The Distributional Effects of COVID-19 and Mitigation Policies

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The Distributional Effects of COVID-19 and Mitigation Policies[*]

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Abstract

This paper develops a quantitative life cycle model in which economic decisions impact the spread of COVID-19 and, conversely, the virus affects economic decisions. The calibrated model is used to measure the welfare costs of the pandemic across the age, income, and wealth distribution and to study the effectiveness of various mitigation policies. In the absence of mitigation, young workers engage in too much economic activity relative to the social optimum, leading to higher rates of infection and death in the aggregate. The paper considers a subsidy-and-tax policy that imposes a tax on consumption and subsidizes reduced work compared to a lockdown policy that caps work hours. Both policies are welfare improving and lead to less infections and deaths. Notably, almost all agents favor the subsidy-and-tax policy, suggesting that there need not be a tradeoff between saving lives and economic welfare.

Keywords: pandemic, coronavirus, COVID-19.

JEL Classification Codes: D62, E21, E32, E62, I14, I15.

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1 Introduction

The COVID-19 pandemic represents dual public health and economic crises, and has spawned a quickly emerging literature on the economics of pandemics. Furthermore, the pandemic and mitigation efforts have had unequal impacts across the distribution: The virus has been particularly dangerous for older individuals, while mitigation policies, such as shutdowns, have affected working-age individuals, particularly those with lower income and wealth.

This paper develops a quantitative life cycle model in which economic decisions, such as how much to work and how much to consume, impact the spread of the virus and vice versa. The calibrated model is used to measure the welfare costs across the age, income, and wealth distribution and to study the effectiveness of various mitigation policies. In the absence of mitigation, young workers engage in too much economic activity relative to the social optimum, leading to higher rates of infection and death in the aggregate. This paper considers two budget-neutral mitigation policies: a subsidy-and-tax policy that subsidizes reduced work—funded by a tax on consumption—and a lockdown policy that caps work hours. The subsidy-and-tax and lockdown policies lower the peak infection rate by 1.2 and 0.3 percentage points, respectively, and save approximately 470,000 and 46,000 lives, respectively. In terms of welfare, the lockdown policy benefits older individuals at the expense of younger, particularly low-wage workers. The approval among almost all agents for the subsidy-and-tax plan suggests that with well-designed policies, there need not be a tradeoff between saving lives and economic well being.

The model includes many, but not all, of the features relevant to studying the aggregate and distributional consequences of the pandemic and mitigation efforts. First and foremost, the model has heterogeneity by age, which is important because COVID-19 presents very different mortality risk by age, and various mitigation policies such as shutdowns mostly affect working-age individuals. Furthermore, lower income individuals appear less able to work from home (see, for example, Bick et al. 2020, Bartik et al. 2020, Dingel and Neiman 2020, Gascon and Ebsim 2020 and Mongey and Weinberg 2020), suggesting that heterogeneity across income is an important feature. The model builds on the epidemiological SIR model of virus transmission that has become common in the literature.[2] Additionally, many studies have documented that the way viruses typically spread outside the home is through

[2]See Hur and Jenuwine (2020) for a review of this literature.

work or consumption-related activities, and like Eichenbaum et al. (2020), the model allows for these transmission mechanisms. Since many mitigation efforts are focused on reducing labor and consumption activities, I model endogenous labor supply, the ability to work from home, and optimization of consumption and saving. Finally, the model has other features that have become common in the literature such as hospital capacity constraints.

Related literature

The model combines the heterogeneous-agent overlapping-generations model (see, for example, Conesa et al. 2009, Favilukis et al. 2017, Heathcote et al. 2010, and Hur 2018) with an extension of the standard SIR epidemiological model similar to those used in Eichenbaum et al. (2020), Glover et al. (2020), and Jones et al. (2020). Workers face idiosyncratic productivity shocks and borrowing constraints within an incomplete market setting as in Aiyagari (1994), Bewley (1986), Huggett (1993), and Imrohoroğlu (1989).

The paper is most related to Bairoliya and Imrohoroglu (2020) and Glover et al. (2020). Bairoliya and Imrohoroglu (2020) study quarantine policies in a quantitative life cycle model with heterogeneity across age, health, income, and wealth. They primarily focus on studying the effects of selective quarantines based on age and health. Glover et al. (2020) study optimal mitigation policies in a model with three types of agents: retirees, young workers in the essential sector, and young workers in the non-essential sector. Relative to Glover et al. (2020), this paper features heterogeneity across not only age, but also income and wealth, and complements both papers by analyzing mitigation policies that specifically target the behavior of these different groups.

The epidemiological part of the model borrows from the economics literature that builds on the SIR model, originally developed by Kermack and McKendrick (1927). Atkeson (2020) was one of the first papers to use the SIR model in an economics context. Alvarez et al. (2020), Eichenbaum et al. (2020), Farboodi et al. (2020), and Jones et al. (2020) study optimal mitigation in SIR models extended with lockdowns, economic-epidemiological feedback, social distancing, and work from home with learning-by-doing, respectively. Bodenstein et al. (2020) and Krueger et al. (2020) study the SIR model with multiple sectors. Birinci et al. (2020), Garibaldi et al. (2020), and Kapicka and Rupert (2020) incorporate search and matching frictions into the SIR framework, while Berger et al. (2020), Chari et al. (2020), and Piguillem and Shi (2020) extend the SIR model to focus on testing and quarantine.

Chudik et al. (2020) extend the SIR model to allow for compulsory and voluntary social distancing and estimate the model using data from Chinese provinces, while Argente et al. (2020) extend the SIR model with city structure, estimated with South Korean mobile phone data. Bognanni et al. (2020) develop a SIR model with multiple regions and estimate it on daily county-level US data. Aum et al. (2020) study the effects of lockdowns in a model with heterogeneous age, skill, and occupation choice, while Kaplan et al. (2020) study the distributional effects of the pandemic in a heterogeneous agent new Keynesian model.

By studying the heterogeneous welfare consequences of COVID-19 and mitigation efforts, this paper complements the empirical literature that has documented the early effects of the pandemic and various mitigation policies on different segments of the population, such as Chetty et al. (2020). Adams-Prassl et al. (2020) and Wozniak (2020) use survey data to document that COVID-19 has disproportionately impacted young and low-wage individuals in the US. Alstadsæter et al. (2020) use register data from Norway to document that pandemic-induced layoffs have disproportionately affected not only young and low-wage, but also low-wealth individuals. Additionally, Bertocchi and Dimico (2020) focus on differential effects of the COVID-19 crisis across race, Alon et al. (2020a,b) study the differences across gender, and Osotimehin and Popov (2020) study the heterogeneous impact by sector of employment.

2 Model

This section presents a model economy used to quantitatively analyze the welfare consequences of COVID-19 and to run policy counterfactuals. The setting combines the heterogeneous-agent overlapping-generations model with an extension of the standard SIR epidemiological model that is similar to those used in Eichenbaum et al. (2020). The economy is inhabited by overlapping generations of stochastically aging individuals. Time is discrete and indexed by $t = 0, ..., \infty$. Workers face idiosyncratic productivity shocks and borrowing constraints within an incomplete market setting. I now describe the model in more detail.

2.1 Individuals

Individuals of age $j \in J \equiv \{1, 2, .., \overline{J}\}$ face conditional aging probabilities given by $\{\psi_j\}$.[3] Mandatory retirement occurs at age $j = J_R$. The period utility function is given by

$$u(c, \ell, h) = \frac{c^{1-\sigma}}{1-\sigma} - \varphi \frac{\ell^{1+\nu}}{1+\nu} + \bar{u} + \hat{u}_h \tag{1}$$

where c is consumption, ℓ is labor supply, and $\bar{u}$ and $\hat{u}_h$ govern the flow value of being alive and being in health state h, respectively.

