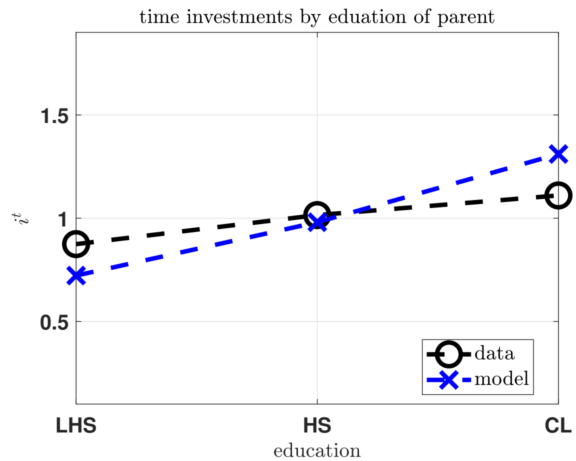
(b) Time Investments

Notes: Average money and time investments by children's biological age in the data (black circles) and model (blue crosses).

Figure 4: Money and Time Investments by Education of Parents



(a) Money Investments



(b) Time Investments

Notes: Average money and time investments by parents' education in the data (black circles) and model (blue crosses). LHS: less than high school ($s = no$), HS: high school ($s = hs$), CL: college ($s = co$).

3.11.2 Intergenerational Persistence in Education

In our calibration we also do not target directly any measure of inter-generational persistence in education. We measure this persistence by the regression coefficient β_1 in a regression of the education of a child on parental education:

$$s = \beta_0 + \beta_1 s^p + \epsilon. \tag{9}$$

In this regression we form two groups, non-college for $s \in \{no, hs\}$ and $s^p \in \{no, hs\}$ and college, for $s = co$, respectively $s^p = co$. Standard estimates of inter-generational education persistence according to this metric range from 0.4 to 0.5 and our (non-targeted) coefficient estimate of $\beta_1 = 0.49$ is in that range.[22]

3.11.3 Evidence on the Long-Run Earnings Impact of School Closures

Our model implies a significant decline of incomes for children affected by the closure of schools. We are not aware of any empirical evidence on the effects of school closures on long-run outcomes of children in the US and therefore resort to the reduced form evidence of Jaume and Willén (2019) on the effects of teacher strikes in Argentina between 1983 and 2014 on long-run economic outcomes of the affected children. Their main estimates refer to the closing of primary schools by

[22] For example, Hertz et al. (2007) report a regression coefficient for the U.S. of 0.46.

half a year, and they report that this leads to a reduction of wages at ages 30-40 by about $2-3\%$. In our model, we consider for our main experiment an exogenous reduction of investments by the government corresponding to a school closure by half a year. We can therefore directly compare the implied average wage loss at biological ages $30-40$ for children who were of biological age 6 in the period of the lockdown predicted in our model to the estimates by Jaume and Willén (2019). Our model predicts an income reduction of -1.21% for these children, which is around one half the size of the estimates from Jaume and Willén (2019), for a different country in a different time period.

3.11.4 Time Investment into Children During the Covid-19 Crisis

Finally, our calibration implies that the time investment response of parents in our full experiment—where government education investments i^g are reduced and where parental households are both subject to a negative productivity shock and a negative hours worked shock calibrated as described above—translates to 1.20 hours per day of increased time investments into children during the period of the lockdown of schools.[23] This lies well in the range of estimates provided on the basis of real time surveys by Adams-Prassl et al. (2020).

4 Aggregate Consequences of the School Closures and Income Recession

We conduct two main thought experiments. First, in Section 4.1 we study the impact of school closures that last for half a year, which in our model with two year periods corresponds to a reduction of government time investments i^g by 25%. Second, in Section 4.2, in addition we subject parents to the asymmetric negative income shocks described in Section 3. Recall that this income shock is mainly driven by a reduction of hours worked and only to a smaller extent by a decline of labor productivity, and that both reductions are more severe for parents with lower educational attainment.

Table 11 summarizes the average consequences of our main experiments for human capital accumulation, educational attainment, earnings and welfare of children. Table 12 displays the on impact behavioral response of parental time and monetary investments in the period of the

[23]We compute this as follows. First, we take the on impact hours responses in the model and compute their average across all children. This gives the average weekly hours increase in our model for a model period. Since each model period spans two years and since this hours response refers to a school lockdown of a quarter of a year, we multiply the resulting number by 4, which gives the model analogue increase per week for the 6 months period of the lockdown. We next divide the resulting number by 7 to compute the increase of hours per day in a week.

Table 11: Aggregate Outcomes for Main Experiments

	baseline	Change for Children of Biological Age						
		average	4	6	8	10	12	14
Panel A: Lockdown of Schools								
				change in %p				
share $s = no$	12.07%	0.85	0.64	1.40	1.08	0.84	0.65	0.50
share $s = hs$	54.64%	0.22	0.20	-0.05	0.16	0.29	0.35	0.36
share $s = co$	33.30%	-1.07	-0.84	-1.34	-1.25	-1.13	-1.00	-0.86
				change in %				
av HK	1.00	-1.50	-1.30	-1.97	-1.75	-1.53	-1.32	-1.12
PDV gross earn	$846,473	-0.95	-0.82	-1.24	-1.11	-0.98	-0.85	-0.72
PDV net earn	$696,076	-0.76	-0.65	-1.00	-0.89	-0.78	-0.67	-0.57
child CEV	-	-0.55%	-0.48%	-0.71%	-0.63%	-0.56%	-0.48%	-0.41%
Panel B: Lockdown of Schools & Income Recession								
				change in %p				
share $s = no$	12.07%	0.84	0.64	1.39	1.08	0.83	0.64	0.50
share $s = hs$	54.64%	0.28	0.26	0.01	0.23	0.35	0.40	0.41
share $s = co$	33.30%	-1.12	-0.90	-1.40	-1.30	-1.18	-1.05	-0.91
				change in %				
av HK	1.00	-1.48	-1.28	-1.96	-1.73	-1.52	-1.31	-1.10
PDV gross earn	$846,473	-0.95	-0.82	-1.24	-1.11	-0.97	-0.84	-0.72
PDV net earn	$696,076	-0.76	-0.65	-1.00	-0.89	-0.78	-0.67	-0.57
CEV children	-	-0.56%	-0.49%	-0.74%	-0.65%	-0.57%	-0.50%	-0.43%

Notes: share $s \in \{no, hs, co\}$: education share in respective education category $s = no$: less than high school, $s = hs$: high school, $s = co$: college; av HK: average acquired human capital at age 16; PDV gross earn: present discounted value of gross earnings assuming labor market entry at age 22 and retirement at age 66; PDV net earn: present discounted value of net earnings; CEV: consumption equivalent variation. Columns for biological ages 4-14 show the respective percentage point changes of education shares, the percent changes of acquired human capital and average earnings, and the CEV expressed as a percent change, for children of the respective age at the time of the school closures. Column "average" gives the respective average response. The CEV is the consumption equivalent variation of the welfare measure (10).

school closures, and Table 13 shows averages of the investment responses over the remaining childhood periods, as well the responses of inter-vivos transfers to the schooling shock. Thus, while Table 12 contains information about the immediate parental response to the crisis, Table 13 takes a longer-run perspective.

