

# Macroeconomic Consequences of Stay-At-Home Policies During the COVID-19 Pandemic

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## Abstract

Older adults and those with underlying medical conditions seem especially vulnerable to the COVID-19 pandemic. U.S. government's efforts to contain the infection, on the other hand, have a disproportionate impact on the working age population. To be able to capture the impact of the pandemic and the resulting mitigation efforts on a population that is heterogeneous by age, income and health status, we use an overlapping generations model that mimics the U.S. economy along those dimensions in 2020. We introduce an unexpected COVID-19 shock in the economy and examine the resulting impact on aggregate output, labor supply, savings, and consumption behavior of the different agents. We find that mitigation efforts that target certain age and health groups result in significantly small disruptions in the economy. Going forward, introducing subsidies to those with underlying health conditions and/or the elderly to self isolate might prove to be a useful path in opening up the economy.

**Keywords:** COVID-19, mitigation, OLG, redistribution.

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# 1 Introduction

There is ample evidence that older adults and those with underlying medical conditions seem especially vulnerable to the COVID-19 pandemic. Meanwhile, efforts to mitigate the spread of the infection in the U.S. have included closing all businesses that are deemed unessential. This has resulted in more than 26 million initial claims for unemployment insurance in five weeks. In order to examine the effects of COVID-19 and the resulting mitigation efforts on the economy, we use an overlapping generations model where agents are heterogeneous with respect to age, income, and health status. All individuals retire exogenously at age 65 and may live up to age 100. Survival probabilities at each age depend on the education level and the health status of an agent. We calibrate this economy based on historical data on demographics, survival probabilities, and health status. Distribution of income, age, and health status in the model matches the most recently available U.S data at which point we subject the economy to a large, unexpected health shock which infects a large fraction of the population and changes their survival probabilities. The government's response to the pandemic includes efforts to quarantine parts of the population. Consequently, a fraction of the population is forced to stay home. Government provides pandemic assistance to help those unemployed. We calibrate the impact of the disease in the population under different assumptions on the progression of the infection and trace the changes in the economy's labor, capital, saving, and output in the short-run and in the long-run for several different scenarios.

We calibrate our benchmark experiments with mitigation to a projected number of 60,000 deaths in the U.S. and a fatality rate of 0.3%. We assume the mitigation measures taken in the U.S. to result in 50% of the population to be unproductive for three months. Since the time period in the model is a year, this corresponds to 12.5% of the population to stay home for a year. While there are significant uncertainties regarding many of these measures, their precise level is less of a concern for the three main experiments we conduct. In these experiments, we keep the fatality rate, the infection rate, and the percent of the population under quarantine the same and just change the population sub-group that faces the stay-at-home orders. In the first case, we implement the lockdown by randomly quarantining 12.5% of the population. In the second case, we quarantine only the older population (73 and older) who make up 12.5% of the population. Finally, in the third case, we quarantine agents based on their health status. Specifically, we impose stay home restrictions on all individuals in the *bad* health state and those 80 and older and in *fair* health state.

Unsurprisingly, we find the largest economic declines to happen under the first scenario, i.e, the case where a random quarantine of 12.5% of the population is imposed. This is primarily due to the fact that an indiscriminate lockdown prevents the healthy and highly productive members of the economy from contributing to the economic activity. On the other hand, quarantining the unhealthy/older individuals with low/zero labor productivity, hurts economic output substantially less. For example, output declines by 13% under random lockdown as opposed to 1.8% where stay home restrictions are based on health status. We interpret the findings from these experiments useful for thinking about ways to opening up the economy. Allowing the workforce to return to work while asking the elderly or those in a bad health state to stay home

may have significant economic benefits. Of course, it is not obvious if, in reality, these three cases would lead to the same infection and fatality rates. On the one hand, the elderly and those in bad health states are the most vulnerable to this pandemic. Such a policy may help reduce the risks they face. On the other hand, some of the current mitigation measures are directed at reducing the interactions between people and may prove more effective in reducing the spread of the disease. There is not enough evidence to help pin down the effectiveness of different mitigation measures in reducing the spread of the disease at the moment, however. Some other possible ways to open up the economy that are discussed involve large scale testing, contact tracing, isolating those who test positive, and allowing individuals with antibodies to go back to work. Given the possible political challenges involved in these options, introducing subsidies to those with underlying health conditions and the elderly might prove to be a useful path in opening up the economy.

We also conduct experiments and document the macroeconomic consequences of COVID-19 assuming no mitigation efforts by the government based on implications of an SIR model.<sup>1</sup> Currently there is significant uncertainty regarding several key parameters governing the health impact of the pandemic. In order to understand the economic consequences of COVID-19, one needs to know the infection rate, the mortality rate, and of course how long the pandemic would last. One of the most important parameters, but also the most difficult to pin down, is the fatality rate — fraction of those infected dying from the disease. A major issue in getting reliable estimates of this parameter is due to the lack of knowledge of the true infection rate in the population. Individuals who are tested are usually those showing mild/severe symptoms. Given that a large fraction of the population may be asymptomatic, hence undiagnosed, makes any available estimate of the fatality rate biased upwards. To navigate this issue, we use data from Iceland which is known to have carried out significant random testing and use a fatality rate of 0.3%. Current experiments conducted in LA county and Santa Clara county point to similar fatality rates. We compare the economic consequences of the pandemic under different assumptions on the reproduction number, which defines the mean number of secondary cases generated by one primary case with no mitigation efforts, based on the SIR model. Using reproduction numbers commonly mentioned in the epidemiology literature we estimate that the pandemic could have infected 84% to 95% of the population in a year if unmitigated. With a fatality rate of 0.3% an unmitigated pandemic would have led to large number of deaths. Next, we compare the results in the unmitigated cases to our benchmark experiment where the government imposed stay-at-home restrictions leads to much lower infection rates. Since mitigation involves agents to be ordered to stay at home, the decline in output in this economy is about double the decline in the economies without mitigation. However, taking into account the value of statistical lives lost in the unmitigated cases easily erases the extra gains in output.

Overall, our main findings indicate significant differences in the economic consequences of who to quarantine during this pandemic. We find that stay home recommendations that are based on health and age reduce the economic severity of the pandemic by more than 10 percentage points of GDP under very conservative

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<sup>1</sup>Standard Inflammatory Response (SIR) model describes the dynamics of the progression of an epidemic. See Kermack and McKendrick (1927), and Anderson and May (1991).

estimates. Going forward, it may be possible to introduce subsidies to the elderly or those with underlying health conditions to self-isolate until a vaccine or a cure is available. Fiscal consequences of such a policy are likely to be much lower than what is currently spent on pandemic assistance which includes providing unemployment insurance to a large fraction of the working-age population.