An individual's health status is given by $h \in \{S, I, R, D\}$: *susceptible* agents are healthy but may contract the virus, *infected* agents have contracted the virus and may pass it onto others, and agents that exit the infection can either *recover* or *die*. Recovered agents are assumed to be immune from further infection.[4] The transition between health states builds on the widely used SIR model, originally developed by Kermack and McKendrick (1927). Susceptible individuals get infected with probability π_{It}, which depends on individual consumption and outside labor (c, ℓ^o) and the aggregate measure of infected individuals (μ_{It}) and their consumption and outside labor (C_{It}, L^o_{It}). Formally,

$$\pi_{It}(c, \ell^o; Z_t) = \beta_c c C_{It} + \beta_\ell \ell^o L^o_{It} + \beta_e \mu_{It}, \tag{2}$$

where $Z_t \equiv \{\mu_{It}, C_{It}, L^o_{It}\}$. This framework allows the virus to be contracted from consumption-related activities, labor-related activities, and from other settings. It also allows a feedback between disease progression and economic activities as in Eichenbaum et al. (2020), Glover et al. (2020), and Jones et al. (2020).

Infected individuals exit the infection with probability π_{Xt} and upon exit, they recover with probability $1 - \delta_{jt}(\mu_{It})$ and die with probability $\delta_{jt}(\mu_{It})$. The fatality rate depends on the individual's age and on the aggregate measure of infected individuals. If we assume that a vaccine and cure are developed and implemented in period $\hat{t}$, then the transition matrix

[3] Given that the model will be used to analyze disease progression at a high frequency, the assumption of stochastic aging greatly reduces the state space and computational burden.

[4] At this point, it is not clear whether individuals that have recovered from COVID-19 have lasting immunity. One could easily extend the model to have shorter durations of immunity.

between health states, for $t < \hat{t}$, is given by

$$\Pi_{jhh't}(c, \ell^o; Z_t) = \begin{array}{c|cccc} & S & I & R & D \\ \hline S & 1 - \pi_{It}(c, \ell^o; Z_t) & \pi_{It}(c, \ell^o; Z_t) & 0 & 0 \\ I & 0 & 1 - \pi_{Xt} & \pi_{Xt}(1 - \delta_{jt}(Z_t)) & \pi_{Xt}\delta_{jt}(Z_t) \\ R & 0 & 0 & 1 & 0 \\ D & 0 & 0 & 0 & 1 \end{array} \tag{3}$$

and for $t \geq \hat{t}$,

$$\Pi_{jhh't}(c, \ell^o; Z_t) = \begin{array}{c|cccc} & S & I & R & D \\ \hline S & 0 & 0 & 1 & 0 \\ I & 0 & 0 & 1 & 0 \\ R & 0 & 0 & 1 & 0 \\ D & 0 & 0 & 0 & 1 \end{array} \tag{4}$$

Each period, workers receive idiosyncratic productivity shocks $\varepsilon \in E$, which follows a Markov process, with transition matrix Γ. Their labor income is given by $w_t \eta_{jh} \varepsilon \ell$, where w_t is the efficiency wage, η_{jh} is the health- and age-profile of efficiency units, and ℓ is total hours worked. Workers may choose to work up to a fraction $\bar{\theta}_j(\varepsilon)$ of their labor hours from home, where $\bar{\theta}_j(\varepsilon)$ is allowed to vary by age and productivity. Retirees are assumed to receive a fixed income of s each period.[5] Individuals can accumulate non-contingent assets k, which delivers a net return of r_t.

Given the sequence of prices $\{w_t, r_t\}$, consumption taxes $\{\tau_{ct}\}$, and aggregate states $\{Z_t\}$, a retiree with age $j \geq J_R$, wealth k, and health h in period t chooses consumption c and savings k' to solve:

$$\begin{aligned} V_{jt}(k, h) = \max_{c, k' \geq 0} \; & u(c, 0, h) + \beta \psi_j \sum_{h' \in H} \Pi_{hh't}(c, 0) V_{j+1,t+1}(k', h') \\ & + \beta(1 - \psi_j) \sum_{h' \in H} \Pi_{hh't}(c, 0) V_{j,t+1}(k', h') \\ \text{s.t. } \; & (1 + \tau_{ct})c + k' \leq s + k(1 + r_t) \end{aligned} \tag{5}$$

where β is the time discount factor. I assume that the value of death is zero and that $V_{\bar{J}+1,t} = 0$, which implies that agents in the last period of life ($j = \bar{J}$) may die due to stochastic aging and, if infected, due to the virus.

[5] This can readily be extended to depend on lifetime earnings as in Hur (2018).

Given the sequence of prices $\{w_t, r_t\}$, consumption and labor income taxes $\{\tau_{ct}, \tau_{\ell t}\}$, and aggregate states $\{Z_t\}$, a worker with age $j < J_R$, wealth k, productivity ε, and health h in period t chooses consumption c, total labor ℓ, outside labor ℓ^o and savings k' to solve:

$$\begin{aligned} v_{jt}(k,\varepsilon,h) = \max_{c,\ell,\ell^o,k'\geq 0} \ & u(c,\ell,h) + \beta\psi_j \sum_{\varepsilon'\in E}\sum_{h'\in H} \Gamma_{\varepsilon\varepsilon'}\Pi_{hh't}(c,\ell^o) v_{j+1,t+1}(k',\varepsilon',h') \\ & + \beta(1-\psi_j)\sum_{\varepsilon'\in E}\sum_{h'\in H} \Gamma_{\varepsilon\varepsilon'}\Pi_{hh't}(c,\ell^o) v_{j,t+1}(k',\varepsilon',h') \\ \text{s.t. } & (1+\tau_{ct})c + k' \leq w_t\eta_j^h(1-\tau_{\ell t})\varepsilon\ell + k(1+r_t) \\ & (1-\bar{\theta}_j(\varepsilon))\ell \leq \ell^o \leq \ell \end{aligned} \tag{6}$$

where $v_{jt}(k,\varepsilon,h) = V_{jt}(k,h)$ for $j \geq J_R$.

2.2 Production

A representative firm hires labor (L_{ft}) and capital (K_{ft}) to produce according to

$$Y_{ft} = K_{ft}^{\alpha} L_{ft}^{1-\alpha} \tag{7}$$

Taking prices as given, the firm solves

$$\max_{L_{ft},K_{ft}} Y_{ft} - w_t L_{ft} - (r_t+\delta)K_{ft}, \tag{8}$$

where δ is the deprecation rate of capital. Optimality conditions are given by

$$w_t = (1-\alpha)K_{ft}^{\alpha} L_{ft}^{-\alpha}, \tag{9}$$

$$r_t = \alpha K_{ft}^{\alpha-1} L_{ft}^{1-\alpha} - \delta. \tag{10}$$

2.3 Law of motion for aggregate states

Let C_{jht} and L^o_{jht} denote aggregate consumption and outside labor, respectively, of individuals with age j and health h in period t. Then, by the law of large numbers, equation (2) implies that new infections within an age-j cohort are given by

$$T_{jt} = \beta_c C_{jSt} C_{It} + \beta_\ell L^o_{jSt} L^o_{It} + \beta_e \mu_{jSt}\mu_{It} \tag{11}$$

where μ_{jSt} is the measure of susceptible age-j individuals in period t. The measure of infected agents is then given by $\mu_{I,t+1} = \sum_{j\in J}\mu_{jI,t+1}$ where, for $j > 1$,

$$\begin{aligned} \mu_{jI,t+1} = {} & \psi_j(\mu_{j-1,It}(1-\pi_{Xt}) + T_{j-1,t}) \\ & + (1-\psi_j)(\mu_{jIt}(1-\pi_{Xt}) + T_{jt}), \end{aligned} \tag{12}$$

and

$$\mu_{1I,t+1} = (1-\psi_1)(\mu_{1It}\,(1-\pi_{Xt}) + T_{1t}).$$

2.4 Equilibrium

We are ultimately interested in studying disease dynamics along a transition path. However, because most of the model parameters are calibrated to an initial pre-pandemic steady state, let's first define a stationary equilibrium in which $\mu_I = 0$. In this case, aggregate consumption and labor of infected individuals is trivially zero. Thus $Z = (0, 0, 0)$ and Π is the identity matrix. Define the state space over wealth, labor productivity, and health as $X = K \times E \times H$ and let a σ-algebra over X be defined by the Borel sets, $\mathcal{B}$, on X.

