The Intergenerational Welfare Implications of Disease Contagion

Pretnar, Nick

University of California Santa Barbara, Laboratory for Aggregate Economics and Finance, Carnegie Mellon University, Tepper School of Business

11 June 2020

The Intergenerational Welfare Implications of Disease Contagion

Nick Pretnar[1,2*]

[1] *University of California Santa Barbara, Laboratory for Aggregate Economics and Finance*
[2] *Carnegie Mellon University, Tepper School of Business*

July 14, 2020[†]

Abstract

Using endogenous, age-dependent measures of the value of statistical lives (VSL), this paper examines the demographic implications of recessions driven by disease contagions. Depending on the age-distribution mortality profile of the disease, long-run welfare losses resulting from the recession may outweigh lost VSL's directly attributable to the disease. This is because disease contagions that induce high levels of hospitalization simultaneously impact aggregate output, via a recession caused by social-distancing, and the productivity of health care services. The efficiency of health investment falls driving down life expectancy (LE). VSL's fall both because LE's fall and the marginal value of health care investment falls. Using the Hall and Jones (2007) model of age-specific, endogenous health investment, it is shown that the COVID-19 crisis of 2020 will lead to lost welfare for young agents that exceeds VSL's lost from the disease. If COVID-19 had the same age-mortality profile as the 1918 Spanish Flu, where more young agents died, contagion-mitigation policies that cause deep recessions would still be socially optimal since more of the high-valued lives of young people would be saved.

Keywords: health, inequality, general welfare, value of statistical life, macroeconomics
JEL Classification: E2, I14, J17

*Postdoctoral Scholar, University of California, Santa Barbara – Laboratory for Aggregate Economics and Finance; Carnegie Mellon University, Tepper School of Business. Mailing address: 2112 North Hall, Santa Barbara, CA 93106-9215; npretnar@ucsb.edu.

†Thanks to William Bednar, Finn Kydland, and Stephen Spear for helpful comments.

1 Introduction

In the United States (U.S.), the initial spring 2020 policy response to the spread of the COVID-19 disease contagion was largely driven by public health experts concerned both with mitigating the impact of an infection surge on the health care system and reducing the total number of deaths. To accomplish this states and municipalities imposed policies to limit social contact. These policies forced certain businesses to close and led to reductions in economic output. While these sacrifices were sold as necessary to contain the spread of the disease and preserve lives, the distributional effects of such policies on different consumers of different ages were left largely ignored.

In this paper it is argued that the economic impacts of the 2020 recession will be felt unequally across the age distribution and may outweigh the welfare loss directly attributable to disease deaths. Through the lens of the overlapping-generations, health-production model of Hall and Jones (2007), it is shown that the welfare outcomes of younger consumers, especially children, are more sensitive to an aggregate economic shock. The model endogenously generates measures both of life expectancy (LE) and the consumption value of a statistical life (VSL) that depend on age, income, and the efficiency of the health care system. When aggregated over the population distribution, it is shown that reductions both in LE and VSL due to recessions that accompany disease contagions may exceed the welfare loss directly attributable to the disease. Further, young agents, as a generation, bear the brunt of this excess burden as long as the age-mortality profile of the disease is skewed older.

Because mortality rates for COVID-19, for example, are skewed toward older adults, disease mitigation mandates that induce an economic contraction are socially sub-optimal as long as total disease deaths remain below 750,000 in the U.S. for the year 2020. In a counterfactual experiment, an alternative disease-mortality distribution is considered, specifically one that resembles the 1918 Spanish Flu which primarily impacted teenagers and young adults. With such a disease, sacrificing income for policies designed to mitigate contagion spread and save lives is more likely to improve aggregate welfare since the high-value lives of young consumers are being saved. Meanwhile with COVID-19, policymakers have fewer paths to aggregate welfare improvement, where some policies that restrict economic output just shift the burden of the crisis from old to young.

The main mechanism of the model works as follows. An aggregate shock simultaneously affects income and the efficiency of health investments. Optimal health care investments and other consumption fall as income falls. With age-specific health investment elasticities, it is estimated that younger consumers experience greater long-run welfare loss to reduced health investment than older consumers despite being relatively unaffected in the short run. This long-run impact reduces their age-specific VSL, which is the primary measure of welfare considered here.

The macroeconomic data justify examination of such a mechanism. The 2020 recession is the first recession since the 1960-1961 recession during which aggregate personal health care services expenditure has declined, falling 3.85% in the first quarter of 2020 from the fourth quarter of 2019.[1] Amidst the current crisis, many hospitals and medical offices effectively shut down for months, foregoing procedures for all but the most immediate of emergencies in order to devote system capacity to disease patients. Consumers have had no choice but to delay or even cancel medical procedures and doctor visits, all while still paying health insurance premiums. As local shutdowns are reversed and these restrictions are relaxed, medical professionals have been forced to deal with a back log of patients which could exacerbate difficulties getting appointments for non-critical procedures. In such an environment, the risk of certain diseases, like cancer, diabetes, and cardiovascular diseases, going undiagnosed increases. Thus, the restrictions on medical procedures amount to a health-care productivity shock, impacting the efficiency of health investment and health outcomes. This paper examines the potential consequences of these shutdowns across the age distribution through the lens of a model in which consumers respond to aggregate income and health productivity shocks by endogenously adjusting their health care investment. This affects year-on-year survival rates, LE's, and VSL's.

Finally, non-health-technology factors unique to the current recession could also be adversely affecting health outcomes, especially for children. In many regions, kids forewent in-person instruction for much of the spring-2020 school semester and thus have had reduced social contact with influential adults. While for many children this may not be problematic, children with learning disabilities and other behavioral issues are more likely to be adversely affected. A review of the literature reveals that increased behavioral issues in children are often associated with adverse health outcomes, which will be discussed in more detail below. Thus, there is reason to believe that residual forces unique to the current recession may also be affecting long-run health outcomes independent of the apparent shock to the efficiency of health services.

This paper thus confronts some of the primary challenges presented by the COVID-

[1] See the National Income and Product Accounts Table 2.8.5. from the U.S. Bureau of Economic Analysis, accessed on July 1, 2020. In addition to the decline in health spending, the 2020 recession associated with the COVID-19 crisis is shaping up to be primarily driven by a decline in consumption: aggregate personal consumption expenditure fell 6.6% month-on-month in March of 2020 followed by an additional 12.6% in April before rebounding 8.2% in May.

19 crisis, with a specific focus on the intergenerational impacts of lost economic output and death from disease contagion. It is thus recognized that policymakers may face the dilemma of enacting policies that reduce short-run deaths but also decrease aggregate output and health-care efficiency which each have long-run, negative impacts on welfare. Depending on the severity of the recession and how deadly the disease is, under many policies the damage to long-run welfare may exceed the short-run benefits. Life expectancy and the consumption value of life for the young are particularly harmed by the indirect economic factors associated with the current recession. Meanwhile, older adults are more at risk from dying from the disease. In order for the consumption value of lost life years associated with COVID-19 to exceed the value of lost years associated with indirect factors resulting from a policy-driven recession, the recession needs to be relatively mild and the number of deaths prevented relatively high. Otherwise, a greater share of the burden is placed on the shoulders of the young.

This paper will proceed as follows. Section 2 will present evidence from the literature arguing why using a welfare measure that depends on health investment is important to understand the distributional implications of the 2020 COVID-19 crisis. Section 3 provides a brief overview of the Hall and Jones (2007) model. Section 4 describes the data used for parameter selection and important outcomes of the estimation. Section 5 simulates various recession and COVID-19 death scenarios to analyze the welfare implications of the 2020 crisis through the model's lens. Finally, Section 6 concludes.

2 Background

2.1 Welfare Implications of COVID-19

Many economists have considered the welfare implications of COVID-19. In a model with no consumer heterogeneity, Eichenbaum, Rebelo, and Trabandt (2020) show that containing the spread of the contagion may be welfare-improving in spite of the severe recession such policies cause. By contrast Bethune and Korinek (2020) show that a more nuanced approach, where infected agents are fully isolated, is socially optimal and yields milder recessions compared to full shutdowns. Bethune and Korinek (2020) acknowledge that in the event such a nuanced approach is infeasible aggressive containment is still optimal though very costly. Glover et al. (2020) advocate for a partial, possibly Swedish-style containment policy. Their approach, like the one in this paper, considers the effects of shutdowns on different age groups, and they find that elderly consumers benefit far more than the young from stringent containment policies that vastly reduce economic activity.

Meanwhile, Correia, Luck, and Verner (2020) attempt to use variation between U.S. cities' economic shutdown policies during the 1918 Spanish Flu pandemic to argue that short-term shutdowns to mitigate disease contagion improve long-run growth. Barro, Ursúa, and Weng (2020) have similar findings. Both results hinge on the fact that working-age adults were most likely to die from the 1918 Spanish Flu, which is not true in the case of COVID-19. But, as is shown here, accounting for differences in the age-mortality distribution matters for optimal-mitigation policies.

The primary contribution of this paper is to consider aggregate welfare implications in a framework with both endogenous LE's and VSL's that are also heterogeneous across ages and depend on health investment. Results and conclusions presented here conform more with results in Bethune and Korinek (2020), Glover et al. (2020), and Krueger, Uhlig, and Xie (2020), suggesting a nuanced response to COVID-19 that does not too drastically limit commercial activity. Such policies can be aggregate-welfare improving as long as they reduce overall COVID-19 deaths sufficiently, depending on the various modeling assumptions.

2.2 The Impact of Recessions and Poverty on Childhood Development

Since this paper argues that the welfare impacts of the COVID-19 recession are disproportionately shouldered by young people, it is important to understand why policymakers and economists should care about this by reviewing the literature on recessions, poverty, and childhood development. Generally speaking, if the 2020 COVID-19 economic recession leads to increases in poverty and malnourishment amongst children and decreases in stimulating contact with adults, like educators and mentors, adverse impacts to long-run welfare should be expected.

Heckman, Pinto, and Savelyev (2013) establish the long-run, positive impacts of interactive early childhood development programs on the life outcomes of an individual participant. Heckman (2008) discusses how ability gaps between advantaged and disadvantaged children start early in life and can be mitigated by substantial, targeted investment in early childhood programs. Early environmental factors due to parenting and familial practices can also lead to better developmental outcomes (Heckman 2008). But financially-stressed families are less likely to have time for full parental engagement, which could negatively affect future outcomes for school-aged children of working parents who are out of school due to COVID-19 shutdowns.

Campbell et al. (2014) find that stimulating early childhood development leads to significantly better health and cognitive outcomes during adulthood. In their study, children subjected to a treatment where they were engaged in "social stimulation interspersed with caregiving and supervised play throughout a full 8-hour day for the first 5 years" of their lives where they were also given "two meals and a snack at the childcare center [and] were offered primary pediatric care" had significantly lower risk for non-communicable diseases in their mid-30s (Campbell et al. 2014). Hoddinott et al. (2011) provide strong evidence that sustained investments in early-life nutrition and childhood development lead to welfare improvements over the life cycle and thus the long run. If the current shutdown not only leads to less stimulating social contact but also limits the ability of impoverished children to benefit from free school breakfast and lunch programs, school closures will have adverse impacts that affect social, intellectual, and physical development.

The evidence on child health outcomes resulting from economic contractions versus expansions is mixed. Ferreira and Schady (2009) review empirical evidence finding that in rich countries, like the U.S., recessions may not have an adverse impact on the health and human capital development of children. Indeed, they find that child health and educational outcomes appear counter-cyclical. The counter-cyclical nature of educational outcomes for children may be due to the outsize, positive effect of the Great Depression on high school graduation rates (Goldin 1999; Black and Sokoloff 2006). Recent microeconomic evidence in the U.S. also suggests that infant mortality may be counter-cyclical (Chay and Greenstone 2003; Dehejia and Lleras-Muney 2004; Ferreira and Schady 2009). But, while infant mortality may be countercyclical, there is evidence that out-of-pocket spending on childhood health care services is pro-cyclical, especially for children with a high baseline level of medical care (Karaca-Mandic, Choi Yoo, and Sommers 2013). Such children often have special needs and are more sensitive to pullbacks in medical care spending. Further evidence from developing countries suggests that on the whole, children's health outcomes are made worse by recession, with potential long-run consequences resulting from malnutrition and stunted growth (Jensen 2000; Stillman and Thomas 2004; Paxson and Schady 2005; Alderman, Hoddinott, and Kinsey 2006; Ferreira and Schady 2009).

Other microeconomic studies focussing on parents' labor market outcomes suggest that economic downturns likely harm childhood development more than they open up opportunities for developmental improvement. Kalil (2013) reviews the preponderance of evidence as to how parental job loss and income instability affect childhood development, concluding that the Great Recession likely adversely affected children's long-run economic outcomes. For example, parental job loss, especially in families with lower socioeconomic status, is associated both with negative effects on educational outcomes and behavioral and emotional health problems for children during their teenage years (Oreopoulos, Page, and Stevens 2008; Ananat et al. 2011; Kalil 2013). Further, the adverse impacts on emotional and psychological health of children experiencing parental job loss appear to persist for at least five years (Kind and Haisken-DeNew 2012). Many studies suggest that mere perceptions of parents' job insecurity are enough to cause stress that leads to poor educational outcomes and behavioral problems (Barling, Dupre, and Hepburn 1998; Barling, Zacharatos, and Hepburn 1999; Conger and Donnellan 2007; Ananat et al. 2011; Schneider, Waldfogel, and Brooks-Gunn 2015). This is because fear and anxiety can tax cognitive skills, adversely affecting behavioral health (Leininger and Kalil 2012; Shah, Mullainathan, and Shafir 2012). Given the high unemployment numbers seen during the 2020 economic crisis, we should expect that familial stresses induced by job insecurities are at play, possibly affecting children's health outcomes.