## 2 The Model

We model the initial steady state of the economy based on the historical behavior of the U.S. economy along several dimensions such as the distribution of income, age and health status. We account for the aging population in the U.S. by changing the population growth rate along the transition path and follow the economy as it reaches a future steady state with a higher old-age dependency ratio as compared to the initial steady state. The transition from the initial steady state to the final one without the disruptions caused by the pandemic form our baseline U.S. economy. Next, we shock the first transition period (2020) by an unexpected health shock and examine the new transition to the same future steady state under several different assumptions on the transmission of the diseases and the containment efforts by the government. We assume that the time period is a year and the impact of the pandemic on infections lasts one year. Eventually the economy converges to the same final steady state as the impact of any pandemic-induced policy or health changes last as long as the youngest generation in the population that got exposed to the shock.

### 2.1 Initial Steady State

Consider an economy populated by  $J$  overlapping generations. In each period a new generation is born whose mass grows at rate  $n$ . Individuals are assumed to enter the economy with several exogenous characteristics that do not change over the life-cycle. Specifically, each individual is assumed to be of some education type  $e \in \epsilon_d$  where  $\Pi^{es}(\epsilon_d)$  denotes the invariant joint probability measure over education type of an incoming generation.

In each period, individuals are characterized by health status  $h \in \mathcal{H}$ . Agents are assumed to enter the economy in the highest health state  $\bar{h}$ . Health then evolves stochastically over the life-cycle. The stochastic process for health status follows a finite-state Markov chain with stationary transitions over time. The Markov process is assumed to differ by age, and level of education, but is otherwise identical and independent across agents:

$$Q_{je}^h(h, \mathcal{H}) = Prob(h' \in \mathcal{H} | h, j, e) = Q_{je}^h(h, \mathcal{H}),$$

Agents of age  $j$ , education  $e$ , and health status  $h$  survive to age  $j + 1$  with positive probability  $\psi_{jeh}$ . At age  $J$ , individuals die with probability one.

In each period, individuals are endowed with a unit of time that may be devoted to leisure or to earning wages in a competitive labor market. An individual's productivity in the labor market has an age-, education-specific ( $\epsilon_{je}$ ), and health specific component ( $\xi_h$ ) estimated directly from the data and an idiosyncratic shock ( $\eta$ ). The stochastic process for the labor productivity shock follows a finite-state Markov chain with stationary transitions over time and which is identical and independent across all agents:

$$Q_t^\eta(\eta, \mathcal{E}) = \text{Prob}(\eta' \in \mathcal{E} \mid \eta) = Q^\eta(\eta, \mathcal{E}).$$

Let  $\Pi^\eta(\mathcal{E})$  denote the invariant probability measure associated with  $Q^\eta$ . All individuals retire exogenously at age  $j_r$ , at which point labor productivity is equal to zero ( $\epsilon_{je} = 0 \forall j \geq j_r$ ) and they receive social security income  $SS_e$  which is a function of their education level.

An agent's preferences over consumption and leisure follow an additive time separable utility function given by:

$$E \left\{ \sum_{j=1}^J \beta^{j-1} u(c_j, \ell_j) \right\}$$

where  $\beta$  is a per-period discount factor,  $c$  consumption, and  $\ell$  hours worked. Expectations are taken with respect to stochastic processes for health status and labor productivity.

### 2.1.1 Market Structure and the Government

We assume individuals are unable to insure against idiosyncratic health and labor productivity risk by trading private insurance contracts. Furthermore, we assume there are no annuity markets to insure against mortality risk. Agents may self-insure by saving one-period risk-free bonds that earn interest rate  $r$ . However, agents are not permitted to maintain a negative asset position between periods (i.e. borrowing is not allowed). A non-negative asset limit ensures agents do not die in debt. Assets from the deceased are distributed evenly in a lump-sum fashion across all individuals entering the economy the following period. These unintended bequests are denoted by  $Tr$ .

The government uses labor income taxes,  $\tau_l$ , to fund the Social Security system. In addition, there are lump-sum taxes  $Tx$  that are used to fund a minimum consumption level,  $\underline{c}$  for the poorest in the society.

### 2.1.2 Technology

Aggregate output ( $Y$ ) is produced by a representative firm using the technology:

$$Y = AK^\alpha N^{1-\alpha} \quad \alpha \in (0, 1), \tag{1}$$

where  $K$  and  $N$  are the aggregate capital stock and labor inputs (measured in efficiency units),  $A$  is total factor productivity, and  $\alpha$  is the capital share. The representative firm maximizes profits such that the rental

rate of capital,  $r$ , and the wage rate  $w$ , are given by:

$$r = \alpha A(K/N)^{\alpha-1} - \delta \quad \text{and} \quad w = (1 - \alpha)A(K/N)^\alpha. \quad (2)$$

### 2.1.3 Decision Problem

At the initial steady state, an individual can be characterized by a vector of state variables  $z = (a, \eta, j, e, h)$ , where  $a$  is current holdings of one-period, risk-free assets,  $\eta$  is a stochastic labor productivity shock,  $j$  is age,  $e$  is level of education,  $h$  is health status. Given this state vector, an agent chooses consumption  $c$ , labor supply  $\ell$ , and next period assets  $a'$  to maximize expected lifetime utility. The decision problem facing an agent is given by:

$$\nu(z) = \max_{c, \ell, a'} \{u(c, \ell) + \beta \psi_{jeh} E_{\eta' h' x'} [\nu(z')]\}$$

subject to

$$c + a' = y_j + (1 + r)(a + Tr(j = 1)) - Tx,$$

where

$$y_j = \begin{cases} w(1 - \tau^\ell) \epsilon_{je} \xi_h \eta \ell & \text{if } j < j_r \\ SS_e & \text{if } j \geq j_r, \end{cases} \quad (3)$$

and

$$a' \geq 0, \quad c \geq 0, \quad 0 \leq \ell \leq 1$$

where value function  $\nu(\cdot)$  is the expected discounted lifetime utility with a given state vector. Note that expectations are taken with respect to stochastic processes for health status and labor productivity. The first constraint is the budget constraint while the final line gives the borrowing constraint followed by feasibility constraints on consumption and labor. Emergency relief is exogenously given when consumption  $\underline{c}$  is unattainable, in which case  $a' = 0$ ,  $c = \underline{c}$ , and  $\ell = \bar{\ell}$ .