Definition. A *steady-state recursive equilibrium*, given fiscal policies $\{\tau_c, \tau_\ell, s\}$, is a set of value functions $\{v_j, V_j\}_{j\in J}$, policy functions $\{c_j, \ell_j, \ell_j^o, k_j'\}_{j\in J}$, prices $\{w, r\}$, producer plans $\{Y_f, L_f, K_f\}$, the distribution of newborns ω, and invariant measures $\{\mu_j\}_{j\in J}$ such that:

1. Given prices, workers and retirees solve (5) and (6).
2. Given prices, firms solve (8).
3. Markets clear:
   (a) $Y_f = \int_X \sum\limits_{j\in J} (c_j(k,\varepsilon,h) + \delta k)\, d\mu_j(k,\varepsilon,h)$
   (b) $L_f = \int_X \sum\limits_{j<J_R} l_j(k,\varepsilon,h) d\mu_j(k,\varepsilon,h)$
   (c) $K_f = \int_X \sum\limits_{j\in J} k d\mu_j(k,\varepsilon,h)$
4. The government budget constraint holds:

$$\int_X \left[\tau_\ell w \sum_{j<J_R} \eta_{jh}\varepsilon\ell_j(k,\varepsilon,h) + \tau_c \sum_{j\in J} c_j(k,\varepsilon,h)\right] d\mu_j(k,\varepsilon,h) = s\int_X \sum_{j\geq J_R} d\mu_j(k,\varepsilon,h)$$

5. For any subset $(\mathcal{K},\mathcal{E},\mathcal{H}) \in \mathcal{B}$, the invariant measure μ_j satisfies, for $j > 1$,

$$\mu_j(\mathcal{K},\mathcal{E},\mathcal{H}) = \int_X \psi_{j-1}\mathbb{1}_{\{k_{j-1}'(k,\varepsilon,h)\in\mathcal{K}\}} \sum_{\varepsilon'\in\mathcal{E}}\sum_{h'\in\mathcal{H}} \Gamma_{\varepsilon\varepsilon'}\Pi_{hh'} d\mu_{j-1}(k,\varepsilon,h) \tag{13}$$
$$+ \int_X (1-\psi_j)\mathbb{1}_{\{k_j'(k,\varepsilon,h)\in\mathcal{K}\}} \sum_{\varepsilon'\in\mathcal{E}}\sum_{h'\in\mathcal{H}} \Gamma_{\varepsilon\varepsilon'}\Pi_{hh'} d\mu_j(k,\varepsilon,h)$$

and

$$\mu_1(\mathcal{K},\mathcal{E},\mathcal{H}) = \int_X (1-\psi_1)\mathbb{1}_{\{k_1'(k,\varepsilon,h)\in\mathcal{K}\}} \sum_{\varepsilon'\in\mathcal{E}} \sum_{h'\in\mathcal{H}} \Gamma_{\varepsilon\varepsilon'}\Pi_{hh'} d\mu_1(k,\varepsilon,h) + \omega(\mathcal{K},\mathcal{E},\mathcal{H}) \quad (14)$$

6. The newborn distribution satisfies:

$$\int_X k d\omega(k,\varepsilon,h) = \int_X \psi_{\bar{J}} k'_{\bar{J}}(k,\varepsilon,h) d\mu_{\bar{J}}(k,\varepsilon,h) \quad (15)$$

3 Calibration

In this section, we begin by calibrating some of the model's parameters to the pre-pandemic steady state and discuss how other parameters are set. We will then use the calibrated model to analyze the distributional effects of the pandemic and mitigation policies. The parameters are summarized in Tables 1 and 2.

3.1 Economic parameters

A period in the model is two weeks. The aggregate measure of individuals in the steady state economy is normalized to one. The number of age cohorts, J, is set to 3, so that $j = 1$ corresponds to ages 25–44 (young), $j = 2$ corresponds to ages 45–64 (middle), and $j = J_R = \bar{J} = 3$ corresponds to ages 65–84 (old). The aging probability $\psi_j = \psi$ is set so that agents spend, on average, 20 years in each age cohort. The wealth of deceased individuals are rebated to a fraction of newborn individuals each period. Specifically, 85 percent of individuals are born with zero wealth, whereas 15 percent of individuals are endowed with 28 times annual per capita consumption.[6]

The age-profile of efficiency units, η_{jS}, is normalized to one for healthy young workers and healthy middle-age workers are assumed to be 35 percent more efficient, to match the wage ratio in the data (2014, *Panel Survey of Income Dynamics*). I assume that the efficiencies of recovered individuals are the same as that of susceptible individuals, $\eta_{jR} = \eta_{jS}$.[7] The

[6] This is based on the fact that 85 percent of households whose heads are between the ages of 21 and 25 had a cumulative net worth of zero in 2016 (*Survey of Consumer Finances*). The calibrated value of the endowment is rather large. Adding additional age groups would mitigate this issue, but would add to the computational burden.

[7] It is too early to conclude about the potentially long-lasting consequences of COVID-19. That said, if needed, the model can easily incorporate these changes in future work.

fraction of labor that can do done from home, $\bar{\theta}_j(\varepsilon)$ is set to match the average share of jobs that can be done from home by occupations grouped into five wage bins, computed based on Dingel and Neiman (2020). The average share of jobs that can be done from home ranges from 0.03 for the occupations in the bottom 20 percent of the wage distribution to 0.66 for those in the top 20 percent.

The time discount factor β is chosen so that the model replicates the US net-worth-to-GDP ratio (2014, *US Financial Accounts*). The parameter that governs the disutility from labor, φ, is set so that the model generates a share of disposable time spent working of 0.3, equivalent to 30 hours per week. I set risk aversion, σ, to be 2 and the Frisch elasticity, $1/\nu$, to be 0.5 (for example, see Chetty et al. (2011), which are both standard values in the literature.