Poverty in general, whether wrought from aggregate shocks or just bad luck, induces stress and results in adverse child-development outcomes (Boyer and Halbrook 2011). Childhood stress can manifest itself as poor physical health outcomes during teenage years (Evans and Schamberg 2009). It can also stunt brain development and limit the ability of the individual to engage in complicated cognitive functions, like deep critical thinking, in the future (Sapolsky 2004). Disparities in academic outcomes in early schooling years brought on by a lack of initial human capital development may be magnified as children progress through school (Cunha et al. 2006). In conclusion, childhood poverty is associated with poor outcomes during adulthood, including a higher propensity for criminal behavior, mental illness, and general health disparities (Evans and Kim 2007; Evans and Schamberg 2009; Nikulina, Widom, and Czaja 2011; Kim et al. 2013).

Thinking about the dynamic, long-run impacts of economic shocks to individuals across the age distribution, especially with respect to health outcomes, will help build inference as to which policies can dampen and mitigate recessions' adverse effects on children. In light of evidence that directly links the health and viability of adults to their early childhood education (Campbell et al. 2014), policies that reduce negative impacts of recessions on childhood cognition should be considered.

2.3 Measuring the Value of Statistical Lives

In this paper, the primary exercise is to analyze a dynamic model that generates endogenous measures of LE and VSL as a result of the consumption and health investment choices of age-heterogeneous agents. While the model will generate a measure of VSL that relies on how marginal changes to health investment improve age-specific, non-accidental mortality rates, in the literature such a measure of VSL is rather uncommon. To the best knowledge of this author, the only other paper that attempts to estimate VSL's using both mortality rates and age-specific health spending is Hall and Jones (2007), from which the model here is borrowed directly with a few slight modifications.

In the empirical literature, VSL's are typically estimated using labor market outcomes. Specifically, one can regress the between-industry wage premium on differentials in industry-specific accidental mortality rates, while controlling for skills and human capital. In the VSL literature, this is known as the "revealed preference" approach. Other approaches, known as "stated preference" approaches, explicitly ask individuals how much they would be willing to accept in exchange for increased risk of death. Viscusi and Aldy (2003) and Kniesner and Viscusi (2019) provide a review of both of these strands of the VSL literature, suggesting that for working-age men, VSL's are \$10 million in 2018 dollars. That is consumption value of an average working-age male's life is around \$10 million. But, some authors have criticized estimates from labor market measures as quantitatively fragile, since skills and human capital are difficult to observe (Siebert and Wei 1994; Leigh 1995; Miller 2000; Hintermann, Alberini, and Markandya 2010). Nordhaus (2002) criticizes measures of VSL from the labor market literature because they fail to account for possible dynamic changes to both future risk and future income, as such estimates only reflect a current risk to current income tradeoff. This is problematic considering that mortality premia have risen along with the health services share of consumption (Nordhaus 2002, 2005). Such a criticism thus provides impetus for alternative models which generate VSL's using health spending and mortality outcomes, as is done in this paper.

Further, using labor market outcomes to quantify VSL's can be limiting since not all age groups actually work. Specifically, VSL's for children and elderly retirees are ignored in such studies. This may be problematic since Aldy and Viscusi (2008) find significant correlations between VSL and age for workers in different age groups. They conclude that VSL follows an inverted-U-shaped profile, where younger workers in their late teens and early twenties and older workers nearing retirement have similar VSL's of around \$5 million in 2018 dollars, while prime-age workers have VSL's over \$13 million. But how can we measure the VSL for, say, a 10-year old when using only labor market outcomes?

To estimate youth VSL's, some studies rely on parents' willingness to pay (WTP) to reduce childhood risks of death or trauma. Byl (2013) uses evidence from the infant car-seat market to show that children's lives are valued at a premium to adults'. This premium is almost double and could be as high as \$17 million in inflation-adjusted 2018 dollars. Jenkins, Owens, and Wiggins (2001), using the market for bicycle helmets, estimate separate VSL's for children and adults, finding the opposite of Byl (2013): adults' lives are typically more valuable. Other authors have used stated-preference surveys to ask adults how much they would pay to reduce the risk by half of a child being killed by a parent or caregiver (Corso, Fang, and Mercy 2011; Peterson, Florence, and Klevens 2018). Such surveys conclude that the level of VSL for children is around \$17 million in 2018 dollars. Hammitt and Haninger (2010) also find significantly higher VSL's for children using a stated-preference survey involving willingness to pay to reduce risk from fatal diseases and traumas — around \$16 million for children versus \$7-12 million for their parents.

While there seems to be a consensus in the literature as to the range of plausible VSL's for adults, there is debate as to the shape of the life-cycle VSL profile when younger age groups are included. The findings presented in this paper, as well as those in Hall and Jones (2007), suggest that VSL's are likely declining, almost monotonically, in age. The results here thus confirm many of the aforementioned WTP studies, while contrasting with the age-profile VSL estimates of Aldy and Viscusi (2008).

This paper takes the health production approach to measuring age-specific VSL's. It is thus assumed that increases in health investment lead to decreases in non-accidental mortality and thus increases in life expectancy. VSL's are then identified parametrically by the marginal cost, in consumption units, of decreasing the non-accidental mortality rate. The approach presented here thus relies on a revealed preference argument: the investments made in children's health care by society as a whole reflect how much value society places on children's lives. Indeed, as will be shown, children enjoy a large VSL premium over their parents when using health investment data.

3 Model

In modeling how a sudden and unexpected disease contagion simultaneously affects both economic and health outcomes, we turn to the centralized endowment economy in Hall and Jones (2007). In their dynamic model, health investment by consumers positively affects health status through a health production function that is both age- and time-dependent. Increases in health status lead to declines in mortality risk, raising the probability the age-a consumer in period t will live to be an age-$a+1$ consumer in period $t+1$. Consumers thus face a tradeoff in choosing consumption c_{at}, which yields flow utility today, versus health investment h_{at}, which increases the probability of future survival and thus the value of future consumption flow utilities. In this manner, health status and thus survival probabilities are endogenous.

The model here departs from Hall and Jones (2007) by assuming the period-length is one year instead of five. Consumers live up to age 100, so in any given period there are

101 cohorts of consumers alive, counting newborns. Each age-a cohort in period t is characterized by a representative agent, so that there is no heterogeneity within age groups, only across age groups and over time. In any given period, there are N_{at} consumers of age a alive. Every consumer is assumed to contribute the same amount y_t to net resources, so that y_t can be thought of as income per-capita. From this assumption, all variation in contributions to aggregate welfare across age groups and over time is strictly dependent on variation of per-capita health investments by age.

Using endogenous health investment, the model generates measures of VSL by age from the marginal cost of health production. This permits analysis as to how different cohorts are disparately impacted by both aggregate output shocks affecting y_t and shocks to health care technology directly impacting health status. Each of these channels will affect welfare measures which rely on VSL's. First, health investment will vary as net resources change, affecting the marginal cost of health production and thus mortality rates. Second, changes in the productivity of health services will directly affect the marginal cost of health production for any given level of health investment. But, this will also induce consumers to adjust their health investments as long as mortality risk is not perfectly inelastic with respect to health investment.

Denote health status as x_{at}, which is a function of health care consumption h_{at}, an aggregate health sector productivity component z_t, and an idiosyncratic, age-specific component w_{at}, so that $x_{at} = f_a(h_{at}; z_t, w_{at})$, where f_a is increasing in all arguments. h_{at} can also be thought of as health investment, since its purchase level has dynamic, long-run implications for survival. w_{at} accounts for factors orthogonal to health technology advancement, like un-modeled decisions related to education or habits like smoking and drug use. Hall and Jones (2007) assume z_t and h_{at} account for some known fraction μ of the decline in U.S. mortality rates over the last half century, while w_{at} accounts for the remainder. This leads to an identification issue which is addressed in Section 4.1, re-visiting some fundamental findings from the health outcomes literature.

Health status, x_{at}, is the inverse of the age-a, period-t mortality rate, $m_{at} = 1/x_{at}$. Survival rates are thus $1 - m_{at} = 1 - 1/x_{at}$. Total mortality is the sum of accidental m_{at}^{acc} and non-accidental m_{at}^{non} mortality. Health care investment decisions h_{at} are assumed to only affect non-accidental mortality, so that health status can be written

$$x_{at} = f_a(h_{at}; z_t, w_{at}) = \frac{1}{m_{at}^{acc} + m_{at}^{non}} = \frac{1}{m_{at}^{acc} + 1/\widetilde{x}_{at}} \tag{1}$$

$$\widetilde{x}_{at}(h_{at}) = A_a(z_t h_{at} w_{at})^{\theta_a} \tag{2}$$

In addition to choosing h_{at}, consumers also choose other consumption c_{at}. They receive flow utility from c_{at} according to the iso-elastic function $u(c_{at}) = \frac{c_{at}^{1-\gamma}}{1-\gamma}$.[2]

Each consumer receives exogenous endowment income y_t which evolves according to some known process. All risk is thus idiosyncratic and endogenous, acting through the survival function. Finally, each period assume consumers have base utility b_{at}, which will be calibrated to ensure that the value of life is zero upon death. As Hall and Jones (2004) discuss in their working paper, b_{at} will usually be positive since calibrated choices of γ are > 1, ensuring that $u(c_{at}) < 0$. There is no savings mechanism and labor is assumed to be supplied inelastically.

Under these conditions and assuming equal Pareto weights for all agents alive in period t, the social-welfare maximizing allocations satisfy

$$V_t(N_t) = \max_{\{h_{at}, c_{at}\}_a} \sum_{a=0}^{\infty} N_{at}\left[b_{at} + u(c_{at})\right] + \beta V_{t+1}(N_{t+1}) \tag{3}$$

$$\text{subject to} \quad \sum_{a=0}^{\infty} N_{at}(y_t - c_{at} - h_{at}) = 0 \tag{4}$$

$$N_{a+1,t+1} = \left(1 - \frac{1}{x_{at}}\right) N_{at} \tag{5}$$

$$x_{at} = f_a(h_{at}; z_t, w_{at}) \tag{6}$$

$$y_{t+1} = e^{g_{yt}} y_t \tag{7}$$

where N_t is a vector with components $N_{1t}, N_{2t}, \ldots, N_{at}, \ldots$ describing the population distribution in t, and $\beta \in (0, 1)$ describes a consumer's time preferences.[3]

Optimal allocations of $\{h_{at}, c_{at}\}_a$ are subject to the equilibrium condition

$$\underbrace{\frac{\beta\, v_{a+1,t+1}}{u_c}}_{\text{Marginal Benefit of Saving a Life}} = \underbrace{\frac{x_{at}^2}{f'(h_{at})}}_{\text{Marginal Cost of Saving a Life}} \quad \forall a, t \tag{8}$$

$v_{a+1,t+1}$ is the standard envelope condition, $\frac{\partial V_{t+1}}{\partial N_{a+1,t+1}}$, which captures how the total future value of social welfare changes in response to variation in the population level of agents surviving from age a in t to become age $a+1$ in $t+1$. Under the parameterization of

[2] Hall and Jones (2007) consider both a flow utility function that only features other consumption and one where consumers benefit from health status. This so-called "quality of life" utility component is omitted here, without loss of generality. Indeed, Hall and Jones (2007) show that regardless of whether the quality of life component is included, VSL estimates are hardly affected.

[3] The planner's optimization problem is the same as that in the working paper Hall and Jones (2004), where base utilities are allowed to be both age- and time-dependent. This specification is preferred to that in the published version of the paper, so that b_{at} can be directly calibrated to match VSL's estimated from health investment technology.

health technology in (2), the right hand side of (8) is $h_{at}\widetilde{x}_{at}(h_{at})/\theta_a$, which is a measure of VSL. In practice, the age- and time-varying utility intercepts b_{at}, can be backed out of (8) to ensure that the empirical estimates of VSL's, using the marginal cost of health production on the right, exactly equal the marginal benefit attributable to household preferences. That is, given data on health outcomes, income, consumption, b_{at} can be calibrated to force (8) to hold.

4 Parameter Selection

Updating both versions of Hall and Jones (2004, 2007), the health production parameters are selected using a regression of survival probabilities on health spending that accounts for possible trends in age-specific residuals, w_{at}. The estimation of $\widetilde{x}_{at}(h_{at})$ is described in detail in Section 4.1, where several assumptions on the fraction of trend decline in mortality associated with technological change, which is denoted by μ, are considered. With health production parameters, productivities, and residuals in hand, age-specific, period-t VSL's can be computed using the marginal cost approach: $VSL_{at} = h_{at}\widetilde{x}_{at}(h_{at})/\theta_a$. Having VSL's, base utilities b_{at}, can be backed out of the equilibrium condition (8) following a procedure described briefly in Section 4.2. Finally, in Section 4.3, given the health production parameters, productivities, and base utilities, the model is solved backwards from 2018 to 1959 by simulating equilibrium choices of c_{at} and h_{at} for y_t computed from NIPA.