Table 12: Parental Decisions in Period of Covid-19 Impact

	baseline	%-Change for Children of Biological Age						
		average	4	6	8	10	12	14
Panel A: Lockdown of Schools								
av mon inv	$1,385	14.67	10.03	15.74	15.21	15.21	15.61	16.24
av time inv	25.17	7.27	4.75	7.62	7.40	7.51	7.87	8.46
Panel B: Lockdown of Schools & Income Recession								
av mon inv	$1,385	14.84	10.11	15.93	15.37	15.38	15.78	16.44
av time inv	25.17	8.50	5.74	8.81	8.59	8.75	9.20	9.91

Notes: Columns for biological ages 4-14 show the percent changes of money investments and time investments in the period of the school closures.

Table 13: Parental Decisions for Main Experiments: Averages over Remaining Childhood

	baseline	%-Change for Children of Biological Age						
		average	4	6	8	10	12	14
Panel A: Lockdown of Schools								
av mon inv	$1,385	5.76	1.23	2.13	3.04	4.51	7.43	16.24
av time inv	25.17	2.93	0.59	1.02	1.49	2.25	3.76	8.46
av ivt	$61,255	0.35	0.17	0.84	0.53	0.31	0.17	0.07
Panel B: Lockdown of Schools & Income Recession								
av mon inv	$1,385	5.74	1.10	2.04	2.95	4.45	7.43	16.44
av time inv	25.17	3.45	0.74	1.24	1.77	2.64	4.42	9.91
av ivt	$61,255	0.01	-0.17	0.45	0.19	-0.02	-0.16	-0.24

Notes: Columns for biological ages 4-14 show the percent changes of money investments, time investments, and inter-vivos transfers for children of the respective age at the time of the school closures. For money and time investments, these are averages of the percent changes of the respective investment over the remaining life-cycle, so, e.g., for a child of age 6 the percent change is the average of the percent changes of investments at ages 6-14 for this child. Column "average" is the raw average across the biological ages of children.

4.1 School Closures

4.1.1 Human Capital Accumulation, Educational Attainment and Earnings

The lockdown of schools leads to a decline in educational attainment when the children affected by the Covid crisis today make their tertiary education decisions at age 16. As the first panel of Table 11 (second column) shows, across all age cohorts the share of children that will end up dropping out of high school (i.e., choosing $s = no$) increases by 0.85 percentage points, and the share of college-educated children will decline by -1.07 percentage points. While these shifts do not appear to be dramatic, they correspond to a 7% increase in the share of children without high school degrees, and a -3.2% decrease in the share of college educated children.

The reason for the reallocation towards lower final educational attainment is the reduction in the amount of human capital the average child arrives with at age 16, which falls by -1.5%. As Table 12, panel A, first column, demonstrates, in response to the Covid-19 school closures parents increase their private investments into children, both in terms of resources as well as in terms of time. However, as discussed in greater detail below, this reaction is not sufficient to fully compensate the loss of government inputs into human capital production in the form of schooling. Consequently, average human capital at age 16 is lower than without the Covid-19 school closure shock, and the children affected by the shock choose on average lower educational attainment. The lower educational attainment together with the lower human capital in turn imply losses in the average discounted value of gross life-time earnings by -0.95%, see the 5th row of Table 11. Thus, a very transitory shock of closed schools for half a year alone leads to a permanent reduction in long-term earnings by almost 1% for the affected children, on average, even after taking optimal parental adjustments into account. In terms of present discounted dollars, this corresponds to an average per-person loss of $\$8,042$ dollars in year 2019 prices.

In order to get a better sense of the magnitude of the future earnings declines, we now discount the present discounted gross earnings losses reported in row 5 of the table, which the children will experience at age 22, to today and aggregate them across all children, using the number of children in the current US population taken from the Human Mortality Database. Relating the resulting aggregate loss to the 2019 US GDP of $\$21.43$ trillion shows that these future earnings losses are equivalent to a loss of -1.37% of 2019 US GDP. Thus, the aggregate indirect economic costs caused by the school closures are quite sizeable. The percentage loss in net earnings (after taxes and transfers) is lower (-0.76%, see the 6th row of Table 11). This is due to the progressive labor income tax schedule, which implies that a reduction of gross earnings on average leads to a reduction of tax payments (or an increase in transfers); the mirror image is of course a corresponding reduction in tax receipts by the government.

The remaining columns of Table 11 show that there is considerable heterogeneity in the size of these effects by the age of the child at the time the schooling shock hits. Overall, the most severely affected age group are the 6 year old children, i.e., those at the start of primary school. For them, the predicted share of high school dropouts increases by 1.4 percentage points, the share of college educated decreases by -1.34 percentage points, and their average long-term gross earnings drop by -1.24%, which corresponds to a present discounted earnings loss of $\$10,496$. Younger children are most affected by the school closures due to the self-productivity and the dynamic complementarity implied by the human capital production function: a decrease in human capital accumulation at younger ages due to the school closures translates into lower human capital and lower optimal parental investment in human capital in the future, as we will discuss in greater detail in Section 4.1.2. Even though the adverse effect of school closures on human capital accumulation and future educational attainment is most severe for young school children, it is non-negligible even for the cohort of the 14-year olds when the Covid crisis hits. For this age cohort, the predicted share of high school dropouts increases by 0.5 percentage points, the share of college educated decreases by -0.86 percentage points, and the present discounted value of their average gross earnings during the rest of life falls by -0.72%, see the last column of panel A in Table 11. Note that compared to age 6 year old year children, children of age 4 are more shielded against the negative effect of experiencing closures of day care centers and kindergarten, due to the lower importance of governmental inputs relative to parental inputs in the human capital production function at that age.[24]

4.1.2 Parental Responses to the School Closures

The previous section painted a fairly dire picture of the long-run outcomes of children impacted by Covid-19 induced school closures. We now document that these effects emerge *despite* substantial efforts of parents to take mitigating actions. In our model, parents have three principal means by which they can cushion the blow to their children of the Covid-19 induced schooling crisis. They can expand their time investments and their resource investments into the children's human capital accumulation during the schooling ages, and they can facilitate attending high school and college by providing children with inter-vivos transfers. Tables 12 and 13, Panel A, show that they do all three. For a given age column $j \in \{4, 6, ..., 14\}$ Table 12 gives the percent change of investments during the impact period, relative to the pre-Covid-19 scenario. The second column displays the unweighted average, across all children ages, of the age-specific percent changes. Table 13 shows the average change across the remaining child years, and therefore takes a longer-term perspective. For example, for children aged 4 during the crisis, Table 13 shows the average change in parental investments from age 4 to 14, while for children aged 14 during the school closure, it captures the change in parental investments only at this age (since it is the last age that the child spends in the household).

On average, parents on impact increase their monetary investments into their children's education by 14.7%, their time investment by 7.3%—which corresponds to about one additional hour per child per day, see footnote 23 above for the relevant transformation—, and their inter-vivos transfers to children, once these children leave the household, by 0.35% (see Table 13). Thus, overall, parents respond to the school closures with positive and substantial additional invest-

[24]Formally, the parameters satisfy $\kappa_0^g < \kappa_1^g = \bar{\kappa}^g$.