To set the flow value of life, I follow Glover et al. (2020) who use a value of statistical life (VSL) of \$11.5 million, which corresponds to 7,475 times biweekly consumption per capita in the United States. For simplicity, we can assume that the VSL is computed based on the consumption of a healthy infinitely-lived representative agent that discounts time at the rate of $\beta(1-\psi)$ in the pre-pandemic steady state, whose present discounted utility is given by

$$v = \frac{(\bar{c}+\Delta_c)^{1-\sigma}}{1-\sigma} + \bar{u} + \frac{\beta(1-\psi+\Delta_\psi)}{1-\beta(1-\psi)}\left(\frac{\bar{c}^{1-\sigma}}{1-\sigma}+\bar{u}\right) \tag{16}$$

where $\bar{c}$ denotes steady state consumption per capita and Δ_c and Δ_ψ denote small one-time deviations to consumption and survival probability. Then, the VSL—defined as the marginal rate of substitution between survival and consumption—can be expressed as

$$VSL = \left.\frac{\frac{\partial v}{\partial \Delta_\psi}}{\frac{\partial v}{\partial \Delta_c}}\right|_{\Delta_c=0} = \frac{\beta}{1-\beta(1-\psi)}\frac{\frac{\bar{c}^{1-\sigma}}{1-\sigma}+\bar{u}}{\bar{c}^{-\sigma}}. \tag{17}$$

Then, by substituting $VSL = 7475 \times \bar{c}$, we obtain

$$\bar{u} = 7475 \times \bar{c}^{1-\sigma}\frac{1-\beta(1-\psi)}{\beta} - \frac{\bar{c}^{1-\sigma}}{1-\sigma}. \tag{18}$$

The capital elasticity in the production function, α, is set to match the aggregate capital income share of 0.36. The consumption tax τ_c is set to zero, while the income tax τ_ℓ and retirement income s are chosen so that retirement income is 30 percent of average labor earnings in the model and the government budget constraint is satisfied. The depreciation rate of capital, δ, is set at an annualized rate of 5 percent per year.

Table 1: Calibration of economic parameters

Parameters	Values	Targets / Source
Discount factor, annualized, β	0.97	Wealth-to-GDP: 4.81 (2014)
Risk aversion, σ	2	Standard value
Disutility from labor, φ	114	Average hours: 30 hours per week
Frisch elasticity, $1/\nu$	0.50	Standard value
Flow value of life, $\bar{u}$	9.51	Value of statistical life: \$11.5 million
Aging probability, annualized, ψ	0.05	Expected duration: 20 years
Efficiency units, $\eta_{jS} = \eta_{jR}$	$\{1, 1.35\}_{j=1,2}$	Wage ratio of age 45-64 workers to age 25-44 workers (PSID)
Factor elasticity, α	0.36	Capital share
Capital depreciation, annualized, δ	0.05	Standard value
Retirement income, s	1.00	30% of average earnings per worker
Labor income tax, τ_ℓ	0.15	Government budget constraint
Consumption tax, τ_c	0.00	
Persistence, annual, ρ_ε	0.94	Author estimates (PSID)
Standard deviation, annual, σ_υ	0.19	Author estimates (PSID)

The labor productivity shocks ε are assumed to follow an order-one autoregressive process as follows:

$$\log \varepsilon_t = \rho_\varepsilon \log \varepsilon_{t-1} + \upsilon_t, \ \upsilon_t \sim N\left(0, \sigma_\upsilon^2\right). \tag{19}$$

This process is estimated using annual wages constructed from the PSID to find a persistence of $\rho_\varepsilon = 0.94$ and a standard deviation of $\sigma_\upsilon = 0.19$.[8] These parameters are then converted to a higher frequency, following Krueger et al. (2016). The process is approximated with a seven-state Markov process using the Rouwenhurst procedure described in Kopecky and Suen (2010).

3.2 Parameters related to COVID-19

The exit rate, π_X is set to 14/18 so that the expected duration of the infection is 18 days, as in Atkeson (2020) and Eichenbaum et al. (2020). For the unconstrained case fatality rates,

[8] The wages are constructed similarly to Floden and Lindé (2001) and the sample selection and estimation procedures closely follow Krueger et al. (2016) and Carroll and Hur (2020). See Appendix A for details.

I use data from South Korea's Ministry of Health and Welfare to compute a fatality rate of 8.47 percent for ages 65–84, 0.94 percent for ages 45–64, and 0.09 percent for ages 25–44. I use South Korean data because testing has been abundant since the outbreak began[9], the peak in infections was early enough that case fatality rates are not biased due to lags in deaths, and hospitals were not overwhelmed, as the number of active cases never exceeded 0.015 percent of the population.[10]

Next, we discuss the hospital capacity constraints and how they affect death rates. Following Piguillem and Shi (2020), I use the functional form

$$\delta_j(\mu_I) = \delta_j^u \min\left\{1, \frac{\kappa}{\mu_I}\right\} + \delta_j^c \max\left\{0, 1 - \frac{\kappa}{\mu_I}\right\} \tag{20}$$

where δ_j^u and δ_j^c denote the unconstrained and constrained death rates and κ denotes the number of infected individuals that can be treated without the constraint binding. According to the American Hospital Association, there are roughly 924,000 hospital beds in the US, corresponding to 0.28 percent of the population.[11] Since not all infected cases require hospitalization, I use a generous capacity constraint, H, of 1 percent. The unconstrained death rates, δ_j^u, are set to match those documented for South Korea, and the constrained death rates are set as $\delta_j^c = 2\delta_j^u$, following Piguillem and Shi (2020).

There is quite a bit of uncertainty regarding the basic reproduction number (R_0), which corresponds to the number of people to whom the average infected person passes the disease absent mitigation efforts, though most estimates range between 2.2 and 3.1 (see for example, Wang et al. 2020 and Fauci et al. 2020). Using equation (11), total new infections in a given period is given by

$$T = \beta_c C_S C_I + \beta_\ell L_S^o L_I^o + \beta_e \mu_S \mu_I, \tag{21}$$

where C_h and L_h^o are the aggregate steady state consumption and labor supply of individuals with health status $h \in H$. In the pre-pandemic steady state, workers are indifferent between working outside or working from home. Thus, I assume that all steady state work is done outside, which can be obtained by introducing an arbitrarily small difference in either

[9] For example, see https://www.bloomberg.com/news/articles/2020-04-18/seoul-s-full-cafes-apple-store-lines-show-mass-testing-success. Aum et al. (2020) also discuss the success of early testing and tracing efforts in South Korea.

[10] Active infection cases in South Korea peaked at 7,362 on March 11, 2020, according to Worldometer. See https://www.worldometers.info/coronavirus/country/south-korea/

[11] See https://www.aha.org/statistics/fast-facts-us-hospitals.

productivity or preference in favor of working outside. If we assume that when the virus is first introduced into the model, we have that $L_S/\mu_S = L_I/\mu_I$ and $C_S/\mu_S = C_I/\mu_I$, then by taking $\mu_S \to 1$, the basic reproduction number is given by[12]

$$R_0 = \frac{\beta_c C_S^2 + \beta_\ell L_S^2 + \beta_e}{\pi_X}. \tag{22}$$

Thus given values for the basic reproduction number, R_0, the exit rate, π_X, the steady state values for aggregate consumption and labor, C_S and L_S, we need to assign values to the fractions of new infections occurring through consumption activities, work activities, and other channels in order to pin down the values for β_c, β_ℓ, and β_e. Evidence on how COVID-19 is transmitted is limited, but in the case of other infectious diseases, Ferguson et al. (2006) report that 70 percent of transmissions occur outside of the household. In another study that investigates the transmission channels of infectious diseases, Mossong et al. (2008) find that 35 percent of high-intensity contacts occur in workplaces and schools. Based on these studies, I assume that one-third of initial transmission occurs through consumption activities, one-third through labor activities, and one-third through other channels.