4.1 Estimating Health Production Parameters

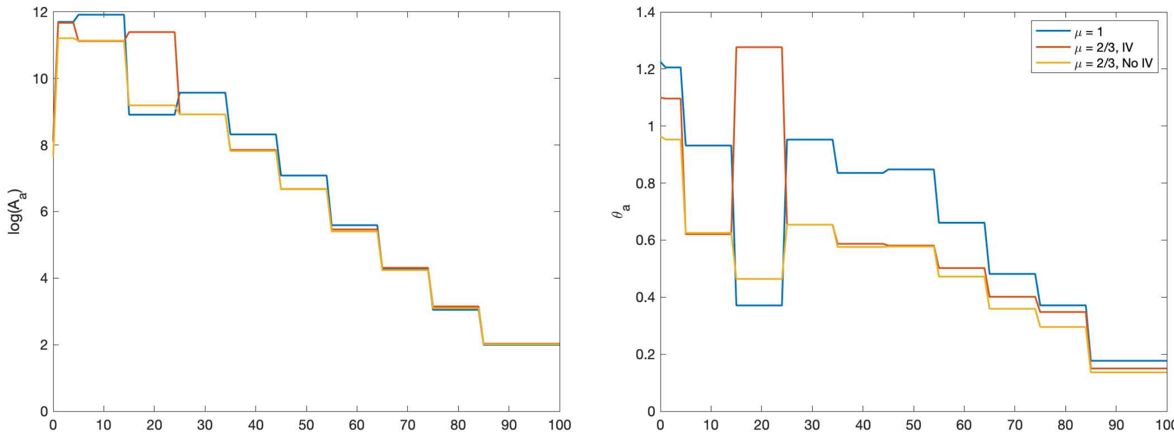
Aggregate NIPA data from 1959-2018 and age-specific health spending data from Meara, White, and Cutler (2004) are used to estimate A_a and θ_a for each a. Aggregate health spending is the sum of personal consumption expenditure (PCE) on health care and government spending on health care. All other non-health-care consumption is the sum of other PCE spending and non-health-related government spending. To compute these data points, we can turn to NIPA's PCE Tables 2.5.3, 2.5.4, and 2.5.5, and the government outlay Tables 3.15.3, 3.15.4, and 3.15.5. Dealing with unit-uniformity issues arising from combining chain-weighted price and quantity indices, the procedures in Whelan (2002) are used to construct new indices for the combined aggregate series using both PCE and government spending. Using the aggregated health spending data, age-dependent health spending distributions are constructed by utilizing the weights for five-year age groups described in Meara, White, and Cutler (2004) and interpolating both within periods across age groups and over time to arrive at annual distributions of health spending from 1959 to 2018 for consumers of ages 0 to 100. A cubic polynomial is used for interpolation over the time dimension. Where extrapolation is required, assume the health spending distribution across ages is stationary after the last year of observations in the sample.[4] Within a period, a simple replication scheme is followed: since health spending data is only available for individual averages over ten-year age groups, the same health spending level is assigned to all individuals within an age group. For age-specific mortality data, several sources for both accidental and non-accidental mortality rates are used — for years 1950 to 2003, the National Center for Health Statistics report, *Health, United States, 2003*, and for years 2004 to 2017, the National Vital Statistics Reports, Volume 68, Number 9, *Deaths: Final Data for 2017*, updated on June 24, 2019. Finally, life-expectancy data, which are not directly used in the estimation but matched independent of parameter selection, are taken from Table 4 of the 2017 National Vital Statistics Reports.

With health investment and mortality data, (2) is estimated separately for each age-a consumer unit using a two-step regression procedure where the trend in w_{at} is assumed orthogonal to health outcomes $\widetilde{x}_{at}$ whenever it is also assumed that some fraction μ of mortality trend decline is attributable to non-technological factors. Note that when $\mu = 1$ all trend decline in mortality is assumed to be attributed to technological change acting through either z_t or y_t via h_{at}. For more details on this identification argument see the discussion in Hall and Jones (2007).

Here, two separate assumptions on μ are considered and the orthogonality restriction for the trend in w_{at} is assessed using a C-test on the difference in two Sargan/Hansen statistics described in detail in Hayashi (2000). In all cases the growth rate in z_t is assumed to be identical to growth in y_t, i.e. $g_z = g_y$. This assumption is affirmed by empirical work in Horenstein and Santos (2019) who find little evidence to suggest productivity growth in the health sector substantially differs from GDP growth. In the first exercise, it is assumed that $\mu = 1$, so that all decline in mortality is due to technical advancement. In the $\mu = 1$ case, the orthogonality of trend in w_{at} is irrelevant. Alternatively, examining the case where $\mu = 2/3$ as in Hall and Jones (2007) allows for the orthogonality restriction on trend growth in w_{at} to be tested. The C-test fails to reject such a restriction, so $g_{wa}\, t$ is used as an instrumental variable (IV). This empirical result jibes with the original findings in Hall and Jones (2007) and other studies which suggest that factors not related to health spending have played an important role in mortality rate declines (Fogel 2004; Grossman 2005; Cutler, Deaton, and Lleras-Muney 2006). The preferred health production specifica-

[4] This extrapolation assumption was tested where the extrapolated data using the Meara, White, and Cutler (2004) age-specific health spending estimates were compared against data from the Centers for Medicare & Medicaid Services (CMS 2019). Differences between the age-distributions of health investment are insignificant. The results of this test are available upon request.

tion is thus the 2SLS estimation where $\mu = 2/3$ and $g_{wa}\, t$ is used as an IV.



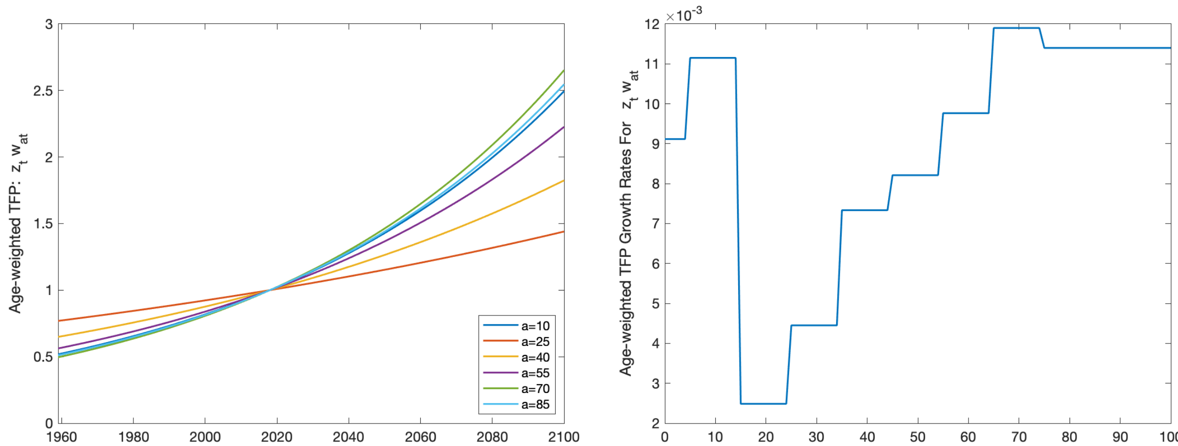
(a) Health Production Intercept

(b) Elasticity w.r.t. Health Investment

Figure 1: Here, plots of the estimates for $\ln A_a$ and θ_a are presented. The cases where $\mu = 1$ and $\mu = 2/3$ with no trend instrument track each other in terms of the declining profile by age. The IV versus non-IV regressions yield similar estimates except for the 15-25 age group. All estimates of θ_a are significant at the 1% level.

Figure 1 presents estimates for the time-independent health production parameters, where age indexes the horizontal axes. The stair-step feature of the estimates reflects the interpolation scheme assigning the same health and survival rates to everyone in ten-year age groups. In the $\mu = 2/3$ case, the introduction of the linear-trend IV only significantly affects inference as to the elasticity of health outcomes θ_a for 15-25 year olds, which can be seen by looking at the differences in the gold versus red lines in Figure 1b.

Focussing on θ_a, notice that this elasticity appears to consistently decline in age, with the exception of the jump for teens and young adults. Its negative, $-\theta_a$, is the elasticity of the preventable mortality rate with respect to health spending. It thus represents the percent change of a percentage-point decline in mortality with respect to health spending. To fix intuition as to why θ_a mostly declines with age, consider the non-accidental mortality rates of a 30-year old and a 70-year old. Currently, a 30-year old has a probability of dying before he reaches age 31 of approximately 0.0006, or 0.06%, while a 70-year old has a probability of dying before reaching age 71 of 0.0175 or 1.75%. Estimates of θ_{30} and θ_{70} for the $\mu = 2/3$ case with no IV are 0.6540 and 0.4012 respectively. A 1% increase in health spending by a 30-year old thus leads to a 0.65% reduction in the mortality rate, so that the new mortality percentage is 0.02%, amounting to an absolute reduction of 0.04%. Meanwhile, for a 70-year old, a 1% increase in health spending leads to mortality declining from 1.75% to 1.05%, or 0.7% in absolute terms. Thus, despite the fact that $\theta_{70} < \theta_{30}$, a 1% increase in health spending for a 70-year old actually has a greater impact on overall mortality-rate decline because the 70-year old is starting at a base rate that is substantially lower than that of the 30-year old.



(a) Productivity Levels, 2018 = 1

(b) Productivity Growth Rates

Figure 2: These plots illustrate both the evolution of age-weighted health productivities (a) and the age-specific growth rates (b). In panel (a) estimates are projected out to 2100 to illustrate the differential rates at which returns to health care investment evolve for different age groups. In panel (b), estimated health productivity growth rates from 1959 to 2018 show that younger and older adults benefitted the most from residual returns to health care efficiency z_t and other age-specific indirect factors w_{at} over the latter half of the twentieth century.

Figure 2 shows the age-weighted productivity levels and growth rates over time under the assumption $\mu = 2/3$. Age-weighted growth is $(1/\mu - 1)(g_{ha} + g_z) + g_z$. Both older and younger age groups experience faster health productivity growth than working-age adults. The measure of productivity presented here accounts both for changes in the total factor productivity of health services z_t and changes to the idiosyncratic, age-specific component w_{at}, which captures other exogenous factors, unrelated to health services productivity. These include everything from improvements to public-school lunch and nutrition programs for children to heightened on-the-job safety standards for adults, as well as the effects of changes to pollution, urban density, and other environmental forces. w_{at}, especially for young agents, will capture the aforementioned residual, non-health-technology impacts of the 2020 recession, such as factors resulting from school closures adversely affecting young agents' health outcomes. Multiplied together, $z_t w_{at}$ then captures the degree to which returns to health productivity z_t are either enhanced or dampened by these other age-dependent factors.

4.2 Estimating Base Utilities, b_{at}

To compute b_{at}, an estimate of VSL_{at} is needed so that the health production function TFP and elasticity estimates can reconcile both c_{at} and h_{at} in a full decision-theoretic equilibrium environment. The right-hand side of (8) is a measure of VSL_{at}, which can be computed using only health data and fitted health production parameters. Thus, after fitting the health production function, with an estimate for VSL_{at} in hand and assuming that $v_{101,t} = 0$ for all t, $\beta\, v_{a+1,t+1}$ can be backed out and the model's full Lagrangian expression can be used to compute

$$v_{at} = b_{at} + u(c_t) + \beta\, v_{a+1,t+1} + u_c\,(y_t - c_t - h_{at}) \tag{9}$$

where u_c is the marginal utility of consumption, and output per-capita, consumption per-capita, and health investment are data. Note that, given the problem here is that of a planner efficiently allocating resources, it is without loss of generality that $c_t = c_{at}$ since, by the Second Welfare Theorem, there exist implicit transfers reconciling this efficient allocation for a de-centralized environment.[5] With b_{at} in hand, it remains only to vary γ and β to solve for equilibrium values of c_t and h_{at} generated by the full decision-theoretic model.

4.3 Equilibrium VSL's and Life Expectancy

Given γ, β is selected to match consumption growth g_c from a classical Euler equation, so that $\beta = (1 + g_c)^{\gamma}/1.04$, where 1.04 is assumed to be the gross interest rate and $g_c = 0.0168$ — average per-capita consumption growth from 1959-2018. Given b_{at} and the health production parameters, the model is solved using several values of γ selected over the interval $(1, 2]$. $\gamma = 1.25$ best matches the life expectancy of newborns and the aggregate share of health spending in 2018. Figure 3 presents model-generated equilibrium LE's of newborns under different values of γ along with LE estimates from data. The model's equilibrium appears to adequately capture the increasing profile over time. $\gamma = 1.25$ is used for the upcoming simulations because the equilibrium time series under this assumption appears to provide the closest match to LE's from the data in 2018. Further, lower values of γ are associated with greater leveling-off in long run LE growth, which is also apparent in the data, especially in the decade after the Great Recession.

In equilibrium, the model generates estimates for working-age adults' VSL's in line with VSL estimates from labor market outcomes. Table 1 presents these estimates for the

[5] Hall and Jones (2007) also recognize this fact, as evidenced by their calibration scheme.