## 2.2 COVID-19

We model COVID-19 as a health shock totally unexpected in its scale. We calibrate the progression of the disease in the population under different assumptions on the mitigation process. Some individuals in the economy get hit with this unexpected health shock in 2020, become infected, and face a big change in their survival probabilities. Infection status  $x$  effects both the labor productivity, which now takes the form  $\epsilon_{je}\xi_h\theta_x$  and the survival probability  $\psi_{jehx}$  of the agents. In addition, some fraction of the population is ordered to stay home and are not able to work. We assume that individuals who become unemployed due to the lockdown receive government provided temporary pandemic assistance (PA). The decision problem is given by:

$$V(z) = \max_{c,l,a'} \{u(c,l) + \beta\psi_{jehx}EV(z')\}$$

subject to

$$c + a' = y_j + (1+r)(a + Tr(j=1)) - Tx,$$

$$y_j = \begin{cases} w(1-\tau^\ell)\epsilon_{je}\xi_h\eta^\ell & \text{if } j < j_r \text{ and } q=0, x=0 \\ w(1-\tau^\ell)\epsilon_{je}\xi_h\theta_x\eta^\ell & \text{if } j < j_r \text{ and } q=0, x=1 \\ PA & \text{if } j < j_r \text{ and } q=1, \forall x \\ SS_e & \text{if } j \geq j_r \text{ for } \forall q, \forall x \end{cases} \quad (4)$$

$$a' \geq 0, \quad c \geq 0, \quad 0 \leq l \leq 1$$

## 3 Calibration

We calibrate the model in two steps. In the first step, we calibrate a set of parameters outside the model. In the second step, we assume that the initial balanced growth economy is 2019 and jointly calibrate the remaining parameters to match moments in the U.S. economy in that year. The following subsections describe our calibration exercise in detail.

### 3.1 Preferences and Demographics

Each model period is one year. Individuals enter the economy at age 20 (model period  $j=1$ ) and die with probability one at age 100 (model period  $J=80$ ). The growth rate of new 20 year old individuals in each cohort ( $n$ ) for the initial steady state is set at 0.3% in order to match an old-age dependency ratio of 28% in 2020 (UN 2019).<sup>2</sup> We assume that retirement is exogenous for all agents at age 65 (model period  $j_r=45$ ),

<sup>2</sup>The old age dependency ratio is of people older than 64 to those aged 20-64.

which is the *Normal Retirement Age (NRA)* for claiming Social Security (SS) benefits in the U.S.<sup>3</sup>

Preferences over consumption and leisure are assumed to follow a standard Cobb-Douglas utility function:

$$u(c_j, \ell_j) = \frac{[c_j^\gamma (1 - \ell_j)^{1-\gamma}]^{1-\sigma}}{1 - \sigma},$$

where  $\sigma$  controls risk aversion and  $\gamma$  determines the relative weight of consumption. Note that utility exhibits decreasing absolute risk aversion, which is standard in most reasonable preference classes. We set the value of  $\gamma = 0.39$  to match the average fraction of time working to a third of the time endowment. We assume  $\sigma = 3.56$ , which implies an inter-temporal elasticity of substitution,  $\frac{-1}{\gamma(1-\sigma)-1}$ , of 0.5. The time discount factor  $\beta$  is set to 0.96 match an annual capital-output ratio of 3.0.

### 3.2 Labor Productivity

The labor productivity in the model comprises of the stochastic component  $\eta$ , the health specific component  $\xi_h$ , and a deterministic age- and education-specific component  $\epsilon_{je}$ . We estimate the Markov chain for the stochastic component of productivity by assuming an underlying AR(1) process in logs:

$$\ln(\eta') = \rho \ln(\eta) + \epsilon_\eta, \quad \epsilon_\eta \sim N(0, \sigma_\eta^2).$$

Parameters governing the stochastic process for productivity shocks are taken from Fuster, A. İmrohoroğlu, and S. İmrohoroğlu 2007.<sup>4</sup> We then use the Tauchen method to approximate this process with a Markov chain over four discrete states.

We allow the fixed education state to take two possible values  $\{\overline{college}, non - \overline{college}\}$ . We use data from the U.S. Census Bureau to fix the share of college graduates to 28.6% in the model.<sup>5</sup> We use the deterministic age- and education-specific labor productivity  $\epsilon_{je}$  estimates from Conesa, Costa, et al. 2018. Finally, we set  $\xi_h$  to 1 for agents in best health state. For the bottom two health states, we set  $\xi_h = 0.78$  and  $\xi_h = 0.66$  to match the ratio of earnings for agents in fair and best health and poor and best health states respectively.

### 3.3 Health and Mortality

Health can take three possible values  $\{good, fair, bad\}$  in the model. We identify these health states in the Health and Retirement Study (HRS) data from the self-reported health status variable.<sup>6</sup> Health transitions

<sup>3</sup>Social Security benefits can be claimed as early as age 62 and NRA is slightly different for different birth cohorts. SS benefit claim is also independent from labor supply decisions. However, we simplify these aspects of the program in the model to reduce computational burden.

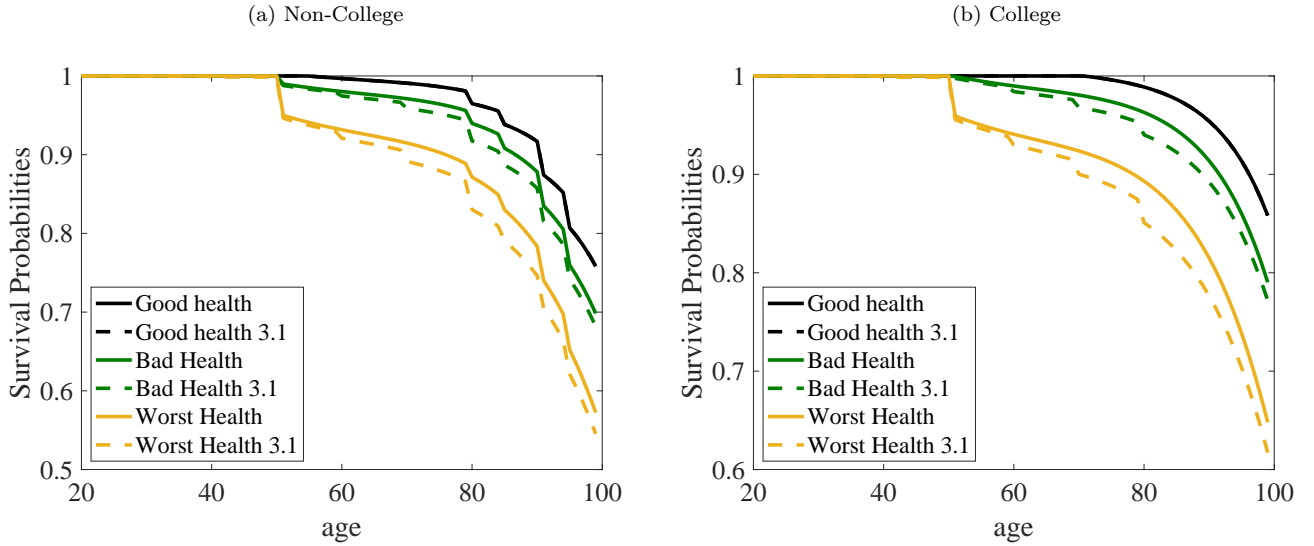
<sup>4</sup>The authors use an income process which is education specific. We adjust their estimate for the average population.