For the value of being infected, Glover et al. (2020) assume a 30 percent reduction in the flow value of life for an average infected agent with mild symptoms and a 100 percent reduction in the flow value of life for an average infected agent with severe symptoms. I take an intermediate value of 50 percent by setting $\hat{u}_I = -0.5(\bar{c}^{1-\sigma}/(1-\sigma) + \bar{u})$ and set $\hat{u}_S = \hat{u}_R = 0$.[13]

Next, I discuss how the efficiency units change when an individual gets infected. It is reasonable to expect that those with no symptoms would suffer little, if any, efficiency loss, whereas those that experience very severe symptoms would suffer something close to a 100 percent efficiency loss. Without sufficient evidence regarding how COVID-19 affects labor productivity and the fraction of infected individuals suffering severe symptoms, I assume that infected individuals suffer a 50 percent loss in efficiency.[14]

[12]These assumptions allow the calibration of these epidemiological parameters using steady state values. These may also be reasonable assumptions, given that the very first infected individuals may not change their behavior given the lack of testing and information regarding the pandemic in the early stages.

[13]The results are robust to a 30 percent reduction in the flow value of life, as shown in Appendix B

[14]Appendix B shows that the main results are robust to assuming a 30 percent loss in efficiency.

Table 2: Calibration of Epidemiological parameters

Parameters	Values	Targets / Source
Infection exit rate, π_X	0.78	Expected infection duration: 18 days
Unconstrained death rate,		Fatality rates in South Korea
$\delta_1^u \times 100$	0.09	
$\delta_2^u \times 100$	0.94	
$\delta_3^u \times 100$	8.47	
Constrained death rate, δ_j^c	$2\delta_j^u$	Piguillem and Shi (2020)
Hospital capacity, κ	0.01	See discussion above
Transmission parameters,		Basic reproduction number, $R_0 = 2.2$,
consumption-related, β_c	0.08	and initial transmission equally
labor-related, β_ℓ	14.20	likely through three channels
other, β_e	0.57	
Flow value of infection $\hat{u}_I$	–4.57	50 percent reduction in
		flow utility value of average agent
Efficiency units η_{jI}	$0.5\eta_{jS}$	See discussion above

4 Pandemic

This section uses the model to investigate the distributional consequences of the pandemic and various mitigation measures. First, I will explore how the endogenous transmission model—one in which economic interactions change the spread of the virus—differs from an exogenous transmission model—one in which the spread of the virus only depends on the number of susceptible and infected agents. This can also be thought of as the role of private mitigation. Second, I will explore the effect of various mitigation policies. In particular, I contrast a *lockdown*, implemented in the model by imposing a maximum labor supply of 20 hours per week for all agents, with a *subsidy-and-tax* policy that subsidizes working less than 20 hours per week, funded by a tax on consumption. While both policies reduce infections and deaths and raise welfare, the subsidy-and-tax policy delivers a higher welfare gain and is favored by almost all agents in the economy, whereas the lockdown benefits older individuals at the expense of younger, low-wage workers.

The economy starts in the pre-pandemic steady state in period $t = 0$. Then, in period $t = 1$ (April 1, 2020), the virus is introduced into the model so that 0.1 percent of the population is infected. I assume that a vaccine and cure is developed and fully implemented by April 1, 2022, after which the model transits back toward its steady state.[15] An important caveat is that, while the steady state analysis was done in general equilibrium, the transition path analysis is done in partial equilibrium, meaning that wages and capital rental rates are fixed at their steady-state levels. I also do not require the government budgets to be balanced nor do I change the measure of newborns and their wealth distribution throughout the transition. This implies that, as a result of the pandemic, the measure of agents in the economy may be less than 1 during the transition.

To solve the transition, the economy begins in the steady-state distribution, μ_j, at $t = 0$. Then, the virus is introduced in $t = 1$, and I solve for a sequence of value functions, $\{V_{jt}, v_{jt}\}_{t=1}^{\infty}$, policy functions, $\{c_{jt}, \ell_{jt}, \ell_{jt}^o, k'_{jt}\}_{t=1}^{\infty}$, distributions μ_{jt}, fiscal policies, $\{\tau_{ct}, \tau_{\ell t}\}_{t=1}^{\infty}$, for $j \in J$, such that given prices, households make optimal decisions and distributions are consistent with shocks, the invariant distribution of newborns, and household decisions.

4.1 Endogenous virus transmission

To better understand how the baseline model—the "SIR Macro" model with endogenous transmission—works, we can contrast it with the alternative "SIR" model with exogenous transmission, where $\beta_c = \beta_\ell = 0$. In the SIR model, we set $\beta_e = 1.71$ so that the model has the same basic reproduction number, $R_0 = 2.2$, as in the baseline SIR Macro model.

Figure 1 shows that even though the SIR Macro and SIR models begin with the same reproduction number (panel a), the SIR Macro model exhibits a quicker decline in the reproduction number and consequently a lower number of infections (panel b) and deaths (panel c). This is because, in response to the pandemic, agents in the SIR Macro model reduce their consumption and hours dramatically, as can be seen in Figure 1, panels (d) and (e).

Taking a closer look at the baseline model, consider the policy functions for consumption and outside labor of susceptible agents across the age, income, and wealth distribution (Figure 2). The decline in hours and consumption is broad based. However, the decline in

[15] While there is a lot of uncertainty regarding when a vaccine might be approved and distributed, this approach allows the computational burden to be reduced dramatically. An alternative approach would be to model the arrival of a vaccine and cure probabilistically.

Figure 1: Engodenous vs. exogenous transmission (no mitigation)