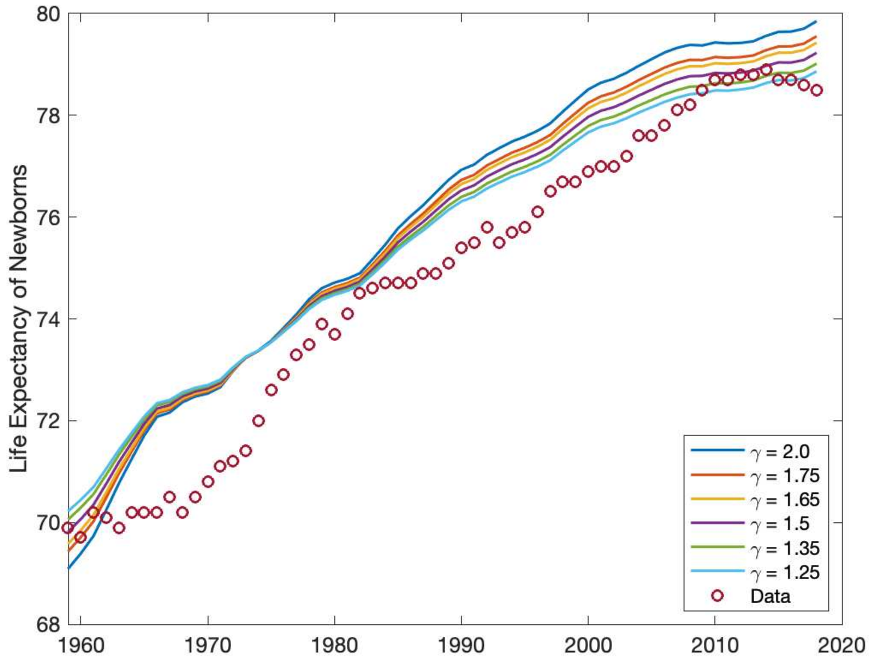


Figure 3: This plot presents the life expectancy of newborns from the simulated model equilibria under different values of γ alongside life-expectancy data taken from the National Vital Statistics Reports. In all separate simulations where γ is varied, it is assumed that $\mu = 2/3$ and health production function estimates from the 2SLS model are used. The preferred specification has $\gamma = 1.25$, which most closely matches life expectancy data in 2018, the last year in the present data sample.

preferred specification where $\mu = 2/3$, $\gamma = 1.25$, and health production parameters are taken from the 2SLS regression with a trend IV. Both cumulative VSL's and VSL's divided by age-specific LE, where the latter is a measure of the value of life per year of life saved, are presented. 2018 VSL estimates for 30, 40, and 50 year olds in the baseline model range from \$4 to \$9 million. Estimates using Mincer-style regressions on wages and industry-specific mortality risk, which are thoroughly reviewed in Kniesner and Viscusi (2019), suggest values within this range. Meanwhile, VSL estimates for children are notably higher and exceed the ranges of estimates from microeconomic studies looking at parents' WTP for child-safety products and reviewed in this paper in Section 2.3.

Notice that, not only do children have higher VSL's measuring the expected consumption value of their remaining life years (top half of table), but some, particularly 10-year-olds, also have higher VSL's per life-year remaining (VSL/LE in the bottom half of the table). Now consider the fact that there are far more children between the age of say 5 and 15 than elderly people between the age of say 75 and 85. Suppose an arbitrary

Table 1: Equilibrium VSL's, $\gamma = 1.25$, $\mu = 2/3$ with IV

	Value of Life in Thousands of 2018$						
Age	1960	1970	1980	1990	2000	2010	2018
0	2010.966	3330.654	4763.997	6525.515	7996.263	8935.804	9552.773
10	5854.994	8033.472	11068.602	16009.304	21853.497	29520.890	34287.264
20	1889.003	2223.565	2679.445	3655.983	4916.239	6113.957	6841.157
30	2672.409	3614.118	4547.095	6298.397	8388.125	8932.166	8281.171
40	1534.607	2344.928	3161.870	4411.828	5495.411	6220.439	6202.894
50	793.792	1347.851	1890.560	2717.719	3485.834	4009.968	4404.305
60	506.081	914.671	1332.577	1944.938	2556.526	3049.265	3482.870
70	439.982	799.947	1166.095	1714.775	2247.303	2666.708	3100.446
80	452.276	799.654	1124.982	1622.251	2103.413	2426.037	2763.816
90	412.520	716.010	979.319	1383.096	1769.241	2017.137	2194.594
	Value of Life per Year of Life Remaining in Thousands of 2018$						
Age	1960	1970	1980	1990	2000	2010	2018
0	28.958	46.452	64.840	86.651	104.302	115.317	122.684
10	97.375	129.009	173.109	243.731	326.261	435.649	503.326
20	37.353	42.167	49.285	65.235	85.832	105.394	117.244
30	64.834	83.254	101.022	135.150	175.666	184.334	169.622
40	47.771	68.404	88.287	118.234	143.133	159.137	156.979
50	33.427	52.384	69.720	95.470	118.329	133.165	144.156
60	30.552	50.277	68.955	95.161	120.207	139.696	156.764
70	41.031	67.271	91.862	127.021	159.315	183.833	209.797
80	70.835	113.389	150.135	204.224	253.941	285.457	321.687
90	109.947	175.853	229.368	309.328	382.910	428.040	465.715

drop in economic activity causes all VSL/LE's to decline by a fixed percentage across the board. The per-capita hit to children will be higher than to others since they have such high starting VSL/LE baselines. Further, the total impact on each age group will be higher for younger cohorts than older ones because there are more youths than senior citizens. In the context of a disease whose mortality rates are disproportionately skewed toward older people, policies designed to curb the spread of disease in order to preserve lives while simultaneously causing an economic recession thus amount to a transfer of welfare from young to old. This phenomenon is explored in more detail in the simulations in Section 5.

5 The Welfare Impacts of Disease Contagion

Aggregate shocks will affect income and possibly health investment and thus health outcomes. Aggregate shocks coupled with a global pandemic will also affect the efficiency of health investment when it comes to generating health outcomes. This is because a pandemic strains health care systems due to large numbers of people with acute illnesses requiring immediate care. Indeed, this potential capacity problem was the main reason why many localities quickly enacted measures to mitigate the spread of COVID-19 in the early weeks of the contagion. For April and May, many U.S. localities allowed only essential medical procedures to occur, so that consumers were forced to put off preventative care and elective surgeries despite still paying insurance premiums which would cover such procedures. Money spent for health care during this time was thus spent less efficiently as multiple weeks and months passed with preventative and elective care put on hold. Thus, while those policies were implemented to seemingly maintain capacity and efficiency in the health care system, health outcomes *beyond* those directly related to the COVID-19 pandemic may still have been adversely affected. While health efficiency shocks are represented by a drop in z_t, the 2020 recession has also likely brought on residual shocks to w_{at}. Aside from the adverse residual effects on childhood development which have been discussed, gym closures may restrict adults' exercise regimens, and families confined to close-quarters for months on end may be more likely to engage-in and/or experience abusive behavior, amongst other possible outcomes.

In terms of the model here, the U.S. economy therefore experienced two simultaneous aggregate shocks to welfare, independent of health outcomes that directly result from the COVID-19 pandemic: 1) a reduction in y_t affecting health investment choices; 2) a reduction in $z_t w_{at}$ affecting the efficiency of those same choices. COVID-19 overwhelmingly affects individuals with compromised immune systems who are older. The degree to which COVID-19 causes premature deaths for consumers of different ages combined with the degree to which consumers of different ages are differentially affected by both shocks to y_t and $z_t w_{at}$ will determine how the present crisis adversely impacts individuals across the age distribution.

In this section, equilibrium outcomes under several scenarios are considered in order to account for uncertainty around the magnitude of the economic shocks, as well as mortality directly caused by the COVID-19 contagion. Specifically, life expectancies, and VSL's for people of all ages change in response to income and health productivity shocks. Several shock scenarios are simulated relative to a baseline where y_t and $z_t w_{at}$

continue to grow at their pre-COVID rates.[6] The simulations can be divided into two camps: 1) those where both y_t and $z_t w_{at}$ are shocked, while accounting for differential COVID-19 mortality risk across the age-distribution; 2) the same as the first simulation, except replacing COVID-19 mortality risk with age-specific estimates for the 1918 Spanish Flu. The latter counterfactual exercise is undertaken in order to assess the importance of the disease contagion's age-mortality distribution on both aggregate and distributional welfare outcomes.

In each broad camp, there are six separate scenarios for income and health productivity shocks.[7] The first income shock scenario builds on the Congressional Budget Office's (CBO) May 2020 projections of output loss due to the policy-driven recession (CBO 2020). The CBO estimates a -5.6% annual growth rate for 2020 followed by 4.2% for 2021. An L-shaped recession is considered in scenario two, where output falls -5.6% in the first year and recovers thereafter only at the post-Great Recession rate of 0.98%. Next, a quasi-V-shaped recession is considered where output falls by 5.6% in 2020 and rises by 5.6% in 2021. Finally, these exercises are repeated after adjusting the magnitude of the initial shock to -10%.

The six scenarios for health productivity shocks directly correspond to the income shock processes. Assume that health productivity shocks and recovery rates are proportional to those of y_t. For example, suppose that output continued to grow at the post-Great Recession rate, and call the level of 2020 per-capita output associated with this growth $\overline{y}_{2020}$. Then, a -5.6% year-on-year shock to 2019 output leads to a reduction in 2020 output relative to $\overline{y}_{2020}$ of $-0.056 - 0.0098 = -0.0658$. Now, note that baseline $g_z + g_{wa}$ can be computed under the assumption that $\mu = 2/3$ and a further assumption that z_t grows at the same rate as y_t. In every different shock and recovery scenario and for each age-a agent in each subsequent period after the shock, the log of age-specific productivities $z_t w_{at}$ can be rescaled by the proportional growth factor (in this example, -0.0658)

[6] Specifically, assume that had COVID-19 not occurred, y_t would continue to grow at its post-Great Recession annual rate of 0.0098 and $z_t w_{at}$ would evolve along its constant, age-specific growth path presented in Figure 2a.

[7] It should be noted that all shocks are modeled in the "MIT" sense. That is, they occur suddenly and without expectation. Indeed, consumers and thus the social planner are not thought to have any idea that such a shock were to ever be possible, thus failing to plan for it. The model is first solved for equilibrium outcomes using output growth and population projections out to year 2100, assuming that no adverse shock pertaining to a contagion has occurred in 2020. Then, having equilibrium consumption and health investment decisions in hand, per-capita income y_t and health productivities suddenly decline, corresponding to the recession and recovery characteristics described above. In this formulation, with a period length of one year, 2019 is the last period prior to the shock affecting output in 2020. Recovery begins in 2021 in every scenario, and the simulations are conducted by solving the model backwards from 2100 where per-capita growth after 2021 is projected out at the model-implied post-Great Recession (after 2009) annual average of 0.98%.

relative to the baseline. Having now shocked both y_t and $z_t w_{at}$, equilibrium outcomes can be computed.

5.1 Joint Income and Health Investment Productivity Shocks Accounting for COVID-19 Mortality Risk

COVID-19 itself, being an acute event, has little impact on the LE of the young, because mortality rates from the disease are skewed toward older people. Rather, LE is impacted through channels residual to the COVID-19 crisis, such as the drop in income and health investment due to the economic fallout. This section considers the distributional implications of the economic shutdown while accounting for health productivity shocks and shocks to mortality directly resulting from the crisis. Indeed, shutting down the economy amounts to a transfer of welfare from the young to the old. Depending on the ultimate severity of the crisis, the value of life years lost attributable directly to people dying from the COVID-19 disease may be exceeded by the value of life years lost due to the non-COVID-19 residual economic impacts.

Note that the analysis here takes no stand on whether shutting down the economy to reduce COVID-19 deaths is somehow optimal. Rather, the focus here is on the trade-off between the value of short-run lives saved and long-run lives lost when VSL's are age-dependent and health investment heterogeneity ensures that consumers of different ages are differentially-affected by economic shocks. Unlike work in Bethune and Korinek (2020), Eichenbaum, Rebelo, and Trabandt (2020), Glover et al. (2020), and Krueger, Uhlig, and Xie (2020) the model here contains no mechanism endogenously linking output loss to reductions in total disease-related deaths. Rather, income and total disease deaths are exogenous. Since there is so much uncertainty surrounding how the economic crisis and, ultimately, the disease contagion will play out, this assumption allows for direct comparison of outcomes under differing degrees of simultaneous economic and disease contagion. Specifically, the exercises here involve simulating VSL's and LE's under different combinations of output shocks and total disease deaths to understand how welfare loss is distributed between generations. The goal of such an exercise is to understand how people of different ages are affected by these simultaneous occurrences.

As of July 9, 2020, over 126,000 people in the U.S. had died of COVID-19 (JHUM 2020). According to the Centers for Disease Control and Prevention (CDC), over 59% of deaths were individuals 75 years of age or older, and over 80% of deaths were individuals 65 years of age or older (CDC 2020c). Letting $m^{covid}_{a,2020}$ denote the age-specific mortality rate from COVID-19 taken from the CDC's provisional COVID-19 death counts, the mortality distribution associated with COVID-19 can be computed. Specifically, since the CDC currently reports the total number of deaths by age for each week of the pandemic back to February 1, 2020, there exists data for the conditional age-distribution of all current COVID-19 mortalities. Figure 4 presents the age-distribution of COVID-19 deaths where each line corresponds to a different week of the pandemic. Notice that the age-specific death distribution has been stable over time and skews older.