<sup>5</sup>Current Population Survey, Annual Social and Economic Supplement, 2018.

<sup>6</sup>The Health and Retirement Survey asks respondents to self report their health on a scale of 1 to 5 where 1 is “Excellent”, 2 is “Very Good”, 3 is “Good”, 4 is “Fair” and 5 is “Poor”. For computational simplicity, the 5-point scale is converted into a 3



Figure 1: Survival Probability by Age, Health and Education R0=3.1



across these states are then estimated by running an ordered probit of self-reported health status on previous year health status, education, cohort, and a quadratic function of age. We assume that individuals are in the best health state until age 50. This is mainly due to the fact that we do not observe these transitions for younger individuals in our micro dataset.<sup>7</sup>

Survival probabilities in the model vary with age, education and health status  $\psi_{jeh}$ . These probabilities cannot be directly derived from HRS as it does not sample the institutionalized population. So we estimate these survival probabilities in two steps following Conesa, Kehoe, et al. 2020. First, we estimate the raw profiles from the HRS data. The HRS Tracker file has information on death dates of the respondents which are used to construct age and health specific survival probabilities by running an ordered probit model of death indicator on self-reported health status, age quadratic, education and cohort dummies as mentioned earlier. In a second step, we adjust these profiles to match both the age-specific survival probabilities in the National Vital Statistics System data and the education survival premium. Figure 1 summarizes the survival probabilities by age, health, and education status. In addition, the dashed lines show the changes that take place in the survival probabilities due to the COVID-19 shock under a non-mitigated case that is explained in more detail in Section 3.5.

point scale by grouping individuals of “Excellent” and “Very Good” health into the good health category and those in “Good” and “Fair” into the “fair” category

<sup>7</sup>The HRS is a longitudinal sample of non-institutionalized individuals in the U.S., over the age of 50.

### 3.4 Government Transfers

The Social Security replacement rate is set to 44% following Fuster, A. İmrohoroğlu, and S. İmrohoroğlu 2007. We set the consumption floor at 2.26% of income per capita in the baseline economy to match the average annual Supplemental Nutrition Assistance Program benefits reported by the United States Department of Agriculture. The government also funds a pandemic relief package – a lump sum transfer of 25% of income per capita — for those who experience a quarantine shock. Table 1 summarizes the calibration of the economic parameters.

Table 1: Economic Parameters

Parameter	Value	Source / Target
Cohort growth $n$	0.3%	Dependency ratio = 28%
Retirement age $j_r$	65	Age of SS eligibility
Share of college graduates	28.6%	U.S. Census Bureau
Discount factor $\beta$	0.96	K/Y = 3.0
Risk aversion $\sigma$	3.56	IES = 0.5
Consumption weight $\gamma$	0.39	Average hours = 0.33
Persistence $\rho$	0.83	[Fuster et al., 2007]
Variance $\sigma_\eta^2$	0.022	
Capital income share $\alpha$	0.36	
Period depreciation $\delta$	5.9%	[Castaneda et al., 2003]
Social Security replacement rate	0.44	[Fuster et al., 2007]
Pandemic Assistance	25%	
Consumption floor $\underline{c}$	0.026	SNAP
Labor on floor $\bar{\ell}$	0.33	Assumption

### 3.5 COVID-19 Shock

We calibrate the benchmark economy with mitigation to a projected number of 60,000 deaths in the U.S. One of the most important parameters but also the most difficult to pin down is the fatality rate — fraction of those infected dying from the disease. A major issue in getting reliable estimates of this parameter is due to the lack of knowledge of the true infection rate in the population. Individuals who are tested are usually those showing mild/severe symptoms. Given that a large fraction of the population maybe asymptomatic, hence undiagnosed, makes any available estimate of the fatality rate biased upwards. To navigate this issue, we use data from Iceland which is known to have carried out significant random testing to obtain a the fatality rate (0.3%).<sup>8</sup> However, the fatality rate by itself does not provide information on the age and health distribution of fatalities. It is important for the model to capture the fact that the fatalities from the disease are concentrated disproportionately among the elderly and the unhealthy individuals. We use age specific fatality rate estimates from Riou et al. 2020 and scale the survival probabilities for the bottom two health groups using the age and health specific scale. For the latter, we assume that those in the worst health states

<sup>8</sup>Recent USC-LA County study also points to fatality rates of 0.1-03% (<https://reason.com/2020/04/20/l-a-county-antibody-tests-suggest-the-fatality-rate-for-covid-19-is-much-lower-than-people-feared/>).

are affected twice as badly as those in the middle health state. We also do not scale the mortality for those below the age of 40 in the model as the fatality rates are very low for those below 40. Table 2 summarizes the age-specific fatality rates used in our experiments. The fatality rate of 0.3 along a death rate of 0.018 (60,000 deaths in the U.S. population) implies 6.1% of the population to be infected within a year.

Table 2: Fatality Rate = 0.3%

Age group	Fatality rate (%)*	Age-specific scale**
20-29	0.19	0
30-39	0.38	0
40-49	0.82	1x
50-59	2.7	3x
60-69	9.4	9x
70-79	20	20x
80+	36	37x

\*Riou et al. 2020

\*\*x differs by health state and infection scenario.