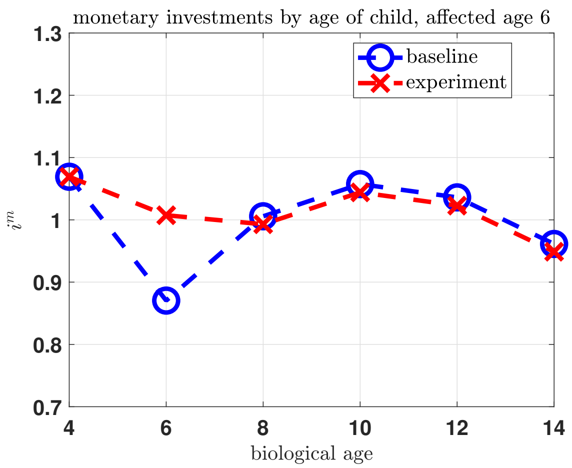
ments into their children in all three dimensions, albeit significantly stronger with their direct human capital investments than with their inter-vivos transfers.

As the remaining columns of the table demonstrate, the exact composition of the parental adjustment depends on the age of the child, but is consistently stronger for resource investments (albeit starting from a fairly low level of $\$1,385$ per year per child) than time investment and eventual inter-vivos transfers (see Table 13). Monetary and time parental investments increase the least for 4 year old children, and the most for 14 year old children, with a fairly flat profile in between. Note that these changes happen against the backdrop of higher pre-Covid investments (especially time investments, see the upper-left panel of Figure 5) for younger children. In absolute terms, changes in time investments are decreasing in the age of the child starting at age 6, but changes in monetary investments are increasing.

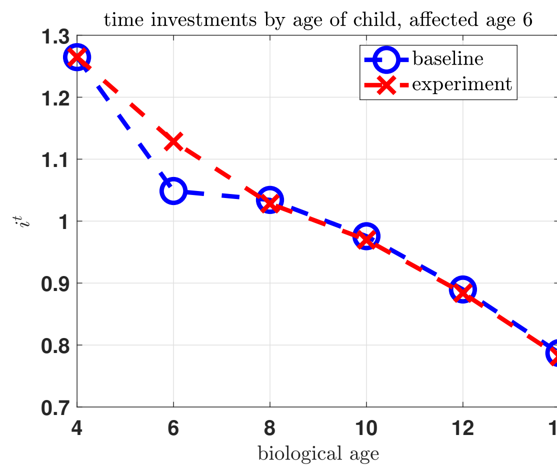
Observe that for none of the children ages, parents find it optimal to completely offset the effect of the public school closure on human capital investment during the period of the crisis, since this would compromise their own consumption and lifetime utility too severely. Consequently, all children leave the crisis period with less human capital than they otherwise would have had. Due to the dynamic complementarity of human capital and investment, this reduction curbs the incentives for private parental human capital investments in all future periods. This effect is more severe, the longer the human capital accumulation phase during school ages still is, that is, it impacts young children the most. Furthermore, even in the crisis period itself, as Table 12 shows, monetary and time investments increase strongest for older children in percentage terms. For time investments, part of this again comes from the fact that baseline time investment is highest for the youngest children. An additional reason lies in the decreasing importance of investment relative to own human capital in the human capital accumulation process over the child life-cycle: this necessitates stronger investment responses by parents of older children, in percentage terms, to counteract the negative effects of the school closures. Last, parents of young children have on average lower incomes and assets than parents of older children, making it more likely that they are borrowing constrained. Thus, for them it is relatively more attractive to increase future inter-vivos transfers than current resource investments into their children. This mechanism is particularly relevant for asset poor young parents, which constitute the largest fraction of borrowing constrained households in our model.

We display the *dynamic* adjustments of time- and monetary investments into children that are six years old at the time of the school closures in Figure 5. Panels (a) and (b) depict time- and monetary investments of parents of these children over their life cycle, both in the benchmark no-crisis scenario and in the presence of the school closures. Panel (c) of the same figure shows the resulting evolution of human capital as the child progresses through school ages following the Covid-19 shock, and Panel (d), for better visualization, displays the human capital stock over the

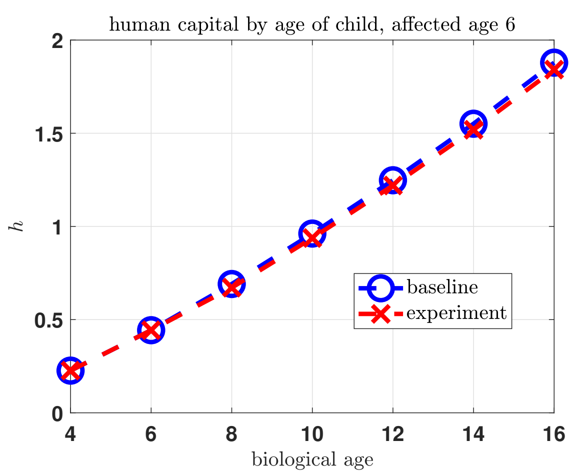
Figure 5: Money and Time Investments and Human Capital over Remaining Child Life-Cycle for Children of Age 6



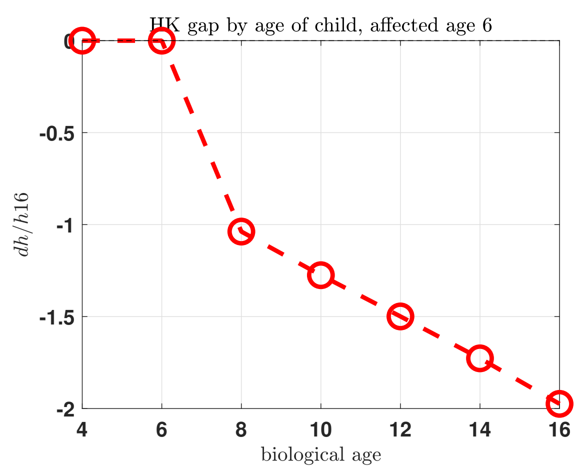
(a) Money Investments



(b) Time Investments



(c) Human Capital



(d) Change of Human Capital

Notes: Average investments for children of age 6 over their (remaining) life-cycle and acquired human capital at respective age. Blue circles: baseline steady state, red crosses: experiment. Panel (a): money investments, panel (b): time investments, panel (c): acquired human capital, panel (d): change of acquired human capital, expressed relative to baseline human capital at age 16. Since these are averages for children of age 6 in the period of the lockdown the initial points at age 4 for investments and at ages 4 and 6 for acquired human capital are identical in the baseline and in the experiment.

life cycle, in deviation of the no-Covid benchmark (and expressed as % of the age 16 pre-Covid human capital level). In the period of the lockdown, at biological age 6, there is a substantial increase in parental investment. Private resource investments rise by 15.7% and time investment by 7.6%. This is not enough, however, to compensate for the 25% decline in government inputs during this two-year period (half a year of lost schooling), and thus at biological age 8 human capital is at a slightly lower level than in the no-Covid scenario.[25] In response, future human capital investment incentives are dampened due to the dynamic complementarity feature of the human capital production function. Therefore, both time- and especially resource investments are lower in subsequent periods (at older ages of the child), with the consequence that the child 10 years after the crisis (at age 16) enters the tertiary education phase with less human capital, therefore opting (on average) for lower educational attainment and the associated reduction in lifetime earnings. However, the widening of the human capital gap shown in Panel (d) of Figure 5 is primarily due to the self-productivity feature of the human capital production function. If in all periods *after* the lockdown parents were to keep their investments at the (higher) baseline level, the observed human capital gap at age 16 would close by merely 4%. Thus, the main driver of the human capital loss at age 16 for children of age 6 at the time of the Covid school closures is the fact that the crisis reduces human capital accumulation on impact (even when partially offset by parental investments) which makes children less effective learners as teenagers and thus results in lower human capital at the age when the tertiary education decision is being made.