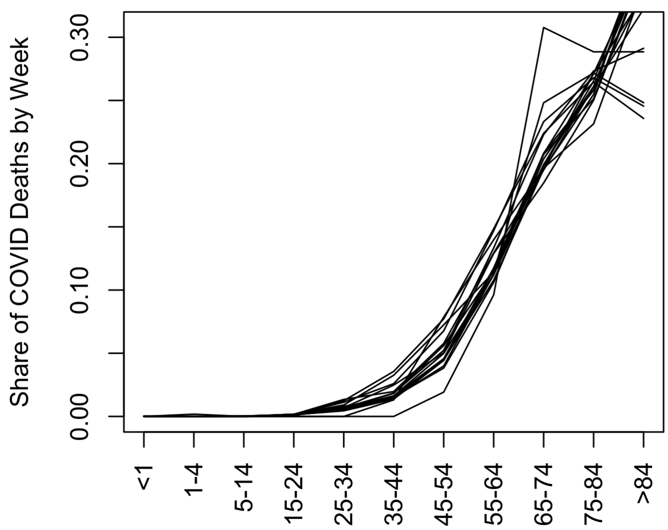


Figure 4: Age bins are on the horizontal axis. The different lines represent the distribution of COVID-19 deaths by age conditional on getting the disease for different weeks of the pandemic. The sample begins the week starting Sunday, March 8, 2020, and concludes with the week ending Saturday, June 27, 2020 (CDC 2020c). The conditional age-specific death distribution appears stationary over time.

While Figure 4 shows the probability of dying from COVID-19 conditional on getting the disease, the age-specific marginal probability of dying from the disease, $m^{covid}_{a,2020}$, also depends on the total number of deaths and the population levels of different age groups. Using the COVID-19 forecasting models presented at the CDC's main forecasting hub for 4-weeks out,[8] $m^{covid}_{a,2020}$ is computed for seven separate scenarios of total disease deaths: 1) average 4-week deaths across all models cited by the CDC of 145,224 which is closest to 4-week projections from the Notre Dame-FRED COVID-19 forecasts (ND 2020); 2) maximal 4-week ahead deaths of 180,226 predicted by Columbia University's Shaman Group (CU 2020); 3) 250,000 deaths; 4) 500,000 deaths; 5) 750,000 deaths; 6) 1,000,000 deaths; 7) 1,500,000 deaths; 8) 2,000,000 deaths. Scenarios (3) through (8) account for how the crisis

[8]See CDC (2020b) for a full list and description of the models the CDC uses for COVID-19 case and death forecasting and CDC (2020a) for the actual forecasting data.

may possibly unfold over the next 6-8 months.[9]

Assume $m^{covid}_{a,2020}$ is not affected by health investments. In this manner all COVID-19 deaths are treated as accidental. The reasoning behind this assumption is that, given fixed health care resources entering the period, mitigation of the spread and thus severity of COVID-19 requires measures to be taken outside the scope of the model — things like social distancing mandates and forced closure of so-called "non-essential" businesses. Such policies are further assumed, implicitly, only to impact the total number of deaths, and thus they exogenously affect $m^{covid}_{a,2020}$. Finally, the health crisis is assumed to have resolved itself and disappeared by the end of 2020. While one may wonder how productivity variables like z_t and w_{at} are not affected by innovations leading to COVID-19 therapies, consider that improvements to health care efficiency directly pertaining to COVID-19 treatments likely will not be realized until such treatments are widely available in the future, probably after the end of 2020. The same goes for the prevalence of vaccines. In the event that effective cures or vaccines for COVID-19 are found after 2020, such improvements will be captured by future productivities. The crisis associated with COVID-19 is thus limited to the initial, latent period prior to the development and wide dissemination of such treatments, after which COVID-19 is treated in this exercise just like any other disease that circulates widely amongst the populace. Modeling $m^{covid}_{a,2020}$ as exogenous in 2020 reflects the acute nature of the initial spread. After 2020, deaths caused by $m^{covid}_{a,2020}$ will be assumed to be folded into m^{non}_{at} and directly affected by health productivities and investments. That is, for all $t \neq 2020$, $m^{covid}_{at} = 0$. The inverse mortality rate in 2020 is $x_{a,2020} = \frac{1}{m^{acc}_{a,2020} + m^{covid}_{a,2020} + 1/\tilde{x}_{a,2020}}$.

The main mechanism affecting LE's and VSL's is the reduction in survival rates driven by reductions in health investments due both to falling health productivities and income. Since aggregate health investment is not a directly-targeted data moment in the model calibration, for the results presented here to be taken seriously, endogenous health investment generated by the model's equilibrium should resemble real-world measures of health investment. Particularly, we should care about how changes in health investment resulting from the modeled income and health productivity shocks match observed changes in health investment in the data. Note that personal health care spending fell -1.5% year-on-year from the first quarter of 2019 to 2020. Figure 5 compares how simulated equilibrium aggregate health investments under COVID-19 scenario number one, assuming 145,224 deaths, vary year-on-year compared to aggregate personal health care

[9] Recall, however, that since we are analyzing a one-year model period, death shocks associated with the crisis are modeled as aggregates over all of 2020. For this reason, projections (1) and (2) are on the lower end of possible outcomes.

investment data from NIPA. The data are in quarterly intervals but the simulated outcomes are in annual intervals. Notice that the last data point (blue dot) presented for first quarter 2020 resides along the model-predicted path of decline in aggregate health investment. It should be noted, however, that model predictions account for variation in both personal spending and government spending, so the comparison is not exact unless it is assumed that government health investment and personal health investment decline equally in response to the COVID-19 crisis. Under the current crisis it is not unreasonable to assume this since precautionary and elective procedures both for patients using private health insurance and those using government Medicare or Medicaid have been limited for certain periods.

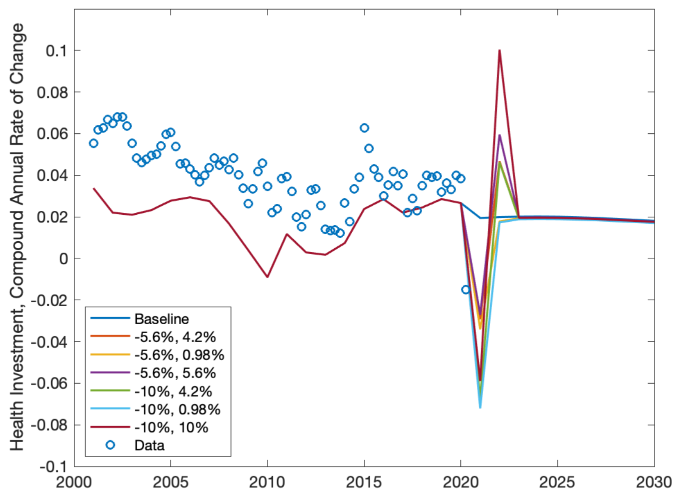


Figure 5: The statistic presented here is annual rates of change of aggregate health investment. The colored lines represent simulated equilibrium aggregate health investment, and the blue dots represent data points for personal consumption expenditure on health care. Since the shocks are simulated in the "MIT"-sense — suddenly and unexpectedly — there are no deviations in aggregate health spending amongst the different model simulations prior to the 2020 recession.

With a satisfactory model fit, we can now analyze the welfare implications of the shock. To understand the effects across the age-distribution, let $\overline{LE}_{at}$ describe the baseline life expectancy in the constant-growth economy and $\widetilde{LE}_{at}$ describe life expectancies, independent of COVID-19 risk, in one of the shocked economies. Recall, the constant growth economy is assumed to feature continued growth in income per-capita of $g_y = 0.0098$, the post-Great Recession growth rate. Let $\overline{VSL}_{at}$ be the endogenous baseline VSL for age-a consumers in period t in the no-recession, constant growth simulation and $\widetilde{VSL}_{at}$ be the VSL independent of COVID-19 risk for one of the shocked economies. The goal is to show how long it takes LE's to recover from the recession, and compare VSL welfare loss due to non-COVID-19 factors against VSL's lost due to COVID-19 deaths. Lost life years per-capita due to non-COVID-19 factors relative to the 2020 baseline are

$$\widetilde{LE}_{at} - \overline{LE}_{a,2020} \tag{10}$$

The per-capita consumption value of each COVID-19 death is measured as foregone baseline VSL's

$$\overline{VSL}_{a,2020}\, m^{covid}_{a,2020} \tag{11}$$

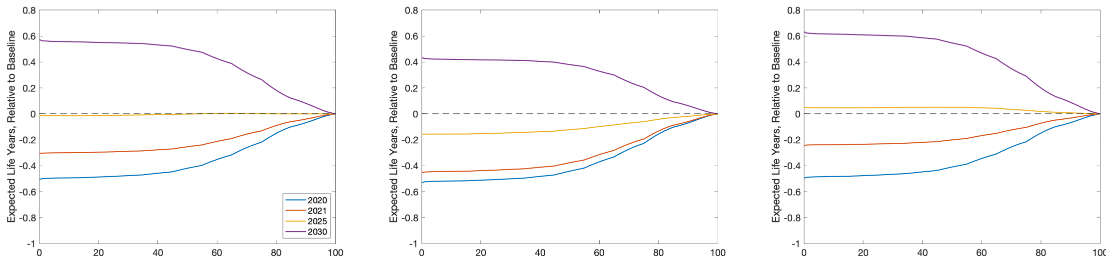
Meanwhile, the consumption value of lost life years per-capita due to non-COVID-19 factors resulting from the economic fallout is just the statistic

$$\underbrace{\left(\overline{VSL}_{at}/\overline{LE}_{at} - \widetilde{VSL}_{at}/\widetilde{LE}_{at}\right)}_{\Delta \text{ VSL Per Year of Life}} \times \underbrace{\left(\overline{LE}_{at} - \widetilde{LE}_{at}\right)}_{\Delta \text{ Life Expectancy}} \quad \forall a, t \tag{12}$$

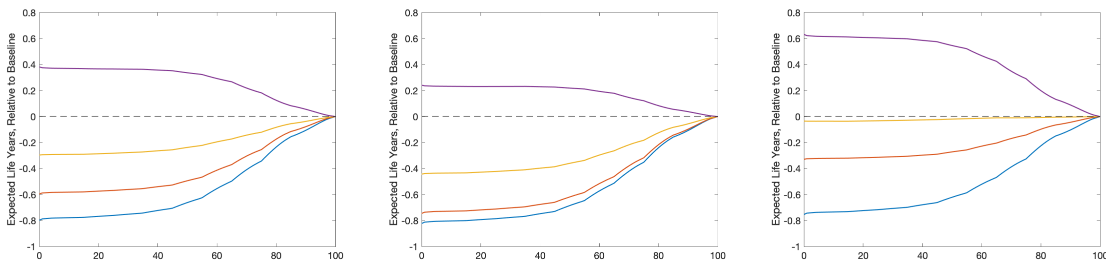
The units of this statistic are 2018 dollars. Note that unlike the statistic in (10), the statistic in (12) does not directly describe how long it takes for VSL's to recover from the recession but rather how welfare deviates from a no-shock baseline along the growth path.

Figure 6 shows the deviations of age-specific life expectancies from pre-pandemic levels described by the statistic in (10). Note that $\widetilde{LE}_{at}$ represents simulated life expectancies by age after subtracting out lost life years directly attributable to the COVID-19 epidemic. Thus, all reductions in life expectancy relative to the baseline are driven by the declines in income and health productivities. The idea here is to understand two things: 1) how long it takes for life expectancy to recover to where it was at the dawn of the recession; 2) how such a recovery varies by age group. In the most severe cases (-10% 2020 shock followed by slow recoveries), life expectancy fails to return to the baseline 2020 level by 2025. This can be seen by noting that the yellow line is below zero for all age groups in panels (d) and (e). Depending on the severity of the recession, younger agents initially lose anywhere from 0.5 to 0.8 life years. Depending on the shape of the recovery, life expectancies may return to the predicted 2020 baseline faster, as in the quick recoveries of panels (a), (c), and (f), where the 2025 life-expectancy profiles have essentially returned to pre-pandemic levels. Still, this exercise shows just how severe the effects a recession that includes simultaneous health productivity shocks may be.