We assume that the mitigation measure involves 50% of the population to be quarantined for a quarter. Given that the model period is a year, this implies 12.5% of the population being quarantined for a year which results in an infection rate to 6.1%. Lastly, we calibrate the decline in the productivity of workers based on the number of days lost due to the illness. Given the average duration of the disease of 18 days, we assume that individuals experience zero productivity for those days, implying an annual productivity drop of 5% in the period of infection.

For the experiments where the pandemic is not mitigated, we calibrate the parameters needed to describe the COVID-19 infection shock using some of the predictions of an SIR model. This model tracks the progression of the disease in a country where the total population is divided into three categories: those who are susceptible to the disease (S), who are actively infected with the disease (I), and those who are no longer contagious (R). Progression of the disease in the population depends on the transition between these states where social distancing measures help reduce the spread. An important parameter in these calculations is the reproduction number which defines the mean number of secondary cases generated by one primary case with no mitigation efforts. There is significant uncertainty regarding this parameter. In our calibration, we consider  $R_0$  equal to 3.1 based on H. Wang et al. 2020 and 2.2 based on Fauci, Lane, and Redfield 2020 which result in 94.7% and 84.4% of the population to be infected within a year respectively.<sup>9</sup> Dashed lines in Figure 1 display the changes in survival probabilities under the unmitigated case with  $R_0$  equal 3.1 for different age, health status, and education groups. The implied transmission rate in the benchmark model with social distancing measures is 1.23 which results in 6.1% of the population to be infected within a year. Table 3 summarizes the calibration of the different cases describing the COVID-19 pandemic.

<sup>9</sup>Imai et. al (2020) estimate an  $R_0$  between 1.5 and 3.5 using data from Wuhan China. Wang et. al (2020) set  $R_0=3.1$  based on the Imai et. al data while Fauci et. al (2020) use an  $R_0$  of 2.2. See Atkeson 2020 for a summary.

Table 3: COVID-19 Scenarios

	Mitigated ( $R_t = 1.23$ )			Unmitigated ( $R_t$ )	
	Case 1	Case 2	Case 3	3.1	2.2
Infection rate (%)	6.1	6.1	6.1	94.7	84.4
Fatality rate (%)	0.3	0.3	0.3	0.3	0.3
Deaths rate (%)	0.018	0.018	0.018	0.28	0.25
Quarantine rate (%)	12.5	12.5	12.5	-	-

## 4 Results

Initial steady state of this economy resembles the U.S. in terms of the age distribution, health distribution, and income distribution as well other macroeconomic targets such as the capital output ratio and hours worked. Tables 4 to 6 summarize some of these properties.

Table 4: Income Distribution

	Share of Income (%)				
	Income Quintiles				
	0-20%	20-40%	40-60%	60-80%	80-100%
Data	3	6.5	10.9	18.1	61.4
Model	0.45	3.53	11.17	30.96	53.89

Table 5: Age Distribution

	Age Share			
	20-40	40-60	60-80	80-100
Data	0.36	0.34	0.25	0.05
Model	0.36	0.34	0.23	0.07

Table 6: Health Status by Education

	Education			
	Data		Model	
	Non College	College	Non College	College
Good	0.32	0.53	0.21	0.28
Fair	0.55	0.42	0.55	0.55
Poor	0.13	0.05	0.24	0.17

As discussed earlier, we shock the U.S. economy with COVID-19 in the first transition period. In order to disentangle the behavioral response of the households to the shock from other general equilibrium effects,

we keep wage, interest rate, taxes, Social Security benefit levels, need based government transfers and accidental bequests fixed at baseline transition levels. In the first set of experiments, we examine different mitigation measures in a calibration that is designed to mimic the current projections for the U.S. economy. In Section 4.3 we analyze the impact of the disease on population health and economic outcomes without any mitigation measures from the government to contain the virus. These cases correspond to an  $R_0 = 3.1$  and 2.2 respectively.