In contrast to parental monetary and time investments, inter-vivos transfers increase strongest for the 6 year old children, and then less for older children. Ultimately, parents care about the lifetime utility of their offspring, and not about the means by which they buffer the welfare of children against the adverse schooling shock. Given the dynamic complementarity mechanism explained above, it is relatively more efficient to support younger children more significantly through higher inter-vivos transfers, whereas for older school-aged children, human capital investments are the better option to smooth the Covid schooling shock for their children. Moreover, parents of 6 year old children at the time of school closures are more likely borrowing constrained at that point in time than when the children are 16. Note, though, that even for parents of 6 year old children, inter-vivos transfers at age 16 increase by less in relative terms than monetary investments.

4.1.3 The Welfare Cost of School Closures on Children

Thus far, we have documented that the Covid-induced temporary schooling crisis triggers a reduction in human capital accumulation and educational attainment when currently young cohorts of students enter high-school and college ages. This in turn reduces their earnings capacity dur-

[25] Note that panels (c) and (d) show human capital at the beginning of the period. Thus, the effect of the Covid-19 shock at age 6 on human capital only shows up at age 8.

ing adult life, and, ultimately, their lifetime utility. We now quantify these welfare losses of the children generation from the Covid schooling shock.

To answer this question we define as welfare W_j of children that are of age j at the time of the crisis as average (Utilitarian) expected lifetime utility these children obtain after the education decisions of all members of this group have been made and they have just entered the labor market, i.e. at the college completion age j_c,

$$W_j = \int V(j_c, s, \eta; a, h)\Phi(j_c, ds, d\eta; da, dh \mid j), \tag{10}$$

where $V(j_c, s, \eta; a, h)$ is the value function of children at age j_c, i.e. after all education decisions are made (and children with education $s = co$ have completed college). Furthermore, $\Phi(j_c, s, \eta; a, h \mid j)$ is the distribution of children at age j_c over the relevant state variables: education s, income realization η, assets a and human capital h. The distribution across these states at age j_c is conditional on age j at which the Covid crisis hits. It is the consequence of the distribution of this cohort at age j just prior to the lockdown, and parental and child education decisions since then. In our partial equilibrium lifecycle model with constant prices and constant government policy parameters, the value function of the children $V(j_c; \cdot)$ upon future, post-Covid-19 labor market entry is not affected by the shock (which, at the time of labor market entry at age $j_c > j$, is a shock that lies in the past for all cohorts under consideration). The welfare consequences of Covid school closures are therefore exclusively driven by changes in the distribution $\Phi(\cdot)$. The Covid schooling shock as well as the ensuing parental education investments and child tertiary education choices lead to a different (and typically worse when measured by human capital h and education s) cross-sectional distribution of a given cohort j at labor market entry at age j_c, relative to the no-Covid-19 scenario.

There are three dimensions along which the cross-sectional distribution for a given cohort deteriorates due to the Covid-19 schooling shock. First, children reach a different human capital position h at age j_a when they split off from the parental household; second, they receive different amounts of inter-vivos transfers from their parents and thus start their working lives with different assets; and third, they make different tertiary education decisions and thus start working life at age j_c with a different education distribution.

To quantify the welfare consequences of the school closures, we compute, for each child cohort j, the consumption equivalent variation (CEV) of the Covid-19 schooling shock. That is, we calculate the uniform percentage increase in consumption such that the average labor market entrant of a cohort of age j is indifferent between the welfare consequences arising from the original cross-sectional distribution across states at labor market entry and its Covid-impacted counterpart. As the last row of Panel A in Table 13 shows, the welfare losses from the closing of schools are quite substantial, with a reduction of welfare as measured by the CEV of -0.55% on average. Thus, the highly temporary half-year lockdown of schools has strong long-run welfare consequences for children, worth in the order of -0.55% of permanent consumption, and this despite the increased human capital investments by parents through home schooling, increased resource investments and increased inter-vivos transfers. For the least affected cohorts, children aged 14 at the time of school closures, the welfare losses are still -0.41%, and for the most affected cohort, children of age 6, welfare losses amount to -0.71% of consumption. We view these as substantial welfare losses, considering that the school closures are purely temporary shocks, and parents adjust their behavior optimally to counteract the adverse effects on their offspring.

4.2 School Closures and Income Recession

We now turn to the thought experiment in which school closures are accompanied by adverse income shocks stemming from the economic recession induced by the Covid-19 pandemic and the economic policy response to it (the lockdowns). As described in the calibration section, the reduction of incomes is primarily attributed to lower average hours worked (accounting for 92% of the total income decline) and only to a lesser degree to lower labor productivity (accounting for only 8% of the income decline). Thus, the pandemic-induced economic shock not only implies lower incomes, but also leads to a reduction in the time commitment to work, in turn reducing the marginal utility cost of spending extra hours of time with the children of the household. As a consequence, as Panel B of Table 13 shows, parents now shift their school closure responses away from increased private resource investment to higher private time investments into their children, relative to a world where the income recession is absent.[26] The time investment response now amounts to 1.20 additional hours per child per day instead of 1.02 hour in the school closures experiment. The income shock induced by the recession now also induces a level of inter-vivos transfers that is almost unchanged from pre-Covid levels (see panel B of Table 13), rather than the mild increase observed in the thought experiment with only school closures.

As a consequence of the reduced parental investments, the long-term outcomes of the children further worsen, as Panel B of Table 11 displays. The share of college-educated children drops now by -1.12 percentage points, rather than by -1.07 percentage points in the presence of only school closures. However, acquired human capital at age 16 drops slightly less than in the case of schools closures only, and the drop of long-term gross earnings is of a similar magnitude in both scenarios. This is due to the stronger increase in time investments in the scenario with

[26] On impact in Table 12, monetary investments increase slightly more in the experiment with the income recession than without, due to the strongly increased time investment and the complementarity of time and monetary investment.

an additional income recession, which leads to smaller human capital losses than in the school closures experiment. The fact that college shares decrease more strongly is therefore due to a reduction of the inter-vivos transfers, and not due to a stronger loss of human capital relative to the first thought experiment with school closures only.

The resulting adverse welfare effects are only very mildly larger than in the case of school closures alone. The welfare loss of children increases in absolute terms from -0.55% in the school closures only experiment to -0.56% when the income recession is added. Thus, from the children's perspective, the income recession is almost irrelevant to their welfare.[27] Importantly, it turns out that there are no sizeable interactions of the two experiments.[28] Even if we model the income shock purely as a shock to labor productivity, without affecting parental time endowments committed to work, we still find that the utility loss from school closures alone amounts to around 80% of the total welfare losses of the children. For the welfare of *children*, school closures during the Covid-19 pandemic thus matter much more than the negative income shocks inflicting their parents.

4.3 Children of Age 16

We now briefly comment on age 16 children, which, in the model, have just left the parental household. Therefore, by assumption their parents no longer invest in these children's human capital. Thus, the only margin of adjustment through which parents can buffer the negative shock of the school closures for children at that age are inter-vivos transfers. At the same time, 16 year old children cannot themselves adjust their investment into their human capital. These two features make children of age 16 quite different from the younger children in the model.