Table 2 presents the value of lost VSL's due to the disease crisis and economic fallout. The top half of the table shows the breakdown in VSL's lost due to COVID-19 and



(a) -5.6% 2020, 4.6% 2021 (b) -5.6% 2020, 0.98% 2021 (c) -5.6% 2020, 5.6% 2021



(d) -10% 2020, 4.6% 2021 (e) -10% 2020, 0.98% 2021 (f) -10% 2020, 10% 2021

Figure 6: Age is presented on the horizontal axes and deviation in LE relative to that for the no-shock, constant-growth 2020 baseline level is presented on the vertical axes. In this figure, we only consider simulations where total COVID-19 deaths at the end of 2020 are 250,000, a large but not implausible value. The blue lines describe the lost years of LE by age group in 2020, with the red lines corresponding to the same distribution of outcomes for 2021, the gold lines for 2025, and the violet lines for 2030. Panels (a) through (c) show how LE by age group deviates from a no-shock environment in response to the CBO-predicted 5.6% decline in output followed by various recovery paths. Panels (d) through (f) show how life expectancy deviates from the baseline under a steeper, 10% annual decline in 2020 output. In most cases, it takes until at least 2025 before LE's have returned to their pre-pandemic levels.

non-COVID-19 factors while the bottom half shows the total social loss in VSL's as the sum of the two components. A policymaker looking to reduce aggregate welfare loss due to COVID-19 deaths must first have an idea of how many deaths would occur if no social distancing were in place. Some early models starkly suggested that 1,000,000 people could die in the U.S. if no measures were taken (Ferguson et al. 2020). In such a situation, with no economic shutdown, lost lives due to COVID-19 would amount to \$2.46 trillion. If such projections are believable then policies that lead to economic shutdowns in order to curb disease-spread may be preferred, but only as long as total VSL's lost are reduced relative to the predictive baseline. Relative to the no-recession scenario with 1,000,000 deaths, a policy which reduces deaths to approximately 250,000 at the expense of a -5.6% economic contraction is aggregate welfare improving. However, excessively

Table 2: 2020 Lost Social Welfare Measured in Total VSL's in Trillions of 2018$

	COVID-19 VSL's Lost [a]; VSL's Lost Due to Non-COVID-19 Factors [b]					
	(1)	(2)	(3)	(4)	(5)	(6)
COVID-19 Deaths	$-5.6\%, 4.6\%$	$-5.6\%, 0.98\%$	$-5.6\%, 5.6\%$	$-10\%, 4.6\%$	$-10\%, 0.98\%$	$-10\%, 10\%$
145,224	0.357; 1.544	0.357; 1.679	0.357; 1.487	0.357; 4.097	0.357; 4.318	0.357; 3.720
180,226	0.443; 1.544	0.443; 1.679	0.443; 1.487	0.443; 4.097	0.443; 4.318	0.443; 3.720
250,000	0.615; 1.544	0.615; 1.679	0.615; 1.487	0.615; 4.097	0.615; 4.317	0.615; 3.720
500,000	1.230; 1.544	1.230; 1.679	1.230; 1.487	1.230; 4.097	1.230; 4.317	1.230; 3.720
750,000	1.846; 1.544	1.846; 1.679	1.846; 1.487	1.846; 4.097	1.846; 4.317	1.846; 3.720
1,000,000	2.461; 1.544	2.461; 1.679	2.461; 1.487	2.461; 4.096	2.461; 4.317	2.461; 3.719
1,500,000	3.691; 1.543	3.691; 1.679	3.691; 1.487	3.691; 4.096	3.691; 4.316	3.691; 3.719
2,000,000	4.922; 1.543	4.922; 1.679	4.922; 1.486	4.922; 4.096	4.922; 4.316	4.922; 3.719
	Total Lost VSL's [c]					
	(1)	(2)	(3)	(4)	(5)	(6)
COVID-19 Deaths	$-5.6\%, 4.6\%$	$-5.6\%, 0.98\%$	$-5.6\%, 5.6\%$	$-10\%, 4.6\%$	$-10\%, 0.98\%$	$-10\%, 10\%$
145,224	1.901	2.036	1.844	4.454	4.675	4.077
180,226	1.987	2.122	1.930	4.540	4.761	4.163
250,000	2.159	2.294	2.102	4.712	4.932	4.335
500,000	2.774	2.909	2.717	5.327	5.547	4.95
750,000	3.390	3.525	3.333	5.557	5.863	5.566
1,000,000	4.005	4.140	3.948	6.557	6.778	6.180
1,500,000	5.234	5.370	5.179	7.787	8.007	7.410
2,000,000	6.465	6.601	6.108	9.018	9.238	8.641

NOTE: In the top half of the table, VSL's lost due to COVID-19 deaths are presented on the left side of the semicolon, while lost VSL's due to the economic fallout are on the right side. When the left-hand side exceeds the right-hand side, COVID-19 causes greater direct welfare loss than the economic fallout.

[a] This value is $\sum_a \overline{VSL}_{at} m_{at}^{covid}$ where $t = 2020$.

[b] This value is $\sum_a N_{at} \left(\overline{VSL}_{at}/\overline{LE}_{at} - \widetilde{VSL}_{at}/\widetilde{LE}_{at}\right)\left(\overline{LE}_{at} - \widetilde{LE}_{at}\right)$ where $t = 2020$.

[c] This value is $\sum_a \overline{VSL}_{at} m_{at}^{covid} + \sum_a N_{at} \left(\overline{VSL}_{at}/\overline{LE}_{at} - \widetilde{VSL}_{at}/\widetilde{LE}_{at}\right)\left(\overline{LE}_{at} - \widetilde{LE}_{at}\right)$ where $t = 2020$.

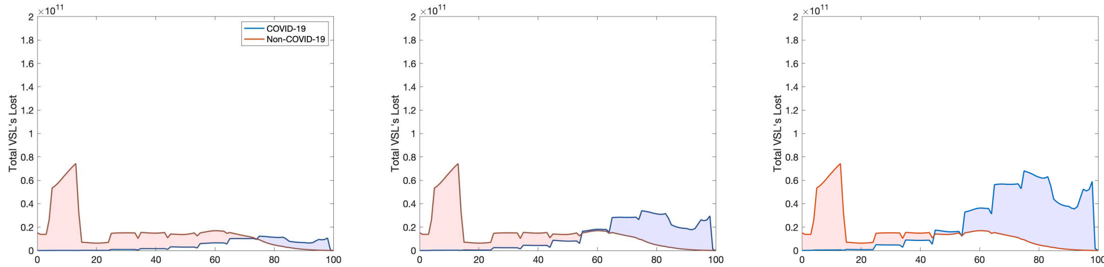
stringent policies that lead to, say, a -10% contraction would increase lost VSL's due to non-COVID-19 factors faster than VSL's saved due to preventing disease deaths.

This story is contingent on the Ferguson et al. (2020) predictions being correct. Suppose, instead, that 750,000 deaths were ex-ante expected, leading to $1.85 trillion in lost VSL's due to disease deaths. In this scenario, inducing an economic contraction to mitigate disease spread is not welfare improving under any of the simulated scenarios. Though there does exist a scenario where a very mild economic contraction associated with social-distancing mandates can be welfare-improving if baseline-predicted total deaths are 750,000 or less, projections suggest that the 2020 recession is far from mild. To determine which disease-mitigation policies are socially optimal, it is important to have both reasonably-confident predictions regarding total deaths and the economic fallout from the policy.

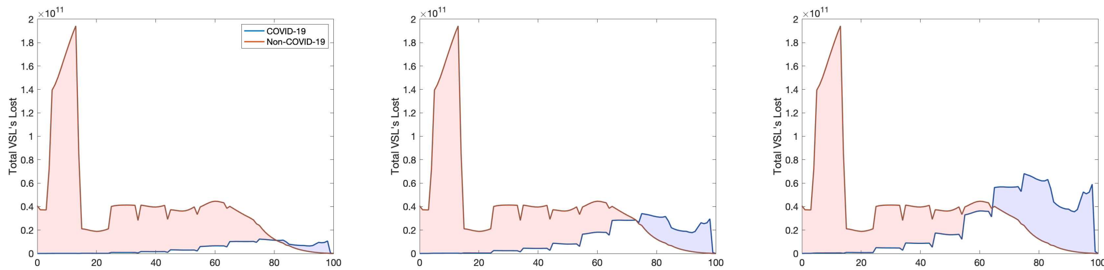
The acceleration of COVID-19 cases at the end of June and beginning of July 2020 has posed an emerging problem for policymakers. Having shut down much of the economy in March, April, and May to mitigate the disease spread, many local and state leaders during the summer of 2020 have been faced with the difficult decision whether to mandate social-distancing once again. It is questionable as to whether the public has the appetite for such policies. Suppose, hypothetically, that the summer resurgence forces total 2020 COVID-19 deaths closer to 500,000, while the recession remains around -5.6% followed by 4.6% growth in 2021. Relative to a baseline of 1,000,000 deaths and no recession, 500,000 deaths and the CBO-predicted contraction amounts to a reduction in aggregate welfare, from a loss of \$2.461 trillion to \$2.774 trillion. In such a case, the policy-induced recession of the spring of 2020 will have been wasted if deaths spike and the total death rate increases substantially. Under this hypothetical scenario, the model's welfare measures suggest a rather unpalatable outcome: it would have been social-welfare improving to do nothing and let the disease spread, sacrificing one million, mostly older, lives.

Figure 7 illustrates how both the COVID-19 disease contagion and the residual economic crisis have disparate effects on the welfare of different age-cohorts. The age-specific values of (11) and (12) weighted by cohort population N_{at} for the year 2020 under different disease-death and economic-shock scenarios are presented. The more red area in the figures, the greater the welfare hit due to the recession, while greater blue area corresponds to a more intense welfare hit due to disease deaths. The disparity between VSL's lost from COVID-19 versus economic factors is driven primarily by the aggregate hit experienced by younger cohorts from the economic fallout. In most cases non-COVID-19 factors have a greater aggregate impact on welfare than COVID-19 itself. This is again due to the fact that there are just more younger and working-age adults who are less susceptible to death from the disease. The deeper the economic shock, say -10% versus -5.6%, the greater VSL's lost due to non-COVID-19 factors, and young agents shoulder a greater share of the aggregate welfare burden. It is thus apparent that policy-induced economic shocks amount to a transfer of welfare from young to old, which is a direct consequence of the unique mortality profile of the disease.

The COVID-19 disease has high mortality rates for elderly consumers, but the economic fallout of the disease impacts young people more, as long as total COVID-19 deaths remain below some threshold. Youths are particularly burdened by the reduction in the consumption value of life brought on from indirect factors. Both reduced LE's and reduced VSL's per-year of life remaining directly impact young people more than actual COVID-19 deaths. Disparities in the adverse welfare consequences wrought by both the disease and economic contagions are a direct result of the age-specific mortality rates of the COVID-19 disease. Indeed, if young people were more likely to die from the disease,



(a) -5.6%, 4.6%; 180,226 Deaths (b) -5.6%, 4.6%; 500,000 Deaths (c) -5.6%, 4.6%; 1,000,000 Deaths



(d) -10%, 4.6%; 180,226 Deaths (e) -10%, 4.6%; 500,000 Deaths (f) -10%, 4.6%; 1,000,000 Deaths

Figure 7: The horizontal axes index age while the vertical axes present the sums, over all age-a individuals, of VSL's lost due either to the COVID-19 disease (blue) or non-COVID-19 factors resulting from the economic fallout (red). Model results under 2020 COVID-19 deaths of 180,226, 500,000, and 1,000,000 are shown. Panels (a) through (c) feature the CBO's predicted aggregate shock of -5.6% followed by a 4.6% recovery in 2021. Panels (d) through (f) feature a deeper shock of -10% followed by a 4.6% recovery in 2021. Shaded areas comprise the difference between lives lost due to COVID-19 versus long-run factors (blue) and vice-versa (red). The more red area that is shaded, the greater the hit to long-run VSL's. The more blue area that is shaded, the greater the hit due to COVID-19 deaths. When the blue area exceeds the red area, the value of lives lost due to COVID-19 exceeds the value of statistical lives lost due to indirect, economic factors. The reverse is also true.

the welfare consequences of an economic shutdown designed to contain its spread would be less dramatic. In such a situation reducing commerce to save lives may be a welfare-improving strategy. However, given the underlying nature of COVID-19, this seems to only be true if the disease is indeed very deadly and the policy-induced recession is not too deep. Otherwise, lost VSL's due to the economic shutdown outweigh the value of potential increases in lost lives due to the disease if such a shutdown had not taken place.

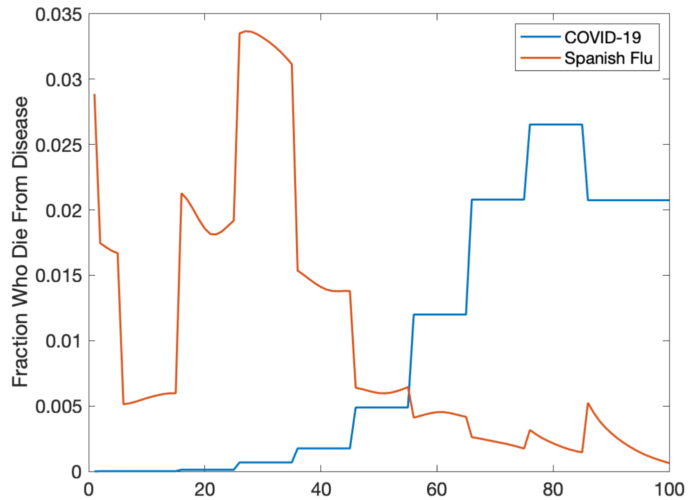


Figure 8: Age is on the horizontal axis. The distribution of total disease-related deaths by age is more heavily skewed to the right for COVID-19. The Spanish Flu of 1918, meanwhile, had a more pronounced effect on children and young adults.