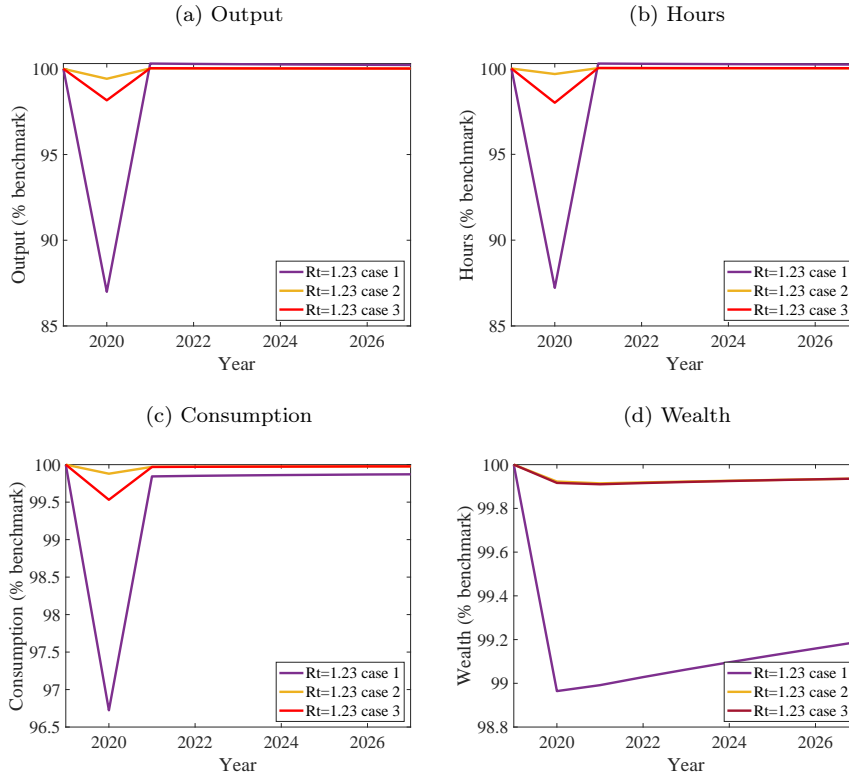
## 4.1 Different Mitigation Measures

In this section, we analyze the economic impact of different mitigation measures, keeping infection rate the same. Specifically, we experiment with different ways of implementing the lockdown under the low infection scenario ( $R_0 = 1.23$ ). In the first case, we implement the lockdown by randomly quarantining 12.5% of the population. In the second case, we quarantine only the older population (73 and older).<sup>10</sup> Finally, in the third case, we quarantine agents based on their health status. Specifically, we impose the lockdown on all individuals in the *bad* health state and those 80 and older and in *fair* health state. It is not surprising that we find the largest economic declines under the first scenario. This is primarily due to the fact that indiscriminate lockdown prevents the healthy and highly productive members of the economy from contributing to the economic activity. On the other hand, quarantining the unhealthy/older individuals with low/zero labor productivity, while maintaining the same infection rate, hurts economic output substantially less.<sup>11</sup> As can be seen from Figure 2, output declines by 13% under random lockdown as opposed to 1.8% where lockdown is based on health status. The decline in output when the elderly are quarantined (Case 2) is much smaller (0.6%) and is solely due to the decline in effective hours worked by the infected working age population. The decline in hours worked in Case 2 is primarily due to some of the working age agents deciding to lower their work hours while infected. In Case 3, there is an additional decline in hours due to some of the agents in *bad* health status to be ordered to stay home as a part of the mitigation measure. Naturally, in case 1, the additional decline in hours is due to a large fraction of the population being ordered to stay home. Both wealth and consumption declines, in the periods of and following the infection, are the highest in the first case as well due to reduced earnings of the productive working-age population.

<sup>10</sup>Note that quarantining any fraction of the retirees (those 65 and older) will result in the same economic outcome. However, we report the lockdown for 73 and older for the sake of keeping the quarantine rate fixed at 12.5% across all experiments. While our assumption of 65 and over being retired underestimates the contributions of that age group to economic output, the labor force participation rate of 73 and over is relatively small in the data.

<sup>11</sup>We assume that quarantining different sub-groups (while keeping the number the same) will result in the same infection rate. In practice, the rate of spread of infection can differ depending on who is quarantined under the lockdown.

Figure 2: Experiments – Different Mitigation Methods

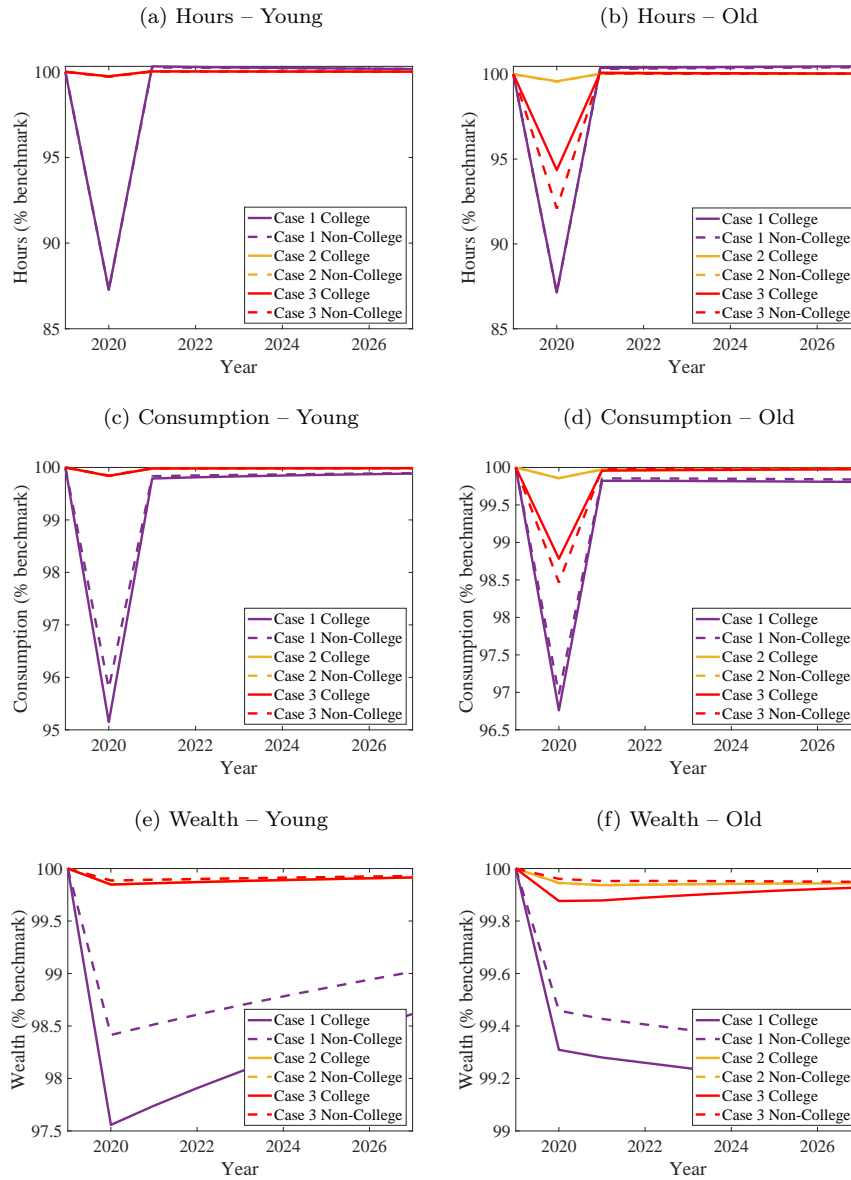


Note: All variables are normalized by their baseline levels to reflect the changes under each experiment relative to baseline transitions.

Figure 3 shows the changes in macroeconomic aggregates by different age and education groups of the productive workforce. The *young* refers to those 20 to 49 years and the *old* refers to those 50 to 64 years old. In these graphs, we first note that contrary to the *old*, the macroeconomic aggregates of the *young* under cases 2 and 3 are exactly identical. This is mainly due to the fact that health starts declining after age 50 in the model, as a result the quarantine based on health or age affect them in the same way — though decline in productivity due to infection. A second interesting observation is that while consumption declines between non-college and college graduates are somewhat similar (4.2 and 4.8% respectively for the young under case 1 for instance), declines in aggregate wealth are somewhat more disparate (1.6 and 2.4% respectively). This is due to the fact that the flat PA amount (25% of average national baseline earnings) corresponds to an income shock of varying magnitudes for different sub-groups in the model. For instance, among the lowest productivity workers, PA for those with a college degree is roughly 55% lower than their baseline earnings and only 32% lower for the non-college group. Finally, somewhat related to the previous point, we find that the aggregate wealth of the non-college old under the health experiment suffers the smallest decline (refer

to figure 3f) due to somewhat generous PA amounts for this group. We discuss the heterogenous response of individuals towards these different mitigation measures and pandemic assistance in more detail in the next section.