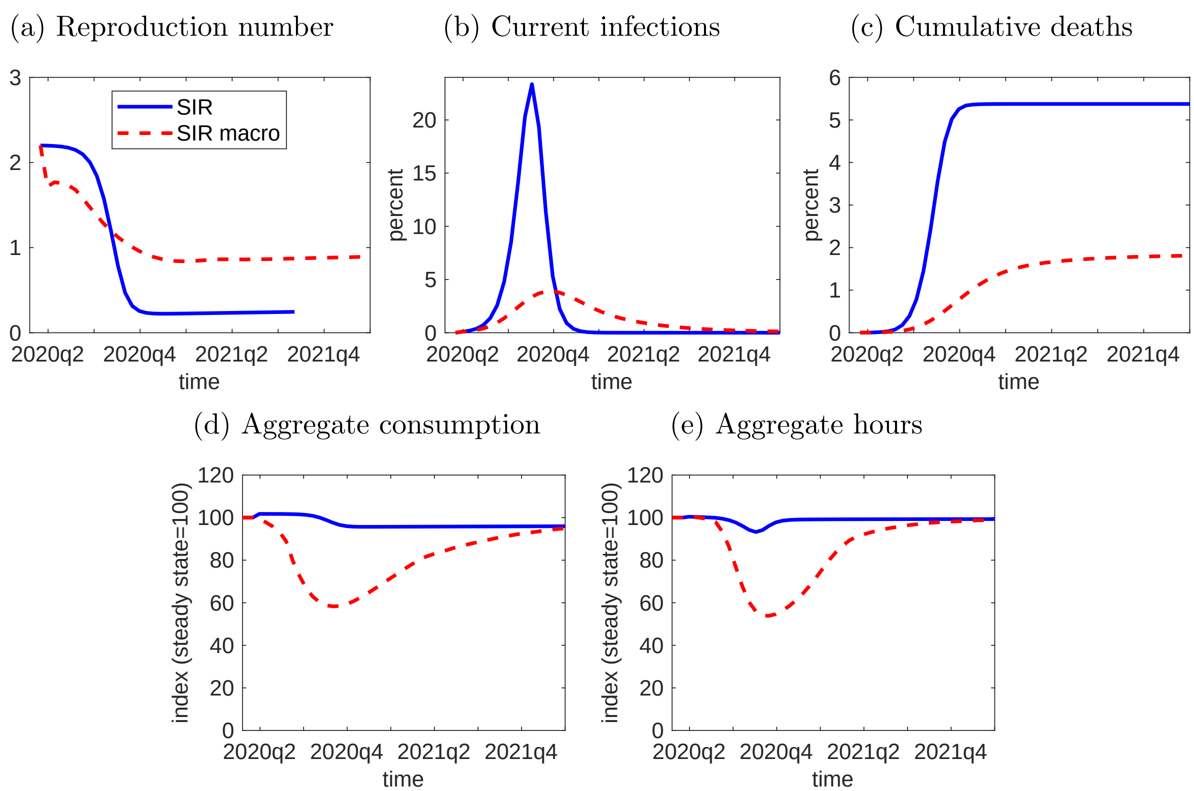
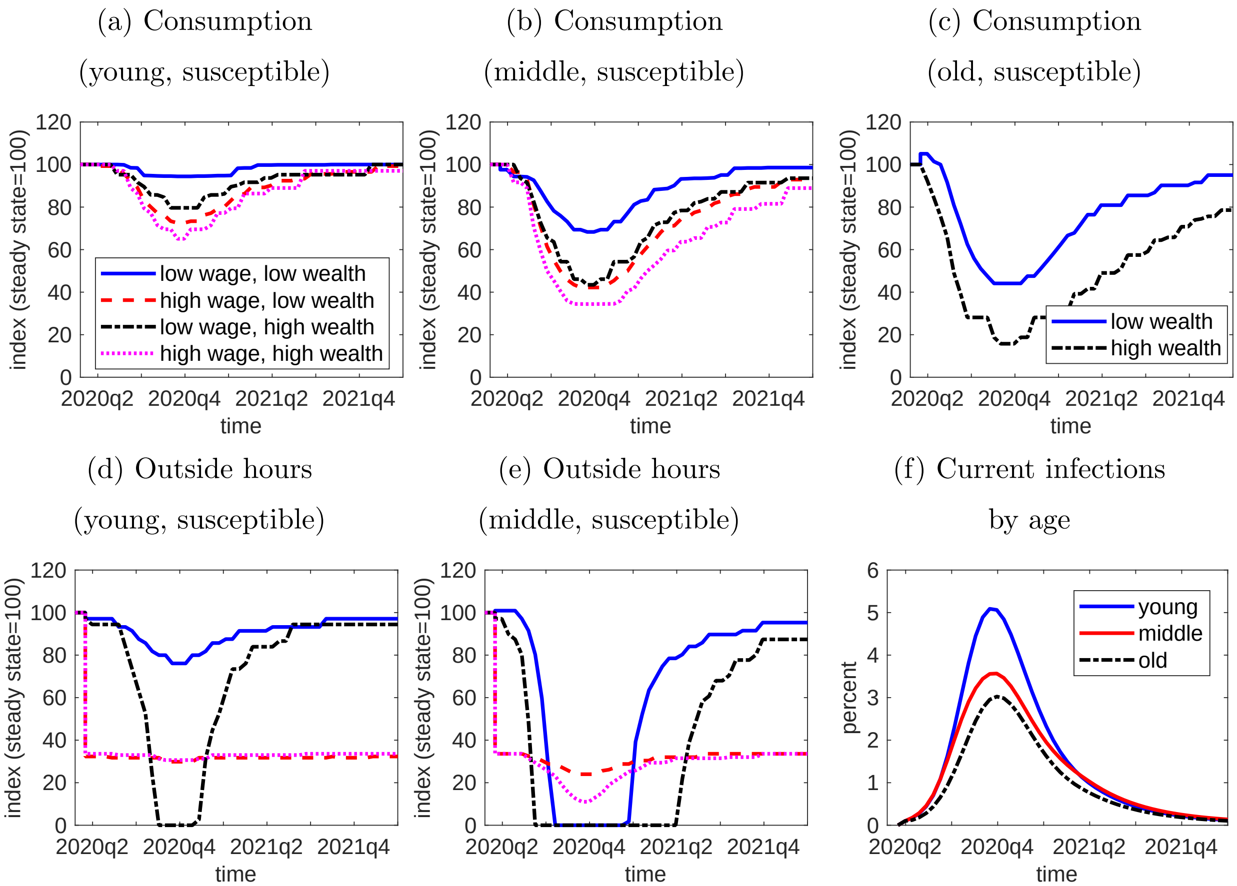


Figure 2: Response to pandemic (no mitigation)



Notes: Low income and high income correspond to 10th and 90th percentiles of the steady state wage distribution. Low wealth and high wealth correspond to the 25th and 75th percentiles of the steady state wealth distribution.

consumption is much greater for middle-aged and old agents than for young agents (panels a–c), and the decline in hours is much larger and more sustained for middle-aged workers than for young workers (panels d–e). This reflects the lower fatality risk for young agents. Moreover, among young workers, the declines in consumption and outside hours are the smallest for low-wage and low-wealth workers. Low-wage, high-wealth workers sit out the labor market altogether during the infection peak, suggesting that the lack of precautionary savings to draw from prevents low-wealth individuals from reducing their labor supply by more. Overall, young workers experience a much larger increase in infections, as shown in panel (f).

4.2 Mitigation policies

The previous subsection highlighted the externalities at work: Young workers do not reduce their consumption and labor as much as their older counterparts and incur higher infections. These responses are individually rational in the sense that young workers do not face high fatality risk. However, higher rates of infection among young agents also lead to higher infections among older individuals, who face higher fatality rates.

In this subsection, we explore several mitigation policies that reduce infection and death rates. In particular, we compare and contrast two different mitigation policies. The first is a blanket *lockdown*, implemented in the model by restricting outside labor supply to less than 20 hours per week for all agents, beginning April 1, 2020, with a gradual relaxation after August 1, 2020. The outside hours cap increases linearly, reaching 40 hours by March 1, 2021, and is no longer binding for any individual after May 1, 2021. The second is a *subsidy-and-tax* policy, which incentivizes reduced work by providing a subsidy amount of 25 percent of consumption per capita, equivalent to roughly $200 per week, for any working-age individual working less than 20 hours per week.[16] The subsidy begins April 1, 2020, with a gradual reduction after August 1, 2020. The subsidy declines to $100 by February 1, 2021, and to zero by April 1, 2022. The subsidy is funded by a 17 percent consumption tax, beginning April 1, 2020, with a gradual phase-out after August 1, 2020, reaching zero by April 1, 2022. The tax and subsidy do not clear period-by-period, but rather they clear in net present value. Thus, both policies are budget neutral from the government's perspective.

Figure 3 panels (a)–(c) plot the evolution of the disease under the laissez-faire scenario as well as the two mitigation scenarios. Relative to the case with no mitigation, both mitigation policies reduce the reproduction number faster, leading to a lower peak in infection rates and less deaths. However, the subsidy-and-tax policy is much more effective in reducing the number of deaths than the blanket lockdown policy. Panels (d) and (e) show that this is obtained by lower hours throughout the transition and generally lower consumption as well.

Figure 4 panels (a)–(c) and (d)–(e) show the policy functions for consumption and outside

[16] Here, I assume that, for administrative purposes, the criteria to qualify for the subsidy is for total hours worked as it may be difficult for the administrator to ascertain what fraction of hours were outside versus at home. This is in contrast to the lockdown policy, where I assume that the hours cap is for outside labor. The idea is that the lockdown is administered at the firm-level whereas the subsidy is administered at the individual level.