5.2 Inverted Disease Contagion Mortality Rates: What if the Spanish Flu Occurred in 2020?

To assess the degree to which the age-specific mortality profile of the COVID-19 disease contributes to the above conclusions, consider COVID-19 in contrast to the mortality profile of the 1918 Spanish Flu. Unlike COVID-19, the Spanish Flu disproportionately affected younger people, which can be seen by inspecting Figure 8 (Luk, Gross, and Thompson 2001; Gagnon et al. 2013). The data used for Spanish Flu mortality rates in the analysis presented here comes from Luk, Gross, and Thompson (2001).[10]

In the simulations here, m_{at}^{covid} is replaced with $m_{at}^{spanish}$. In Luk, Gross, and Thompson (2001) age-specific mortality rates are displayed as number of deaths per 100,000. By applying their mortality distribution to a conceptual 2020 pandemic, it would thus be assumed that the underlying total mortality rate for the Spanish Flu in 1918 would be the same as if the disease had occurred today. This would imply Spanish Flu deaths of 1,115,900 given the U.S. population distribution in 2020. But it may be too strong to assume that the Spanish Flu would be as deadly today as it was in 1918, given advancements in hygiene, early disease detection, health care technology, and our general

[10]Luk, Gross, and Thompson (2001) present mortality rates for broad, 10-year age groups. To arrive at the one-year age groups, the same interpolation scheme as that used for the health spending data is performed here, where it is assumed that all ages within the age group experience the same mortality rate. This generates the stair-step mortality profile in Figure 8.

knowledge as to how diseases spread. To accommodate these possibilities, consider the same eight scenarios for total number of deaths as in Section 5.1 while also simulating the shocks to income and health productivities in the same six ways as before.

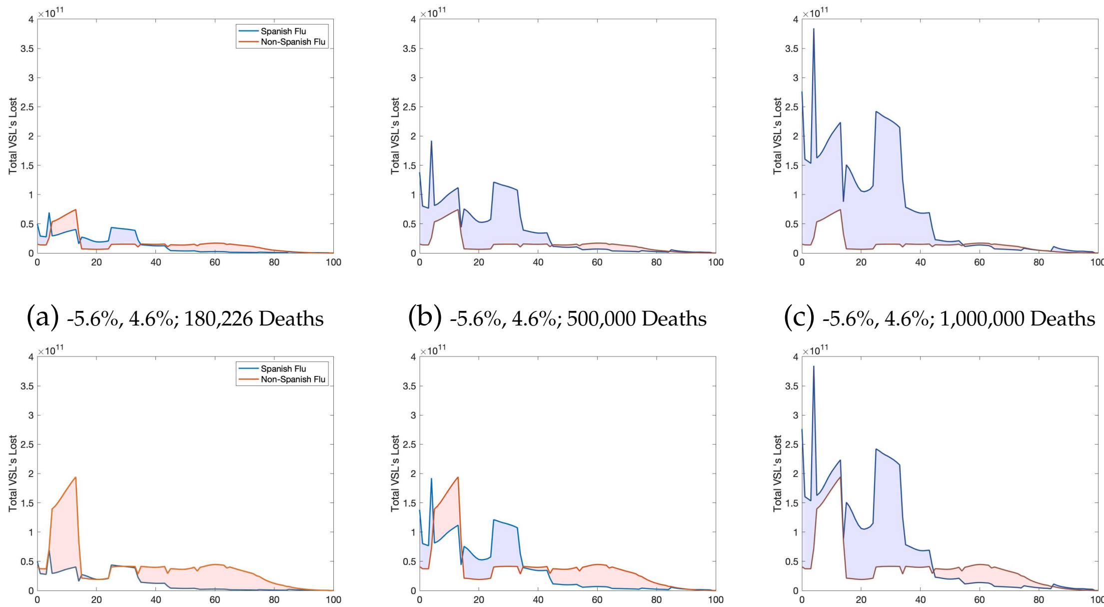
Table 3: 2020 Spanish Flu Counterfactual Lost Social Welfare in Trillions of 2018$

	Spanish Flu VSL's Lost; VSL's Lost Due to Non-Spanish-Flu Factors					
	(1)	(2)	(3)	(4)	(5)	(6)
Spanish Flu Deaths	$-5.6\%, 4.6\%$	$-5.6\%, 0.98\%$	$-5.6\%, 5.6\%$	$-10\%, 4.6\%$	$-10\%, 0.98\%$	$-10\%, 10\%$
145,224	1.096; 1.544	1.096; 1.680	1.096; 1.487	1.096; 4.097	1.096; 4.318	1.096; 3.720
180,226	1.359; 1.544	1.359; 1.680	1.359; 1.487	1.359; 4.097	1.359; 4.318	1.359; 3.720
250,000	1.886; 1.544	1.886; 1.680	1.886; 1.487	1.886; 4.097	1.886; 4.318	1.886; 3.720
500,000	3.771; 1.544	3.771; 1.680	3.771; 1.487	3.771; 4.097	3.771; 4.318	3.771; 3.720
750,000	5.657; 1.544	5.657; 1.680	5.657; 1.487	5.657; 4.097	5.657; 4.318	5.657; 3.720
1,000,000	7.543; 1.544	7.543; 1.680	7.543; 1.487	7.543; 4.097	7.543; 4.318	7.543; 3.720
1,500,000	11.314; 1.544	11.314; 1.680	11.314; 1.487	11.314; 4.097	11.314; 4.318	11.314; 3.720
2,000,000	15.085; 1.544	15.085; 1.680	15.085; 1.487	15.085; 4.097	15.085; 4.318	15.085; 3.720
	Total Lost VSL's					
	(1)	(2)	(3)	(4)	(5)	(6)
Spanish Flu Deaths	$-5.6\%, 4.6\%$	$-5.6\%, 0.98\%$	$-5.6\%, 5.6\%$	$-10\%, 4.6\%$	$-10\%, 0.98\%$	$-10\%, 10\%$
145,224	2.640	2.775	2.583	5.193	5.413	4.816
180,226	2.903	3.039	2.847	5.457	5.677	5.080
250,000	3.430	3.565	3.373	5.983	6.203	5.606
500,000	5.315	5.451	5.259	7.869	8.089	7.492
750,000	7.201	7.337	7.144	9.754	9.975	9.377
1,000,000	9.087	9.222	9.030	11.640	11.860	11.263
1,500,000	12.858	12.994	12.801	15.411	15.632	15.034
2,000,000	16.629	16.765	16.573	19.183	19.403	18.806

NOTE: This table is the hypothetical Spanish-Flu analog of Table 2 after replacing m_{at}^{covid} with $m_{at}^{spanish}$ in the various statistics.

A disease like the Spanish Flu, which affects young more than old, delivers a larger blow to aggregate welfare at every total-death level, since young agents have such high baseline VSL's and there are so many of them relative to their elders. In Table 3 the same aggregate welfare measures for the Spanish Flu counterfactual are presented as in Table 2. In the top half of the table it can be seen that under the CBO's economic shock scenario in column 1, the value of Spanish Flu deaths (left) exceeds lost VSL's due to indirect economic factors (right) for all but the lowest death totals. When the economic shock is more severe, this threshold increases, as can be seen in columns 4 through 6.

Notice that the VSL's lost due to the recession in the top half of the table are almost the same as for COVID-19, yet the VSL's lost directly from the Spanish Flu are far higher. The Spanish Flu is more costly because its age-distribution of mortality rates skews younger. A policymaker trading off 2,000,000 deaths in the event of no recession and no social distancing would be willing to accept a 10% drop in output and a slow recovery for 1,000,000 deaths, as in row 4 and columns 4 through 6 of the bottom half, in order to reduce lost social welfare.[11] Contrast this with the COVID-19 disease where a 10% reduction in output is only optimal if projected deaths would dramatically fall from 2,000,000 absent social distancing to $<$ 250,000, depending on the nature of the recovery.[12] This exercise thus highlights the importance the mortality distribution plays in determining optimal public health policy.



(a) -5.6%, 4.6%; 180,226 Deaths (b) -5.6%, 4.6%; 500,000 Deaths (c) -5.6%, 4.6%; 1,000,000 Deaths

(d) -10%, 4.6%; 180,226 Deaths (e) -10%, 4.6%; 500,00 Deaths (f) -10%, 4.6%; 1,000,000 Deaths

Figure 9: The horizontal axes index age while the vertical axes present the sum, over all age-a individuals, of VSL's lost due either to a hypothetical 2020 outbreak of the Spanish Flu (blue) or other factors resulting from the economic fallout (red). Panels (a) through (c) feature the CBO's predicted aggregate shock of -5.6% followed by 4.6% recovery in 2021. Panels (d) through (f) feature a deeper shock of -10% followed by a 4.6% recovery in 2021. Shaded areas comprise the difference between lives lost due to Spanish Flu versus long-run factors (blue) and vice-versa (red). The more red area that is shaded, the greater the hit to long-run VSL's. The more blue area that is shaded, the greater the hit due to Spanish Flu deaths.

In terms of the welfare effects across the age distribution, the risk-profile of the Span-

[11]To see this, compare the number to the left of the semicolon in the top half of the table. Since VSL's for deaths are measured as VSL's lost relative to the baseline economy where no economic shock occurs, the statistic representing Spanish Flu VSL's lost measures welfare loss in an economy plagued by disease but still growing along the balanced growth path.

[12]Utilize the same comparison as here: inspect the value to the left of the semicolons in the last row of the top half of Table 2 and compare it to total VSL's lost in the bottom half of the same table in the event of a recession that also reduces total deaths.

ish Flu leads to a generational divide that is the opposite of that induced by COVID-19. Notice in Figure 9 that younger consumers experience a double-whammy, with long-run VSL harmed by the economic contagion at the same time that many die due to Spanish Flu. Indeed, in Figure 9f when the economic shock is deep and 1,000,000 people die from the disease, long-run VSL's lost by older adults exceed their age-specific hit from the disease, while the opposite is true for the young.

This counterfactual exercise thus demonstrates how the nature of disease risk impacts welfare inference. If COVID-19 had the same mortality risk profile as the Spanish Flu, policies encouraging economic shutdowns to mitigate disease spread may be preferred, especially if they lead to a total reduction in VSL's lost. However, overly-restrictive policies could still cause greater aggregate welfare loss if the underlying death rate of the disease is mis-estimated. In contrast to a disease like COVID-19, the aggregate welfare loss of the old due to a slight reduction in output is smaller than under COVID-19. This is because less old people are alive at the start of the contagion anyway, they are less affected by the disease, and their VSL's are lower to begin with.

6 Conclusion

This paper explores the age-distributional welfare implications of disease contagion through the lens of an overlapping generations model with endogenous health status, survival rates, and health investment that generates age-dependent estimates of life expectancies and the value of statistical lives. These model-implied statistics are used to quantity the welfare implications of simultaneous recessions and disease contagions. Estimated VSL's using revealed preferences for health investment are declining in age and are particularly high for children and young adults. Given the age-profile of VSL's, it is shown that economic shocks, independent of disease contagions, disproportionately harm young people if death-risk skews older. Finally, it is shown that the degree to which the adverse effects of the recession dominate those of the disease depend both on the age-mortality profile of the disease and its overall deadliness.

Through this lens, the intergenerational distributional implications of the 2020 COVID-19 crisis are profound. While the actual COVID-19 virus may take the lives of older individuals at higher rates, it is the younger generations that appear to bear the long-run costs of the crisis, regardless of whether social-distancing efforts actually lead to aggregate welfare improvements. This is apparent while even abstracting from possibly unbalanced income shocks that may affect young people more. It is thus shown, in a planner's problem where the only objective is to efficiently allocate resources across generations, that the costs of this crisis are born by younger cohorts. This is a direct consequence of the mortality profile of COVID-19: if COVID-19 were instead more like the Spanish Flu, social distancing mandates that lead to substantial income losses are more likely to be welfare improving.

Moving forward, researchers should more deeply explore the implications of this exercise by examining microeconomic data pertaining to the effect of the shutdown on the health and welfare of children and young adults. While the results here are extrapolatory in nature due to being estimated during the early innings of the 2020 COVID-19 crisis, they should provide a useful framework to help both researchers and policymakers form new questions. Namely, if the intergenerational welfare disparities are indeed true, how can we minimize the harm to young people while still preserving lives? Perhaps policies that encourage school and work attendance for children and young adults could supplement social-distancing recommendations that target at-risk, older individuals. Such a nuanced approach, among others, could help minimize the intergenerational welfare hit to young while still keeping the mortality rates of the disease in check.

References

Alderman, Harold, John Hoddinott, and Bill Kinsey. 2006. "Long term consequences of early childhood malnutrition". *Oxford Economic Papers* 58 (3): 450–474. (Cit. on p. 5).

Aldy, Joseph E, and W Kip Viscusi. 2008. "Adjusting the value of a statistical life for age and cohort effects". *The Review of Economics and Statistics* 90 (3): 573–581. (Cit. on pp. 7, 8).

Ananat, Elizabeth Oltmans, et al. 2011. *Children left behind: The effects of statewide job loss on student achievement*. Tech. rep. National Bureau of Economic Research. (Cit. on p. 6).

Barling, Julian, Kathryne E Dupre, and C Gail Hepburn. 1998. "Effects of parents' job insecurity on children's work beliefs and attitudes." *Journal of Applied Psychology* 83 (1): 112. (Cit. on p. 6).

Barling, Julian, Anthea Zacharatos, and C Gail Hepburn. 1999. "Parents' job insecurity affects children's academic performance through cognitive difficulties." *Journal of Applied Psychology* 84 (3): 437. (Cit. on p. 6).

Barro, Robert J, José F Ursúa, and Joanna Weng. 2020. *The coronavirus and the great influenza pandemic: Lessons from the "spanish flu" for the coronavirus's potential effects on mortality and economic activity*. Tech. rep. National Bureau of Economic Research. (Cit. on p. 4).

Bethune, Zachary, and Anton Korinek. 2020. *Covid-19 infection externalities: Trading off lives vs livelihoods*. Tech. rep. National Bureau of Economic Research. (Cit. on pp. 3, 4, 20).