Figure 3: Experiments – Different Mitigation Methods (Age and Human Capital)



*Note: All variables are normalized by their baseline levels to reflect the changes under each experiment relative to baseline transitions.*

Note that we have assumed that under all these experiments, infection rates would stay the same (6.1%). Of course, it is not obvious if in reality these three cases would lead to the same infection or fatality rates. On the one hand, the elderly and those in bad health states are the most vulnerable to this pandemic. Stay home policies specifically geared towards them may help reduce the risks they face. On the other hand, some of the current mitigation measures are directed at reducing the interactions between people and may prove more effective in reducing the spread of the diseases. There certainly is not enough evidence to help pin down the effectiveness of different mitigation measures in reducing the spread of the diseases at the moment. However, it is possible to have a rough idea about how much higher the infection rate would have to be for the economic outcomes in these three cases to be the same. For example, in the case where quarantine applies to the elderly only, the infection rate would have to increase from 6.1% to almost to the entire working age individuals for output to decline 13% as it does under the random lockdown case. Moreover, while the infection rate might be higher under Cases 2 and 3, fatality rate might not be if the elderly and the unhealthy do follow the stay home recommendations.

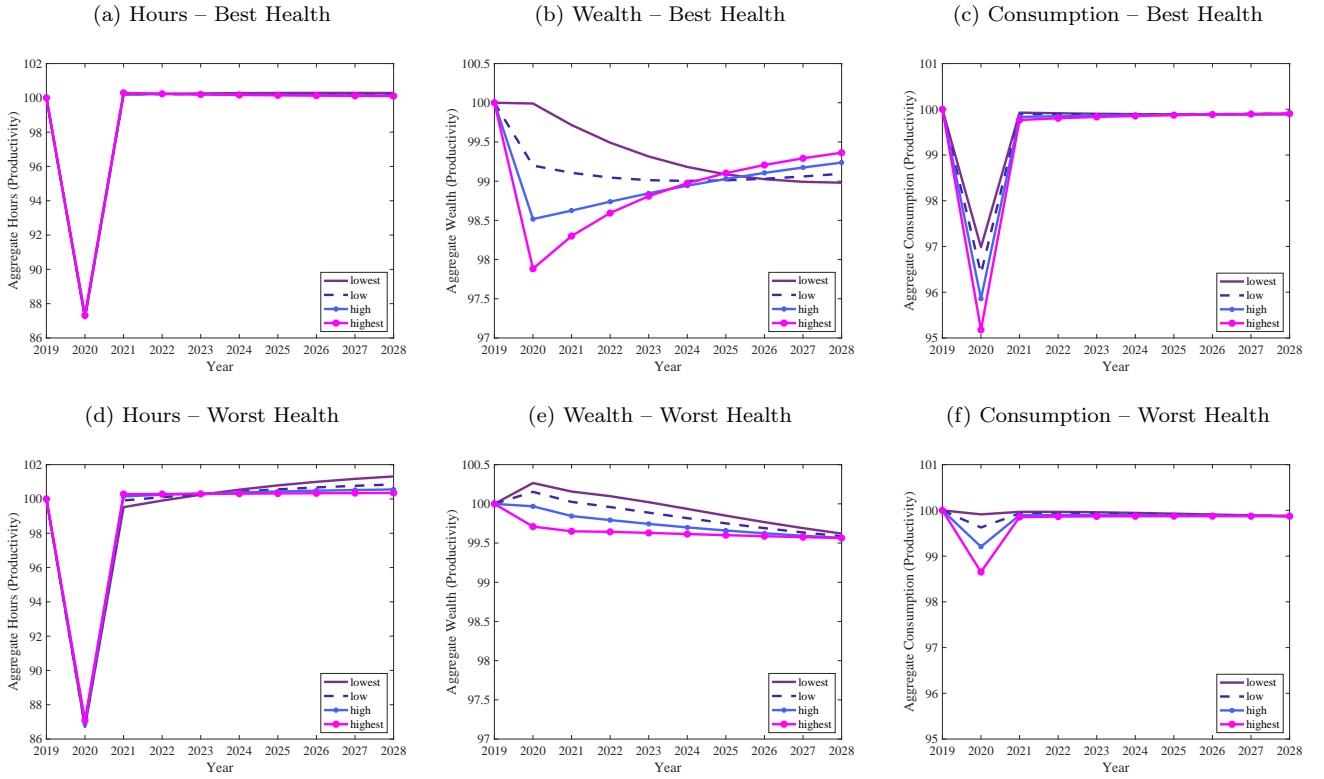
## 4.2 Response to Pandemic Assistance

In all our experiments with some mitigation measure in place, we assume that the government provides pandemic assistance to the fraction of the population affected by the lockdown. This aid is set at 25% of average national baseline income for all. As a result, we find interesting heterogeneity in the impact of the lockdown on different sub-groups. First note that flat PA amounts corresponds to an income shock of varying magnitudes for different health, productivity and education type in the model. For instance, for those in the lowest productivity group and without a college degree, PA is 31.7% lower than their baseline earnings. At the same time, for those with a college degree and on top of the productivity distribution, PA is 89.2% lower.

Figure 4 shows macroeconomic aggregates by the idiosyncratic productivity and health levels of the workers relative to the baseline in the random lockdown case. We find that while the decline in hours remains the same for each group, wealth and consumption changes differ significantly. For instance, aggregate consumption drops by roughly 4.8% for the highest productivity group in the best health state and only 0.09% for those in the lowest productivity and worst health group. Analogously, we find that wealth of the former group decreases by 2.1% and of the latter increases by 0.26%. This is mainly due to the fact that PA turns out to be quite generous for the latter group – roughly 200% higher than their baseline earnings. At the same time, for those in the best health and highest productivity level, PA is 87.6% lower.



Figure 4: Experiments – Aggregates by Labor Productivity and Health



Note: All variables are normalized by their baseline levels to reflect the changes under each experiment relative to baseline transitions.