Figure 3: Disease transmission (with and without mitigation)

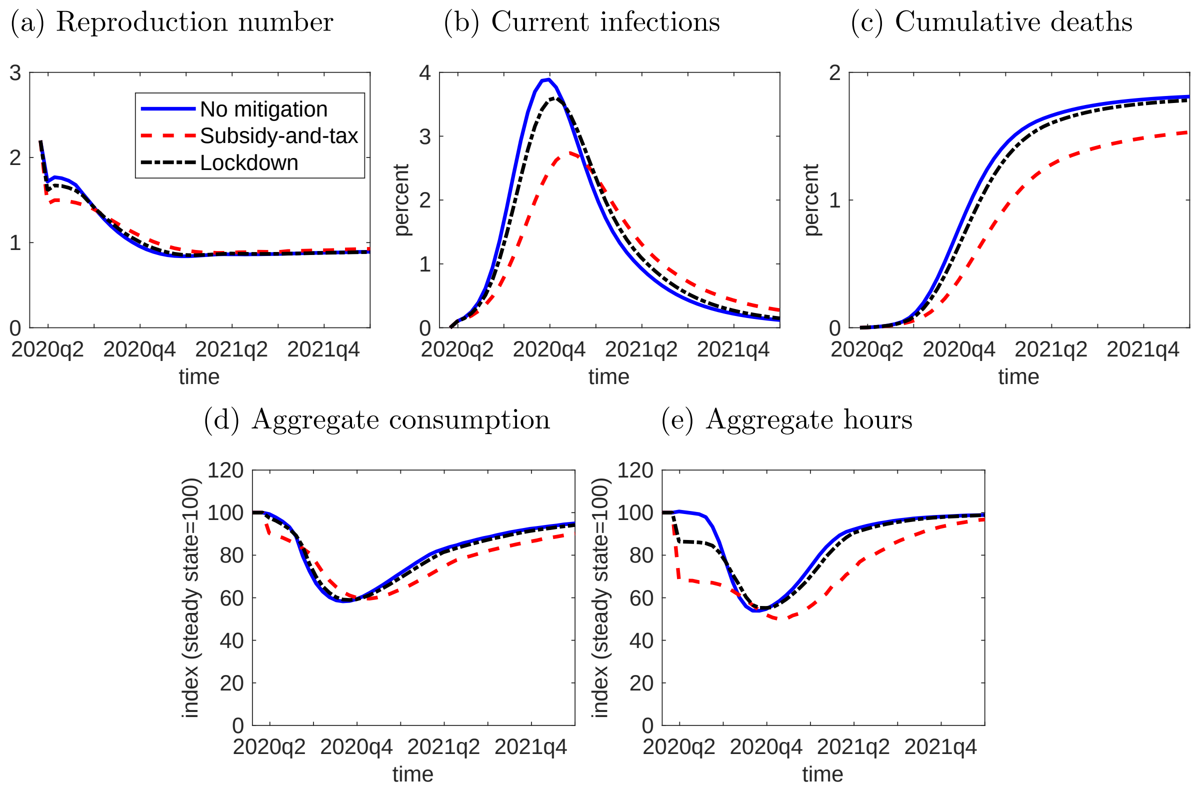
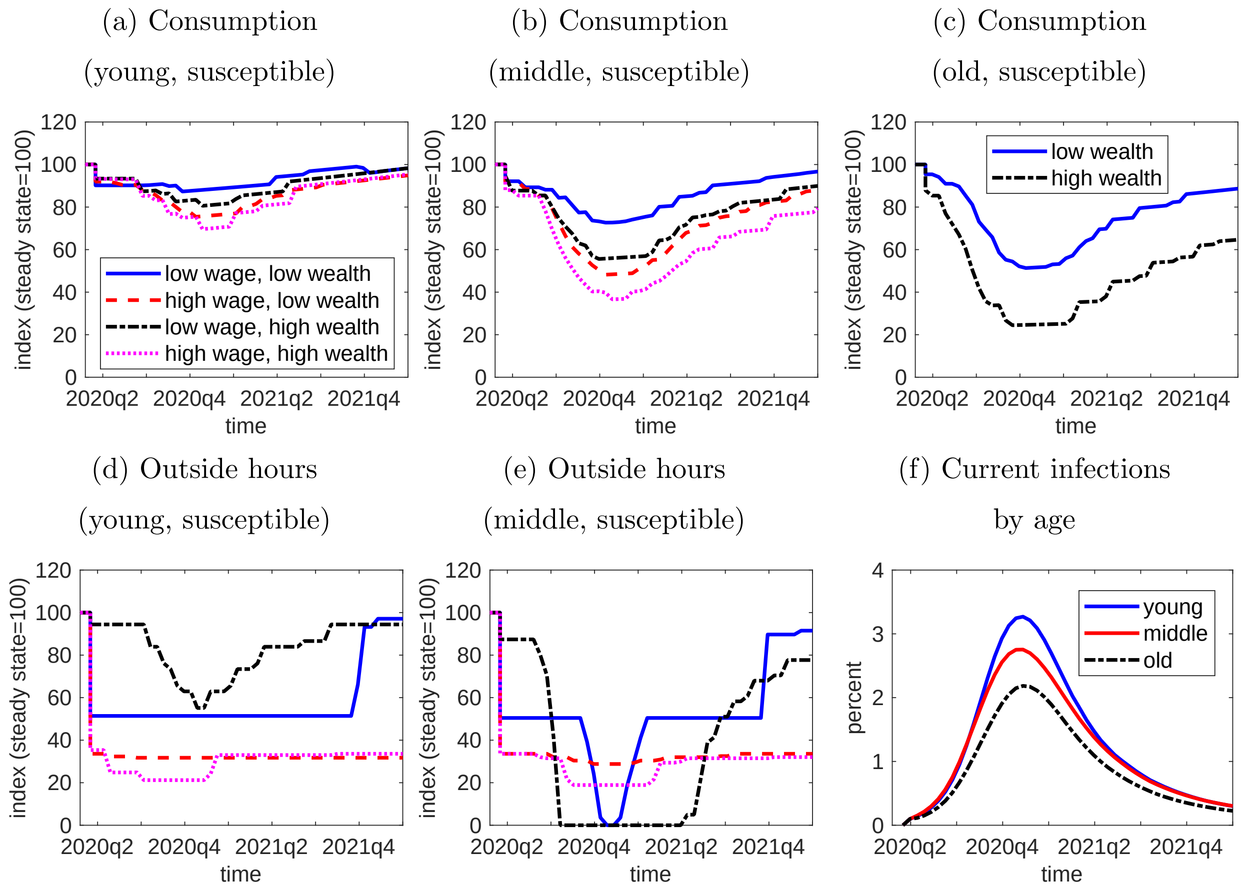


Figure 4: Response to pandemic (subsidy-and-tax)



Notes: Low income and high income correspond to 10th and 90th percentiles of the steady state wage distribution. Low wealth and high wealth correspond to the 25th and 75th percentiles of the steady state wealth distribution.

hours, respectively, for susceptible individuals under the subsidy-and-tax policy. Relative to the case with no mitigation, the reduction in consumption and outside hours is more broad-based, including declines in consumption and hours for young low-wage, low-wealth workers. As a result, the peak infection rate for young agents declines from 5.1 percent to 3.3 percent (panel f).