In results documented in Appendix A, we consequently find that the present discounted value of gross earnings of children aged 16 decreases by -0.62% in the school-closures-only experiment, and by -0.71% once the pandemic-induced income recession is added. The associated welfare losses for children of age 16 are -0.36% and -0.46%, respectively. Observe that in the school-closures-only experiment children of age 16 incur smaller welfare losses than children of age 14 or 12 despite earnings losses of a similar magnitude. This is due to the fact that parents of age 16 children increase their inter-vivos transfers by considerably more than for the two younger cohorts, since this is their only mechanism to shield these teenagers from the negative impact of the Covid shock.

[27] From the parents' perspective, the income recession however clearly matters for welfare, as discussed in Section .

[28] We also conducted an experiment where we only considered the asymmetric shock to parental incomes, and the effects in the whole experiment are almost identical to the sum of its parts—the sum of the effects from the reduction of government investments only and the effects of the parental income reductions only.

4.4 Fiscal Implications

Although our model is not designed to address the long-run fiscal implications of current expenditure programs, it entails predictions for the revenue side of the government. As shown in Table 14, the present discounted value of tax revenues from the children generation decreases by more than the incomes of households. The average reduction of the present discounted value of all tax revenues is -1.35% compared to a decline in the present discounted value of gross earnings of -0.95% shown above. As with the difference in the reduction of the present discounted value of gross and net earnings shown in Table 11, the reason for this sharper drop in the value of tax revenues is the progressive income tax schedule. In our experiment with school closures alone, the present discounted value of tax revenues from *labor* income falls by -3.86%, because an average gross labor income decrease leads to an even larger decrease in average tax payments due to the progressive income tax code. In contrast, revenue from capital income taxes does not drop but even slightly increases, because the increased inter-vivos transfers offset the reduction of asset accumulation in response to the earnings decline. Again due to the increased inter-vivos transfers, revenue from consumption taxes drops by less than revenue from labor income taxes, because the child generation partially use the inter-vivos transfers to finance consumption.

Table 14: Change of Present Discounted Value of Tax Revenues [in %]

Revenue source	All	Lab. Inc.	Cap. Inc.	Cons.
Lockdown of Schools				
	-1.35	-3.86	0.15	-0.52
Lockdown of Schools & Asymmetric Income Shock				
	-1.37	-3.86	0.10	-0.54

Notes: The table shows the change in the present discounted value of tax revenue (in %) in the two main experiments. Revenue source: All: sum of all tax sources; lab.: from labor income taxes; cap.: from capital income taxes; cons.: from consumption taxes.

4.5 The Welfare Cost of School Closures for Parents

As documented in Table 13, parents react to the closure of schools by increasing monetary and time investments into their children as well as by expanding inter-vivos transfers. To do so, they have to reduce their own consumption and leisure, resulting in a loss to their own lifetime utility. To quantify how these behavioral responses translate into welfare consequences for the parental generation we define welfare of a parent of age j in the time period of the lockdown as:

$$W_j^p = \int V(j, s, m, \eta; a, h)\Phi(j, ds, dm, d\eta; da, dh), \quad (11)$$

Here $V(j, \cdot)$ is the parental value function and $\Phi(j, \cdot)$ is the cross-sectional distribution of parents of age j, predetermined in the period of the lockdown.

Notice that in the school closures only experiment, parental utility is reduced through three channels. First, parents increase their monetary and time investments into their children at the expense of own their consumption and leisure. Second, they increase their inter-vivos transfer payments, also at the expense of their own consumption. Third, through the altruistic preferences the value function of parents encodes the value function of their children and thereby also the reduction of the life-time utility of children. The experiment with the additional income recession adds a fourth channel through reduced parental incomes.

As shown in Table 15, parents on average experience a substantial reduction of their lifetime utilities. In the school closure experiment the average welfare loss, measured as the CEV of the welfare measure (11) is -0.66%, which is larger than the average welfare loss for the children generation reported in Table 11. The age pattern of the welfare losses follows that of the age of their children—for parents with children of age 6 and older their CEV-based welfare losses are decreasing in the age of the child. However, the age gradient in the losses is less pronounced than that of the children. This is due to the fact that in the school closures experiment the dominant force for the welfare effects on parents is the reduction of lifetime utility of their children as well as the increase of the inter-vivos transfer payments, which feature the same age pattern. The welfare effects are not mainly driven by the increase of parental human capital investments through money and time, since this reaction would suggest the opposite age pattern (see Table 13 showing that parental investments increase most for children of age 14).

The second row of Table 15 confirms this argument by showing parental welfare losses under the assumption that the altruism channel is not active, i.e. welfare losses of children do not enter into parental utility (but with parental behavior continuing to be determined as in the benchmark model). In that case, the welfare loss of parents due to the school closures would amount to -0.12% rather than -0.66%, and are fairly uniform across the age of the children. Thus, it is the utility loss of their children which is mainly responsible for the welfare losses of the parents. Finally, the additional income reduction in the recession adds about 0.11% to the Covid-19 induced welfare losses (from -0.66% to -0.77%), again confirming that even for the parents school closures rather than income losses are the main source of welfare losses from the crisis.

Table 15: CEV [in %] for Parents

		Biological Age of Children in Household					
	average	4	6	8	10	12	14
Lockdown of Schools							
Full model	-0.66%	-0.52%	-0.73%	-0.73%	-0.71%	-0.66%	-0.61%
No Altruism	-0.12%	-0.11%	-0.13%	-0.13%	-0.13%	-0.12%	-0.11%
Lockdown of Schools & Income Recession							
Full model	-0.77%	-0.62%	-0.84%	-0.85%	-0.82%	-0.78%	-0.73%
No Altruism	-0.23%	-0.21%	-0.24%	-0.24%	-0.24%	-0.24%	-0.23%

Notes: Welfare consequences for parents expressed as a consumption equivalent variation (CEV) of welfare measure (11). "Full model": including the welfare effects from altruism towards children; "No altruism": altruism switched off.

5 Heterogeneity of the School Closure Effects

5.1 Heterogeneity by Parental Characteristics

The aggregate results presented above mask important heterogeneity in income- and welfare losses by parental characteristics. We focus on three dimensions of parental heterogeneity, namely parental education, net worth and martial status, and summarize the importance of this heterogeneous effects by the differences in the CEV-based welfare losses derived from (10). The results concerning parental education are contained in Table 16, Table 17 summarizes the results with respect to parental assets, and Table 18 contains those related to marital status.

Focusing first on parental education, we observe that the welfare losses, as measured by the CEVs, from the Covid-19-induced school closures are largest (-0.67%) for children whose parents are high school dropouts, and smallest (-0.40%) for children of college-educated parents. Higher parental education and the associated higher parental income partly shield children from the negative impact of the school closures through positive investments and increased inter-vivos transfers by their parents. The differences in losses of children by parental education become somewhat smaller if the Covid-19 economic recession is added to the school closures, but the qualitative patterns remain intact—children of high-school drop-out parents lose most while children of college-educated parents lose least. The reason why losses become slightly less steep in parental education is the additional time endowment available to parents as a result of the income shock, which positively affects parental time investment responses. Importantly, since the income shock is asymmetric, the increase of the parental time endowment in the recession is disproportionally larger for children of parents with lower education.