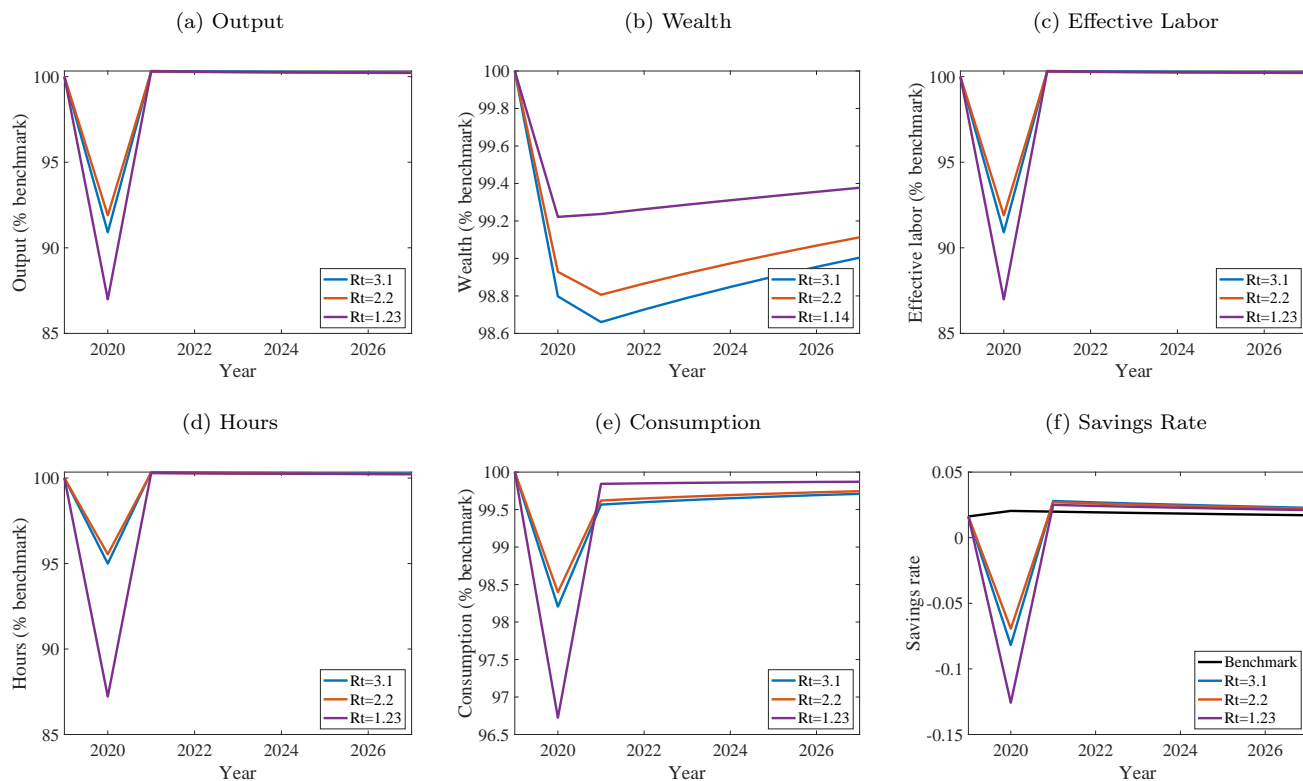
### 4.3 Different Infection Rates

Figure 5 shows the time paths of various macroeconomic variables, now under different infection rates. In the first transition period (2020) when the shock hits the economy, there are large economic declines under each scenario. For instance, output drops by roughly 10 and 8 percent in the no mitigation scenarios corresponding to  $R_t = 3.1$  and  $2.2$  respectively as compared to 13% percent in the mitigation scenario discussed above. While the decline in output in the former two cases is driven primarily by loss in worker productivity due to widespread infection levels, decline in the latter scenario is due to the interruption of economic activity due to the lockdown.

Note that while the impact of the shock on output lasts for a single period it persists for roughly twenty periods for consumption and aggregate wealth. This holds true in the model for two reasons. First, in the period of the shock, individuals draw down their wealth due to reduced earnings in all three cases. However, the period after the shock sees a big decline in aggregate wealth/consumption in the no-mitigation cases due

to large scale deaths. A fraction of infected individuals die in the next period with positive wealth which does not get distributed back into the economy. Second, our assumption of fixed baseline interest rate implies a small open economy where capital moves freely. As a result, reduction in aggregate wealth does not result in further reductions in output.

Figure 5: Experiments – Aggregates



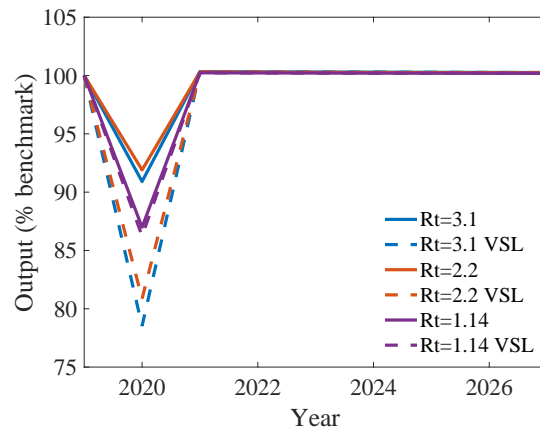
*Note: All variables are normalized by their baseline levels to reflect the changes under each experiment relative to baseline transitions.*

It should be noted that the reduction in output in figure 5a does not take into account the cost of widespread infection to public health – value of lives lost to the disease. One way to incorporate the impact of the lives lost is to adjust the decline in output for the value of statistical lives (VSL) lost under each case. We use the age-specific estimates of VSL from Aldy and Viscusi 2008 to adjust the decline in output with the value of lives lost in each infection scenario.<sup>12</sup> The dashed lines in Figure 6 show the decline in output after adjusting for the VSL lost due to the disease. It is no surprise that after accounting for the high death rates under the no-mitigation scenario, output declines in the no-mitigation cases supersede that

<sup>12</sup>The authors provide estimates for ages 20 to 62. We assume that VSL of a 62 year old applies to the group 63-65. We further assume that people older than 65 have a VSL of \$1 million.

of the mitigation case.

Figure 6: Adjusting for Value of Statistical Life



## 5 Conclusions

Efforts to mitigate the spread of COVID-19 in the U.S. have included closing businesses that are deemed unessential. This has resulted in more than 26 million initial unemployment insurance claims in five weeks. Without large scale testing of the population, it is not clear how the economic activity may resume. In this paper, we show significant differences in the economic consequences of who to quarantine during this pandemic. We find that stay-at-home recommendations that are based on health and age reduce the economic severity of the pandemic by 10% of GDP under very conservative estimates. Going forward, it may be possible to introduce subsidies to the elderly or those with underlying health conditions to self-isolate until a vaccine or a cure is available. The fiscal consequences of either of these policies is likely to be much lower than what is currently spent on providing unemployment insurance to a large fraction of the working age population.

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