Qualitatively, the blanket lockdown policy has similar properties as the subsidy-and-tax policy in the sense that they both reduce consumption and labor, infection, and death rates. However, in terms of welfare, measured in consumption equivalents, the blanket lockdown policy is vastly inferior.[17] The subsidy-and-tax policy reduces the average welfare loss from

[17]Specifically, the consumption equivalent is defined as what percentage change of remaining lifetime

Table 3: Welfare consequences of pandemic and mitigation policies

	consumption equivalents (percent)				
	low wealth		high wealth		average
	low wage	high wage	low wage	high wage	
No mitigation					–19.3
young	–2.7	–3.6	–3.8	–4.7	
middle	–11.4	–14.7	–15.2	–20.4	
old	–29.6		–45.3		
Subsidy-and-tax					–17.5
young	–2.3	–3.7†	–3.3	–4.5	
middle	–9.7	–13.2	–13.5	–18.5	
old	–26.7		–41.6*		
Lockdown					–19.2
young	–3.1†	–3.6	–3.8	–4.7	
middle	–11.5	–14.6	–15.1	–20.3	
old	–29.2		–44.9*		

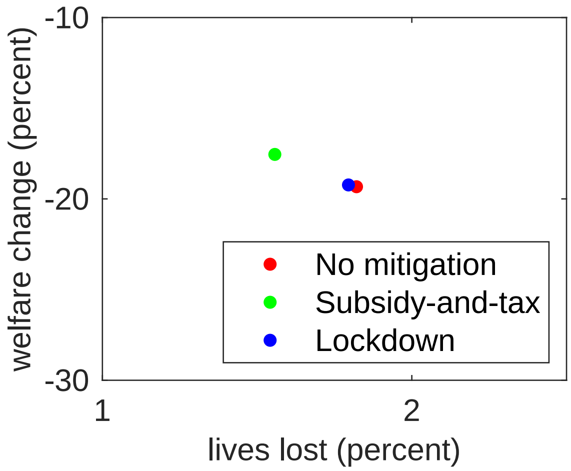
Notes: Low (high) wage corresponds to below (above) the median wage. Low (high) wealth corresponds to below (above) the median wealth. * and † denote the largest and smallest welfare gains from the mitigation policies, respectively.

the pandemic by 1.8 percentage points, whereas the lockdown policy reduces the average welfare loss by only 0.1 percentage points, as can be seen in Table 3. This is because the lockdown policy is mainly favored by older agents who most value the lower risk of death induced by the policy and is opposed by young low-wage, low-wealth workers for whom the lockdown policy is most binding. For middle-aged workers, the benefit of the lower death risk is mostly offset by the cost of the hours cap. Overall, the lockdown policy is favored by 84.4 percent of the initial population. In contrast, the subsidy-and-tax policy is is favored by almost all agents in the economy.

There has been plenty of debate about the tradeoff between output and health. It is also the case that the mitigation policies studied in this paper induce larger output losses than

consumption in the steady state would make the individual indifferent to the pandemic and, if applicable, mitigation policies.

Figure 5: Welfare and lives



the no mitigation case. However, in terms of welfare, for the appropriately designed policy, there seems to be no tradeoff, as can be seen in Figure 5.

5 Conclusion

In this paper, I developed a quantitative life-cycle economic-epidemiology model that was used to measure the heterogeneous welfare consequences of COVID-19, with and without mitigation efforts. The paper also shows that, with well-designed policies, there is no trade-off between economic well-being and saving lives. In particular, a policy that subsidizes individuals to work less hours, funded by a tax on consumption, saves nearly a half-million lives and is favored by almost all individuals, regardless of age, income, or wealth.

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A Estimation of Wage Processes

The sample selection and estimation procedure closely follows the procedure described in Krueger et al. (2016) and Hur (2018). I use annual income data from the PSID core sample (1970–1997), selecting all household heads, ages 23 to 64. For waves before 1993, I use the variable Total Labor Income of Head, which is the sum of wages, tips, labor part of farm and business income, and other items. For waves after 1993, I compute total head labor income as the sum of the head's labor income (excluding farm and business income), head's labor part of business income, and 50 percent of household farm income, divided by two if married. Next, I construct wages by dividing head's total labor income by hours, where hours is the sum of hours worked, hours unemployed, and sick hours. I drop observations with missing education, with wages that are less than half of the minimum wage, with top-coded income, and with fewer than 1,000 hours per year. On this sample, I regress the log wage on age and education dummies, their interaction, and year dummies. I then exclude all individual wage sequences shorter than 5 years, leaving final samples of 4,524 individuals, with an average length of 9 years. On these samples, I compute the autocovariance matrix of the residuals. The stochastic process in equation (19) is estimated using GMM, targeting the covariance matrix, where the weighting matrix is the identity matrix. I thank Chris Tonetti for providing the Matlab routines that perform the estimation.

B Sensitivity analysis

B.1 Efficiency during infection

In the baseline calibration, I assumed that the efficiency of infected individuals was 50 percent that of susceptible and recovered individuals. Table 4 shows the results when the efficiency of infected individuals is assumed to be 70 percent that of susceptible and recovered individuals. The distributional effects of pandemic and mitigation policies are very similar to the baseline. Notably, assuming a smaller efficiency loss during infection *increases* the welfare loss of the pandemic and *increases* the welfare gain from mitigation policies. This is because infected individuals engage in more economic activity, relative to the baseline calibration, leading to higher infections and deaths in the aggregate. Without mitigation, the peak infection rate is 4.1 percent, compared to 3.9 percent in the baseline.

Table 4: Welfare consequences (with $\eta_{jI} = 0.7\eta_{jS}$)

	consumption equivalents (percent)				
	low wealth		high wealth		average
	low wage	high wage	low wage	high wage	
No mitigation					–19.7
young	–2.8	–3.7	–3.9	–4.8	
middle	–11.7	–15.0	–15.5	–20.7	
old	–30.2		–45.9		
Subsidy-and-tax					–17.7
young	–2.4	$-3.8^{\dagger}$	–3.4	–4.6	
middle	–9.9	–13.4	–13.7	–18.8	
old	–26.9		-42.0^{*}		
Lockdown					–19.5
young	$-3.2^{\dagger}$	–3.7	–3.9	–4.8	
middle	–11.8	–14.9	–15.4	–20.6	
old	–29.7		-45.4^{*}		

Notes: Low (high) wage corresponds to below (above) the median wage. Low (high) wealth corresponds to below (above) the median wealth. * and † denote the largest and smallest welfare gains from the mitigation policies, respectively.

Table 5: Welfare consequences (with $\hat{u}_I = -2.74$)

	consumption equivalents (percent)				
	low wealth		high wealth		average
	low wage	high wage	low wage	high wage	
No mitigation					–19.2
young	–2.3	–3.1	–3.3	–4.1	
middle	–11.2	–14.5	–15.0	–20.1	
old	–29.8		–45.5		
Subsidy-and-tax					–17.4
young	–2.0	$-3.3^{\dagger}$	–2.8	–3.9	
middle	–9.5	–12.9	–13.2	–18.2	
old	–26.8		-41.8^{*}		
Lockdown					–19.0
young	$-2.7^{\dagger}$	–3.1	–3.3	–4.0	
middle	–11.4	–14.3	–14.9	–20.0	
old	–29.4		-45.0^{*}		

Notes: Low (high) wage corresponds to below (above) the median wage. Low (high) wealth corresponds to below (above) the median wealth. * and † denote the largest and smallest welfare gains from the mitigation policies, respectively.

B.2 Utility loss during infection

In the baseline calibration, I assumed that infection was associated with a 50 percent reduction in the flow value of the average healthy individual. Here, I investigate how the results change if an infection causes a 30 percent reduction. Table 5 shows that the distributional effects of pandemic and mitigation policies are largely unchanged from the baseline. Assuming a smaller utility loss during infection *decreases* the welfare loss of the pandemic for young individuals, but *increases* the welfare loss for old individuals. This is because the smaller utility loss induces more economic activity among susceptible individuals, relative to the baseline calibration, leading to higher infections. Without mitigation, the peak infection rate is 4.0 percent, compared with 3.9 percent in the baseline. This leads to a larger welfare loss for old individuals, who face a greater fatality risk.