Black, Sandra, and Kenneth Sokoloff. 2006. “Long-Term Trends in Schooling: The Rise and Decline (?) of Public Education in the United States”, 1st ed., ed. by Eric Hanushek and Fins Welch. Amsterdam: Elsevier. (Cit. on p. 5).

Boyer, Bruce A, and Amy E Halbrook. 2011. “Advocating for children in care in a climate of economic recession: The relationship between poverty and child maltreatment”. *Nw. JL & Soc. Pol'y* 6:300. (Cit. on p. 6).

Byl, Jacob P. 2013. “Protecting the innocent with a premium for child safety regulations”. *U. Mass. L. Rev.* 8:264. (Cit. on p. 7).

Campbell, Frances, et al. 2014. “Early childhood investments substantially boost adult health”. *Science* 343 (6178): 1478–1485. (Cit. on pp. 4–6).

CBO. 2020. *Interim Economic Projections for 2020 and 2021*. Online; accessed July 9, 2020. Congress of the United States; Congressional Budget Office. `https://www.cbo.gov/system/files/2020-05/56351-CBO-interim-projections.pdf`. (Cit. on p. 19).

CDC. 2020a. *2020-06-29-model-data*. Online; accessed July 6, 2020. Centers for Disease Control and Prevention. `https://www.cdc.gov/coronavirus/2019-ncov/covid-data/files/2020-06-29-model-data.csv`. (Cit. on p. 21).

— . 2020b. *Forecasts of Total Deaths*. Online; accessed July 6, 2020. Centers for Disease Control and Prevention. `https://www.cdc.gov/coronavirus/2019-ncov/covid-data/forecasting-us.html`. (Cit. on p. 21).

— . 2020c. *Provisional COVID-19 Death Counts by Sex, Age, and Week*. Online; accessed July 6, 2020. Centers for Disease Control and Prevention. `https://data.cdc.gov/NCHS/Provisional-COVID-19-Death-Counts-by-Sex-Age-and-W/vsak-wrfu/data`. (Cit. on pp. 20, 21).

Chay, Kenneth, and Michael Greenstone. 2003. “The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession”. *The Quarterly Journal of Economics* 118 (3): 1121–1167. (Cit. on p. 5).

CMS. 2019. *Age and Gender: Health Expenditures by Age and Gender*. Online; accessed July 6, 2020. Centers for Medicare & Medicaid Services. `https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/Age-and-Gender`. (Cit. on p. 12).

Conger, Rand D, and M Brent Donnellan. 2007. "An interactionist perspective on the socioeconomic context of human development". *Annu. Rev. Psychol.* 58:175–199. (Cit. on p. 6).

Correia, Sergio, Stephan Luck, and Emil Verner. 2020. "Pandemics Depress the Economy, Public Health Interventions Do Not: Evidence from the 1918 Flu". Revision, June 11, 2020, *SSRN Working Paper*. (Cit. on p. 4).

Corso, Phaedra S, Xiangming Fang, and James A Mercy. 2011. "Benefits of preventing a death associated with child maltreatment: Evidence from willingness-to-pay survey data". *American Journal of Public Health* 101 (3): 487–490. (Cit. on p. 8).

CU. 2020. *COVID-19 Findings, Simulations*. Online; accessed July 6, 2020. Columbia University, Shaman Group. `https://blogs.cuit.columbia.edu/jls106/publications/covid-19-findings-simulations/`. (Cit. on p. 21).

Cunha, Flavio, et al. 2006. "Interpreting the evidence on life cycle skill formation". *Handbook of the Economics of Education* 1:697–812. (Cit. on p. 6).

Cutler, David, Angus Deaton, and Adriana Lleras-Muney. 2006. "The determinants of mortality". *Journal of Economic Perspectives* 20 (3): 97–120. (Cit. on p. 12).

Dehejia, Rajeev, and Adriana Lleras-Muney. 2004. "Booms, Busts, and Babies' Health". *The Quarterly Journal of Economics* 119 (3): 1091–1130. (Cit. on p. 5).

Eichenbaum, Martin S, Sergio Rebelo, and Mathias Trabandt. 2020. *The macroeconomics of epidemics*. Tech. rep. National Bureau of Economic Research. (Cit. on pp. 3, 20).

Evans, Gary W, and Pilyoung Kim. 2007. "Childhood poverty and health: Cumulative risk exposure and stress dysregulation". *Psychological Science* 18 (11): 953–957. (Cit. on p. 6).

Evans, Gary W, and Michelle A Schamberg. 2009. "Childhood poverty, chronic stress, and adult working memory". *Proceedings of the National Academy of Sciences* 106 (16): 6545–6549. (Cit. on p. 6).

Ferguson, Neil, et al. 2020. *Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand*. Tech. rep. Imperial College COVID-19 Response Team. (Cit. on pp. 25, 26).

Ferreira, Francisco, and Norbert Schady. 2009. "Aggregate Economic Shocks, Child Schooling, and Child Health". *The World Bank Research Observer* 24 (2): 147–181. (Cit. on p. 5).

Fogel, Robert William, et al. 2004. *The escape from hunger and premature death, 1700-2100: Europe, America, and the Third World*. Vol. 38. Cambridge University Press. (Cit. on p. 12).

Gagnon, Alain, et al. 2013. "Age-specific mortality during the 1918 influenza pandemic: unravelling the mystery of high young adult mortality". *PLoS One* 8 (8). (Cit. on p. 29).

Glover, Andrew, et al. 2020. *Health versus wealth: On the distributional effects of controlling a pandemic*. Tech. rep. National Bureau of Economic Research. (Cit. on pp. 3, 4, 20).

Goldin, Claudia. 1999. "Egalitarianism and the Returns to Education during the Great Transformation of American Education". *Journal of Political Economy* 107 (S6): S65–S94. (Cit. on p. 5).

Grossman, Michael. 2005. "Education and Nonmarket Outcomes". In *Handbook on the Economics of Education*, ed. by Eric Hanushek and Finis Welch. Amsterdam: North-Holland. (Cit. on p. 12).

Hall, Robert E., and Charles I. Jones. 2004. *The Value of Life and the Rise in Health Spending*. Tech. rep. National Bureau of Economic Research. (Cit. on pp. 10, 11).

— . 2007. "The Value of Life and the Rise in Health Spending". *The Quarterly Journal of Economics* 122 (1): 39–72. (Cit. on pp. 1, 3, 7–12, 15).

Hammitt, James K, and Kevin Haninger. 2010. "Valuing fatal risks to children and adults: Effects of disease, latency, and risk aversion". *Journal of Risk and Uncertainty* 40 (1): 57–83. (Cit. on p. 8).

Hayashi, Fumio. 2000. "Econometrics". (Cit. on p. 12).

Heckman, James, Rodrigo Pinto, and Peter Savelyev. 2013. "Understanding the mechanisms through which an influential early childhood program boosted adult outcomes". *American Economic Review* 103 (6): 2052–86. (Cit. on p. 4).

Heckman, James J. 2008. "The case for investing in disadvantaged young children". *CESifo DICE Report* 6 (2): 3–8. (Cit. on p. 4).

Hintermann, Beat, Anna Alberini, and Anil Markandya. 2010. "Estimating the value of safety with labour market data: Are the results trustworthy?" *Applied Economics* 42 (9): 1085–1100. (Cit. on p. 7).

Hoddinott, John, et al. 2011. "The consequences of early childhood growth failure over the life course". *Washington, DC: International Food Policy Research Institute Discussion Paper* 1073. (Cit. on p. 5).

Horenstein, Alex R, and Manuel S Santos. 2019. "Understanding Growth Patterns in US Health Care Expenditures". *Journal of the European Economic Association* 17 (1): 284–326. (Cit. on p. 12).

Jenkins, Robin R, Nicole Owens, and Lanelle Bembenek Wiggins. 2001. "Valuing reduced risks to children: the case of bicycle safety helmets". *Contemporary Economic Policy* 19 (4): 397–408. (Cit. on p. 7).

Jensen, Robert. 2000. "Agricultural volatility and investments in children". *American Economic Review* 90 (2): 399–404. (Cit. on p. 5).

JHUM. 2020. *Coronavirus Resource Center*. Online; accessed July 9, 2020. Johns Hopkins University & Medicine. `https://coronavirus.jhu.edu/map.html`. (Cit. on p. 20).

Kalil, Ariel. 2013. "Effects of the great recession on child development". *The ANNALS of the American Academy of Political and Social Science* 650 (1): 232–250. (Cit. on pp. 5, 6).

Karaca-Mandic, Pinar, Sung J Choi Yoo, and Benjamin D Sommers. 2013. "Recession led to a decline in out-of-pocket spending for children with special health care needs". *Health Affairs* 32 (6): 1054–1062. (Cit. on p. 5).

Kim, Pilyoung, et al. 2013. "Effects of childhood poverty and chronic stress on emotion regulatory brain function in adulthood". *Proceedings of the National Academy of Sciences* 110 (46): 18442–18447. (Cit. on p. 6).

Kind, Michael, and John P Haisken-DeNew. 2012. "Sons' unexpected long term scarring due to fathers' unemployment". *Ruhr Economic Paper*, no. 375. (Cit. on p. 6).

Kniesner, Thomas J, and W Kip Viscusi. 2019. "The Value of a Statistical Life". *Forthcoming, Oxford Research Encyclopedia of Economics and Finance*: 19–15. (Cit. on pp. 7, 16).

Krueger, Dirk, Harald Uhlig, and Taojun Xie. 2020. *Macroeconomic dynamics and reallocation in an epidemic*. Tech. rep. National Bureau of Economic Research. (Cit. on pp. 4, 20).

Leigh, J Paul. 1995. "Compensating wages, value of a statistical life, and inter-industry differentials". *Journal of Environmental Economics and Management* 28 (1): 83–97. (Cit. on p. 7).

Leininger, Lindsey, and Ariel Kalil. 2012. "Parents' Financial Stress and Children's Beavior Problems in the Aftermath of the Great Recession". In *Annual meeting of the Association for public policy Analysis, November, Baltimore, MD*. (Cit. on p. 6).

Luk, Jeffrey, Peter Gross, and William W Thompson. 2001. "Observations on mortality during the 1918 influenza pandemic". *Clinical Infectious Diseases* 33 (8): 1375–1378. (Cit. on p. 29).

Meara, Ellen, Chapin White, and David M Cutler. 2004. "Trends in medical spending by age, 1963-2000". *Health Affairs* 23 (4): 176–183. (Cit. on pp. 11, 12).

Miller, Ted R. 2000. “Variations between countries in values of statistical life”. *Journal of Transport Economics and Policy*: 169–188. (Cit. on p. 7).

ND. 2020. *Notre Dame-FRED COVID-19 forecasts*. Online; accessed July 6, 2020. University of Notre Dame, Perkins Lab. `https://github.com/confunguido/covid19_ND_forecasting`. (Cit. on p. 21).

Nikulina, Valentina, Cathy Spatz Widom, and Sally Czaja. 2011. “The role of childhood neglect and childhood poverty in predicting mental health, academic achievement and crime in adulthood”. *American Journal of Community Psychology* 48 (3-4): 309–321. (Cit. on p. 6).

Nordhaus, William D. 2005. “Irving Fisher and the contribution of improved longevity to living standards”. *American Journal of Economics and sociology* 64 (1): 367–392. (Cit. on p. 7).

— . 2002. *The health of nations: the contribution of improved health to living standards*. Tech. rep. National Bureau of Economic Research. (Cit. on p. 7).

Oreopoulos, Philip, Marianne Page, and Ann Huff Stevens. 2008. “The intergenerational effects of worker displacement”. *Journal of Labor Economics* 26 (3): 455–483. (Cit. on p. 6).

Paxson, Christina, and Norbert Schady. 2005. “Child health and economic crisis in Peru”. *The World Bank Economic Review* 19 (2): 203–223. (Cit. on p. 5).

Peterson, Cora, Curtis Florence, and Joanne Klevens. 2018. “The economic burden of child maltreatment in the United States, 2015”. *Child Abuse & Neglect* 86:178–183. (Cit. on p. 8).

Sapolsky, Robert M. 2004. “Mothering style and methylation”. *Nature Neuroscience* 7 (8): 791–792. (Cit. on p. 6).

Schneider, William, Jane Waldfogel, and Jeanne Brooks-Gunn. 2015. “The great recession and behavior problems in 9-year old children.” *Developmental Psychology* 51 (11): 1615–1629. (Cit. on p. 6).

Shah, Anuj K, Sendhil Mullainathan, and Eldar Shafir. 2012. “Some consequences of having too little”. *Science* 338 (6107): 682–685. (Cit. on p. 6).

Siebert, W Stanley, and Xiangdong Wei. 1994. “Compensating wage differentials for workplace accidents: evidence for union and nonunion workers in the UK”. *Journal of Risk and Uncertainty* 9 (1): 61–76. (Cit. on p. 7).

Stillman, Steven, and Duncan Thomas. 2004. "The effect of economic crises on nutritional status: evidence from Russia". *IZA Discussion Paper*. (Cit. on p. 5).

Viscusi, W Kip, and Joseph E Aldy. 2003. "The value of a statistical life: a critical review of market estimates throughout the world". *Journal of Risk and Uncertainty* 27 (1). (Cit. on p. 7).

Whelan, Karl. 2002. "A guide to using chain-weighted data". *Review of Income and Wealth* 48 (2). (Cit. on p. 11).