Table 16: Welfare Consequences (CEVs) by Parental Education

Experiment/Parental Education	$s = no$	$s = hs$	$s = co$
Lockdown of Schools	-0.67%	-0.57%	-0.40%
Lockdown of Schools & Asym. Inc. Shock	-0.66%	-0.59%	-0.44%

Notes: CEV: consumption equivalent variation based on the welfare measure (10) by parental education $s = no$: less than high school, $s = hs$: high school, $s = co$: college.

In Table 17, we delineate the distribution of the welfare consequences by parental net worth, measured at the time children are born into the adult household. Recall from our description in Section 3 that this cross-sectional wealth distribution in the model is directly estimated from the data. Whereas the differences in the welfare losses between net worth quintiles 2 to 4 are not very pronounced, children of parents in the first wealth quintile experience welfare losses of -0.60% from the school closures alone and -0.61% from the full Covid19 crisis. In contrast, the welfare losses of children in the highest asset quintile amount "only" to -0.44% and -0.48%, respectively. This suggests that low wealth holdings and borrowing constraints of parents are a strong impediment to parents trying to increase their private education resource investments into their children, in response to the reduced governmental investment associated with school closures.

Table 17: Welfare Consequences (CEVs) by Parental Assets

Experiment/Asset Quintile	1	2	3	4	5
Lockdown of Schools	-0.60%	-0.57%	-0.57%	-0.55%	-0.44%
Lockdown of Schools & Asym. Inc. Shock	-0.61%	-0.59%	-0.58%	-0.57%	-0.48%

Notes: CEV: consumption equivalent variation of the welfare measure 10 by parental asset quintiles $1 - 5$.

Finally, table 18 shows that the welfare consequences for children from single raising parental households are larger than for children of married couples. The reason for this heterogeneity by marital status is mainly the heterogeneity by education shown in Table 5. Moreover, single households have more children per adult household member than married households, making it more difficult for them to increase monetary and time investments into their children in the presence of school closures. Again, the differences in child losses by parental marital status become slightly smaller in the scenario with an additional income recession (just as the gradient by parental education documented above). For single parents, on average, the positive effect of an increased time endowment and the resulting higher optimal time investment into children during the recession outweighs the negative consequences of an income drop. Therefore, losses in terms of permanent consumption for children of single parents are slightly smaller in the scenario with an additional income recession than in the scenario with the school closures only. As shown in Appendix A, Table 25, this result is driven by the losses of children of high-school dropout parents. For this group the role of inter-vivos transfers is relatively small in the baseline and, therefore, the additional income recession plays only a marginal role for child outcomes.

Table 18: Welfare Consequences (CEVs) by Parental Marital Status

Experiment/Parental Education	$m = si$	$m = ma$
Lockdown of Schools	-0.67%	-0.42%
Lockdown of Schools & Asym. Inc. Shock	-0.66%	-0.46%

Notes: CEV: consumption equivalent variation of the welfare measure 10 by parental marital status $m = si$: single, $m = ma$: married.

We thus far have documented that children of highly educated parents, married parents, and those with substantial net worth, experience lower relative welfare losses. But what is the effect of school closures on measures of intergenerational persistence? In fact, in our experiment with school closures the coefficient in a regression of children's education on parental education, or children's log earnings on parental log earnings, barely change, and remain at 0.49 in the education regression, or at 0.27 in the earnings regression, respectively. In general, the directional change of inter-generational persistence is ambiguous. On the one hand, we find that less well-off parents increase their absolute monetary investment into children substantially less than better-off parents in reaction to the school closures, which increases persistence. As a result, children of less well-off parents lose unambiguously more in terms of human capital as well as earnings—as Table 19 illustrates. This implies that cross-sectional earnings inequality slightly increases—the percentage point change of the Gini coefficient of gross labor earnings at age 40 is 0.17.

Table 19: Losses by Parental Education

Variable /Parental Education	$s = no$	$s = hs$	$s = co$
Human Capital	-1.73%	-1.50%	-1.31%
PDV gross earn	-0.96%	-0.96%	-0.92%
PDV net earn	-0.76%	-0.77%	-0.74%

Notes: % losses of human capital, PDV of gross earnings and PDV of net earnings by parental education $s = no$: less than high school, $s = hs$: high school, $s = co$: college.

On the other hand, children of well-off parents have more to lose when it comes to attending college, the major factor determining future earnings, given that their initial college attendance rates are higher. Indeed, we find that college attendance drops by -1.44 percentage points for children of college-educated parents (whose baseline college attendance rate is 63.58%), but only by -0.56 percentage points for children of high-school dropouts (whose baseline college attendance rate is a mere 11.00%). This effect decreases intergenerational persistence. Thus, the effects on intergenerational education or earnings persistence are ambiguous.

In terms of welfare effects, however, there is a clear ranking with children from better-off parents suffering smaller welfare losses than children with parents at the lower end of the socio-economic distribution. The key to this finding are inter-vivos transfers. Whereas well-to-do parents cannot completely offset the loss of human capital and thus the lower final educational attainment of their children caused by the school closures, they increase the inter-vivos transfers to the children as an additional channel to buffer their welfare losses.[29] This in turn explains why the CEV differences by parental education in Table 16 are significantly larger than the differences in the losses to human capital and earnings documented in Table 19.

5.2 The Impact of Differential Length of School Closures and its Interaction with Parental Background

In this section we study the impact of differential lengths of school closures along the socio-economic dimensions discussed above. Although our main focus is on the implied distributional consequences, first note that the allocational and welfare impacts of school closures are strictly convex in its length. To see this, we now consider a prolonged closure of schools to one full year so that i^g drops by 50% in one model period. Table 20 summarizes the results on CEVs showing that the welfare losses are more than twice as large than under the respective previous experiments. The CEV losses from one year of closed schools is, on average across children, -1.21%, more than twice the -0.55% welfare loss from a six-month duration of the schooling shock. This shows that the loss of human capital accumulation over the life-cycle not only has long-lasting effects, but also that the effects on welfare are strictly convex in the size of the shock due to the self-productivity of human capital.

In the previous thought experiments we have assumed that all children face the same length of school closures. However, in practice the school closure length differed substantially across different school districts. Moreover, many school districts substituted in-person teaching at least partially with online schooling, or initiated hybrid models. The literature thus far provides only scant evidence on the effectiveness of online vs. in-person instruction, and thus it is hard to gauge the long-run consequences of online schooling. First results seem to indicate that online

[29] Note that the same main results—namely essentially no change in intergenerational persistence, but lower welfare losses for children of well-off parents—hold when the asymmetric income shock is added to the school closures.

Table 20: Welfare Consequences (CEVs) of Prolonged School Closure

	6 Month Lockdown	One Year Lockdown
CEV	-0.55%	-1.21%

Notes: Column 1 shows the CEV if schools are closed for six months (the benchmark), column 2 if schools are closed for a whole year.

learning might on average not be effective at all for elementary school children (Engzell et al. (2021)). Moreover, there is evidence that children from disadvantaged households have less access to and/or make less use of digital forms of teaching during the current crisis. Opportunity Insights (Chetty et al. (2020)) reports that student participation in online math work decreased immediately for all children at the start of the school closures, but ultimately decreased by 41% for children from low income ZIP codes by the end of the school year compared to January 2020, by 32% for children from middle income ZIP codes, and not at all for children from high income ZIP codes. This pattern continued into 2021. Similarly, Bacher-Hicks et al. (2020) report less use of online learning tools by children from low-income ZIP codes. It is plausible that both the equipment for digital teaching among teachers, as well as the equipment and the provision of quiet learning spaces for the students depend on socio-economic characteristics. Moreover, there are indications that children from disadvantage households tend to return to in-person schooling later.

While we cannot put hard numbers on the differential use of online learning by parental characteristics, our model allows us to trace out the heterogeneous earnings and welfare effects by parental background when the length of school closures is negatively correlated with socio-economic characteristics of the parents. For example, if one assumes that the school closures in combination with distance learning opportunities correspond to a complete school closure of 3 months for children of college educated parents, but of 6 months for children of high school dropouts, then the welfare impact is -0.67% for the latter group, but only -0.19% for the former group, see Table 21.

To illustrate the heterogeneity of the welfare effects from school closures depending on parental characteristics most starkly, we now compare the average welfare effects for children coming from households with the least favorable parental characteristics, namely single parents without high school degree and belonging to the poorest asset quintile, with the welfare effects for children coming from households with the most privileged characteristics, namely married parents with a college degree and belonging to the highest asset quintile. As Panel A of Table 22 shows, for the children from the most disadvantaged families, the welfare effects of school closures lasting six months amount to -0.73%, while for the children from the most advantaged families they are

Table 21: Welfare Consequences (CEVs) by Duration of School Lockdown and Parental Education

	3 months	6 months	9 months	12 months
pLHS	-0.32%	-0.67%	-1.05%	-1.47%
pHS	-0.27%	-0.57%	-0.90%	-1.27%
pCL	-0.19%	-0.40%	-0.63%	-0.89%

Notes: The table shows the CEVs by parental education if schools are closed for 3, 6, 9 and 12 months, respectively.

only -0.18%. While these are the results for the two most extreme groups, it is true that the different dimensions of parental characteristics are positively correlated, so the heterogeneity of the welfare effects is large.

If we in addition assume that the length of school closures a child faces is positively correlated with her socio-economic status, the differences become larger still. Panel B of Table 22 assumes that poor children face school closures lasting for 12 months whereas rich children only miss 3 months of school. The resulting welfare differences are immense: whereas the children from most privileged backgrounds hardly suffer any welfare losses, those of the poorest children in society exceed 1.6% of permanent consumption. For these children public education is the main source of human capital accumulation, their parents are borrowing-constrained and thus not in a position to increase inter-vivos transfers, and the adjustment in their time investment is insufficient to largely mitigate the impact of the Covid-19 school crisis on their children.[30]

6 Inspecting the Mechanisms

6.1 The Role of Parental Re-optimization

To understand the importance of the reaction of parents to the closure of schools, we analyze the results of a model in which we hold all parental decisions constant. Thus, governmental inputs fall due to the school closures, but parental inputs remain unchanged—both investments into the human capital of their children and their inter-vivos wealth transfers. For simplicity, we focus on the school closures experiment only. Results for this experiment on aggregate effects are summarized in Table 23, which should be compared to Panel A of Table 11.

We observe that the aggregate effects are now larger than in the scenario of school closures and full parental behavioral adjustments. Acquired human capital of children falls now by 1.88%

[30] In fact, these parents even slightly reduce transfers - see Table 22 - due to a higher probability of their children dropping out of high school and starting working full time directly from age 16 onward.

Table 22: Losses of Most Disadvantaged and Most Privileged Children

Panel A: Same Duration of Schools Lockdown						
Group / Variable	HK	gross earn PDV	net earn PDV	IVT	CEV	Pop Share
Most Dis-d	-2.04%	-0.95%	-0.77%	-0.04%	-0.73%	2.63%
Most Privileged	-1.18%	-0.85%	-0.69%	2.95%	-0.18%	2.60%
Panel B: 12 Months vs 3 Months Effective Schools Lockdown						
Group / Variable	HK	gross earn PDV	net earn PDV	IVT	CEV	Pop Share
Most Dis-d	-4.54%	-2.12%	-1.71%	-0.08%	-1.63%	2.63%
Most Privileged	-0.57%	-0.41%	-0.33%	1.43%	-0.09%	2.60%

Notes: % losses of human capital, PDV of gross earnings, PDV of net earnings and CEV for two extreme groups of children. "Most disadvantaged" are those born into families of single high-school dropout parents with initial assets in the first quintile. "Most privileged" are those born into families of married college educated famililies with initial assets in the highest quintile. All variables are shown as % changes relative to the respective baseline level. For exposition purposes, inter-vivos transfer responses are expressed as % of the baseline average per child transfer level.

instead of 1.50% when parents react optimally. The share of high-school dropouts now increases by 1.11 percentage point instead of 0.85 percentage points when parents re-optimize their decisions. However, the share of college-educated children does not drop by more and in fact decreases by slightly less than when parents react optimally to the school closures - by -0.97 instead of -1.07 percentage points before. The reason for a slightly lower drop of the share of college-educated children is the constancy of inter-vivos transfers which induce marginal students to attend college. With re-optimizing parents, inter-vivos transfers would decrease for this group of students because their human capital is lowered from the school closures and thus parents do not find it optimal to transfer wealth to those children. In our main experiment that effect turns out to dominate. The present discounted value of gross earnings now falls by -1.12% rather than -0.95%, and the CEV associated with the school closures is now on average -0.71% instead of -0.55%. Thus, by optimally adjusting their human capital investments into children as well as inter-vivos transfers, parents mitigate the welfare losses of their children caused by the school closures by more than one fifth. Of course, these adjustments are associated with welfare losses to the parents, as described in Section 4.5.

We complement these results by additional decompositions in Appendix A where we hold constant one decision at a time. We show that the average lower child welfare losses when parents re-optimize their decisions are primarily due to the human capital investment responses while the differences in losses by parental background are mainly driven by the inter-vivos transfer responses.

Table 23: Aggregate Outcomes under Constant Parental Decisions

	baseline		Change for Children of Biological Age					
		average	4	6	8	10	12	14
Panel A: Lockdown of Schools								
			change in %p					
share $s = no$	12.07%	1.11	0.90	1.75	1.40	1.10	0.86	0.67
share $s = hs$	54.64%	-0.14	-0.22	-0.49	-0.24	-0.06	0.05	0.13
share $s = co$	33.30%	-0.97	-0.68	-1.25	-1.16	-1.04	-0.91	-0.79
			change in %					
av HK	1.00	-1.88	-1.68	-2.38	-2.16	-1.93	-1.68	-1.44
PDV gross earn	$846,473	-1.12	-0.98	-1.42	-1.29	-1.15	-1.01	-0.86
PDV net earn	$696,076	-0.90	-0.78	-1.15	-1.03	-0.92	-0.80	-0.69
CEV children	-	-0.71%	-0.63%	-0.94%	-0.83%	-0.73%	-0.63%	-0.53%

Notes: This table is the analogue to table 11 where parental money and time investment decisions and inter-vivos transfer decisions are held constant. This is computed by holding parental policy functions constant *and* by aggregating with a hypothetical distribution of children over human capital computed under constant decisions.

6.2 The Role of Asymmetric Income Shocks

Suppose that instead of the asymmetric income shock distribution, it is symmetric across households, and the reduction in hours worked and the probabilities of transiting to, as well as staying in the low income state are the same for all education groups in the economic recession. We re-calibrate these probabilities to again generate a reduction of aggregate income per capita of 4.57%, as in our benchmark calibration. As a consequence, the probability of transiting to the low income realization is now $\pi^r_{hl} = 0.0479$ and the probability of staying there is $\pi^r_{ll} = 0.9616$, which are thus higher for college households and lower for non-college households than in the baseline asymmetric income shock scenario. Likewise, the average reduction of hours is now 6.41% for all households.

Table 24—which is the analogue to the last row of Table 16—summarizes the welfare consequences of children by parental education. As a consequence of the lower incomes of parents with a college degree under the symmetric income shocks, CEVs of children of these parents display stronger welfare losses than in the asymmetric income shock experiment. Their average welfare loss now amounts to -0.46% compared to -0.44%. On the other hand, welfare losses for children of parents with a lower educational degree are slightly reduced compared to the previous results.

Table 24: Welfare Consequences (CEVs) with Symmetric Shocks

Experiment / Parental Education	pLHS	pHS	pCL
Lockdown of Schools & Symmetric Income Shock	-0.66%	-0.58%	-0.46%

Notes: This table is the analogue to the second row of Table 16 now assuming that the income shock is symmetric across all parents.

7 Conclusion

In this paper, we analyze the long-term welfare losses of children caused by school closures in the Covid-19 crisis. We use a partial equilibrium model in which parents differ by marital status, education, income, and assets. The human capital production function of children incorporates governmental inputs through public schooling, as well as monetary and time investments by parents. The Covid-19 crisis is modelled as leading to unexpected school closures of half a year. We have three main results. First, the school closures alone lead to substantial reductions in children's welfare, with a consumption equivalent variation of on average -0.55%. Thus, these temporary measures have substantial permanent effects on the welfare of children. Second, for the affected children's welfare, the school closures themselves are a much more important facet of the Covid-19 crisis than the negative shock to parental income: adding the negative shock to parental in come, the consumption equivalent variation stays almost unchanged and rises in absolute terms to only -0.56%. Last, there is substantial heterogeneity in the welfare effects, with children of well-off parents fairing better after the school closures than children of less well-off parents.

The results of this paper present a sign of caution that the Covid-19 induced school closures have significant long-term consequences on the affected children, and reduce especially the welfare of children from disadvantaged households. Note that our model only incorporates the most direct effects of the school closures on children that are caused by reduced public investment into human capital. There potentially exist additional dimensions along which negative long-term consequences are to be expected and which are not incorporated into our model. First, the lack of social contact during the school closures could directly affect children's welfare, but also their non-cognitive skills and thereby their long-term wages. Second, parents who have to take care of their children during the closures likely experienced increased stress that could affect the well-being of their children, and might induce higher parental risk of job loss or fewer possibilities for career advancement (Alon et al. (2020a)), which could induce less investment into children in subsequent years. On the other hand, in our main experiments we model the school closures as a complete loss in schooling, while many schools tried to maintain some form of schooling through distance learning and virtual teaching. Although these measures might have reduced the long-term impact of the school closures, they have possibly exacerbated their distributional consequences.

We conclude that school and child care closures should be considered as a potentially very costly policy measure to avoid the spread of the Corona virus.[31] However, we want to clearly acknowledge that we have not modelled the potential health benefits of these closures as this would require an explicit model that links disease transmission to school activity. We hope to have provided an informative model of the cost side and view the construction and quantification of such a comprehensive model which includes the benefit side as a next desirable step for future research.

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A Results Appendix

A.1 CEV by Parental Education and Marital Status

Table 25: Welfare Consequences (CEVs) by Parental Education: Single Parents

Experiment/Parental Education	$s = no$	$s = hs$	$s = co$
Lockdown of Schools	-0.73%	-0.67%	-0.56%
Lockdown of Schools & Asymmetric Income Shock	-0.72%	-0.67%	-0.57%

Notes: CEV: consumption equivalent variation of the welfare measure 10 by parental education $s = no$: less than high school, $s = hs$: high school, $s = co$: college.

Table 26: Welfare Consequences (CEVs) by Parental Education: Married Parents

Experiment/Parental Education	$s = no$	$s = hs$	$s = co$
Lockdown of Schools	-0.59%	-0.46%	-0.23%
Lockdown of Schools & Asymmetric Income Shock	-0.60%	-0.50%	-0.29%

Notes: CEV: consumption equivalent variation of the welfare measure 10 by parental education $s = no$: less than high school, $s = hs$: high school, $s = co$: college.

A.2 Responses of Inter-Vivos Transfers

Table 27: % Changes of Inter-Vivos Transfers by Parental Education and Marital Status: Lockdown of Schools

Marital Status/Parental Education	$s = no$	$s = hs$	$s = co$
Single	-0.64%	-1.43%	0.10%
Married	-1.03%	0.41%	0.70%

Notes: Percent changes of inter-vivo transfers by parental education $s = no$: less than high school, $s = hs$: high school, $s = co$: college.

A.3 Children of Age 16

Table 28 shows the effects on inter-vivo transfers, acquired human capital at age 18 and average earnings for children who are of age 16 in the period of the lockdown when they are about to leave the adult household but parents may still decide on the inter-vivo transfers to these children. The table also reports the CEV of the welfare function (10).

Table 28: Effects on Children of Age 16

Lockdown of Schools			
av ivt	HK age 18	PDV gross earn	CEV [in %]
0.34	-1.20	-0.62	-0.36
Lockdown of Schools & Asymmetric Income Shock			
0.05	-1.17	-0.71	-0.46

Notes: Effects on age 16 children. Percent changes for inter-vivo transfers (ivt), acquired human capital at age 18, average earnings and the consumption equivalent variation of the welfare measure, cf. equation (10).

A.4 Decomposition of CEV

According to (10) the welfare of children of a given age is affected by changes of the distribution along assets, human capital and the resulting endogenous education decision of the children. Table 29 decomposes the CEV into these various components by subsequently switching off model elements, in the first part of the table for the experiment with the school closures.

As a first step we hold constant inter-vivos transfers. Consequentially, the cross-sectional asset distribution at age $j_c > j$ is not influenced by this element and the education decision of children is altered. Comparison between column 1 (which is the full model) and column 2 shows that the inter-vivos transfers play a crucial role in the model for the heterogeneity in losses by parental background.

We subsequently hold constant money and time investments by parents, with results shown in column 3 of the table. Relative to the previous experiment this increases the level of the welfare losses for all groups whereas the gradient across groups in terms of the percentage point differences in the CEV is unaltered.

Finally, for the results shown in column 4 of the table, we also hold constant the education decision of children. With this additional adjustment mechanism switched off the level of the CEV decreases further but differentially across groups so that the education gradient decreases. In this last experiment, welfare differences across groups arise from differences in the fixed effects in earnings $\gamma(s, h)$ only. Overall, this decomposition analysis shows that the main drivers for the heterogeneity of welfare consequences among children are the parental inter-vivos transfer responses and the reoptimization of children through their education decisions.

Table 29: CEV Decomposition for Schools Lockdown Experiment

	full model	ivt const	ivt, inv const	ivt, inv, edu const
$s = no$	-0.67%	-0.64%	-0.79%	-0.85%
$s = hs$	-0.57%	-0.57%	-0.72%	-0.80%
$s = co$	-0.40%	-0.48%	-0.63%	-0.73%

Notes: Decomposition of the CEV of welfare function 10. ivt const: inter-vivos transfers are held constant; ivt, inv const: additionally, parental investments through money and time are held constant; ivt, inv const, edu const: additionally, education decisions are held constant.