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# The Distributional Effects of COVID-19 and Optimal Mitigation Policies

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# The Distributional Effects of COVID-19 and Optimal Mitigation Policies\*

Sewon Hur<sup>†</sup>

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## Abstract

This paper develops a quantitative heterogeneous agent-life cycle model with a fully integrated epidemiological model in which economic decisions affect the spread of COVID-19 and vice versa. The calibrated model is used to study the distributional consequences and effectiveness of mitigation policies such as a stay-at-home subsidy and a stay-at-home order. First, the stay-at-home subsidy is preferred because it reduces deaths by more and output by less, leading to a larger average welfare gain that benefits all individuals. Second, Pareto-improving mitigation policies can reduce deaths by nearly 60 percent while only slightly reducing output relative to no mitigation. Finally, it is possible to simultaneously improve public health and economic outcomes, suggesting that debates regarding a supposed tradeoff between economic and health objectives may be misguided.

**Keywords:** pandemic, coronavirus, COVID-19, mitigation, tradeoffs.

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

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# 1 Introduction

Amid the deadliest pandemic since the 1918 influenza outbreak and the largest economic contraction since the Great Depression, policymakers and intellectuals have debated a supposed tradeoff between economic and public health outcomes. On one end of the spectrum, former President Trump on May 6, 2020, asked, “Will some people be affected badly?” and responded “Yes, but we have to get our country opened and we have to get it open soon.”<sup>2</sup> On the other end, New York Governor Cuomo on March 23, 2020, tweeted, “If it’s public health versus the economy, the only choice is public health.”<sup>3</sup> In this paper, however, I show that it is possible to simultaneously improve public health and economic outcomes, suggesting that there need not be a tradeoff between economic and health objectives.

To better understand the economic–health tradeoff (or lack thereof), I build a quantitative model that I use as a laboratory to investigate the effects of various mitigation policies. Building on the economic-epidemiological model developed by [Eichenbaum et al. \(2020\)](#) that allows for rich feedback between economic activities and the spread of the virus, I add two important and necessary ingredients: heterogeneity in age and in income and wealth. Age heterogeneity is necessary to take into account that COVID-19 is particularly dangerous for older individuals, while mitigation policies, such as stay-at-home orders more adversely affect working-age individuals. Heterogeneity in income and wealth is necessary in order to consider the heterogeneous effects of mitigation policies, such as stay-at-home orders that may disproportionately harm low-wage workers, who are less likely to work from home, and low-wealth workers, who lack the resources to weather prolonged time away from work.

In the first part of the paper, I develop a quantitative heterogeneous agent–life cycle model with a fully integrated epidemiological model in which economic decisions such as outside consumption and outside labor affect the spread of COVID-19, and conversely, the virus affects economic decisions. The model also features endogenous labor with the option to work from home and hospital capacity constraints. This is the first paper to develop a quantitative model that integrates economic-epidemiological feedback, heterogeneity across ages, and heterogeneity across income and wealth. For example, earlier works by [Kaplan et al. \(2020\)](#) feature heterogeneity in income and wealth but not in ages; [Glover et al. \(2020\)](#)

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<sup>2</sup>See <https://www.cnbc.com/2020/05/05/trump-acknowledges-some-coronavirus-deaths-will-result-from-reopening.html>.

<sup>3</sup>See <https://twitter.com/nygovcuomo/status/1242264009342095361?lang=en>.

include heterogeneity in ages but not in income and wealth; and [Bairoliya and Imrohoroglu \(2020\)](#) model heterogeneity across age, income, and wealth, but do not allow economic activities to interact with the spread of the virus.

In the second part of the paper, I describe the model’s calibration. The model is solved at a biweekly frequency to study the progression of the disease at a high frequency. The model’s economic parameters are calibrated to match both aggregate and distributional features of the US economy before the pandemic and the model’s epidemiological and clinical parameters are set to match features of COVID-19, such as estimates for the basic reproduction number, age-specific fatality rates, and the time series of COVID-19 deaths in the United States. I also show that the model matches key features of the data, both targeted and non-targeted, and generates time series for relevant aggregate variables such as outside consumption and labor that match the data reasonably well.

In the third part of the paper, I use the calibrated model to study the distributional consequences of the pandemic and mitigation policies. Specifically, I contrast a *stay-at-home order* (lockdown) that imposes a cap on outside hours worked—resembling the various stay-at-home and shelter-in-place orders implemented by local and state governments in response to the pandemic—and a *stay-at-home subsidy* that provides a weekly subsidy of \$600 for individuals that do not work. The subsidy policy has similarities with the Federal Pandemic Unemployment Compensation (FPUC), which provided an additional \$600 in unemployment benefits.<sup>4</sup> For expositional purposes, I refer to the implementation of both the subsidy and lockdown policies as US mitigation policies.

Finally, I investigate the properties of optimal mitigation policies. Specifically, I vary the subsidy amount from \$0 to \$1,200 per week, the subsidy duration from 4 to 14 months, and the speed at which the subsidy phases out, with and without lockdowns of varying intensity. Here, I utilize high performance computing to solve for over 40,000 transition paths, including sensitivity analyses.

The main findings are summarized below.

## **1. In the absence of mitigation policies, private mitigation by individuals is**

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<sup>4</sup>While unemployment benefits typically require involuntary unemployment, the subsidy studied in this model is based on voluntary non-employment. However, this difference is mitigated by the Pandemic Unemployment Act (PUA), which expanded eligibility to include any individuals who are out of work due to the pandemic, including self-employed and gig workers.

**substantial and heterogeneous.** Individuals voluntarily reduce their outside consumption and hours worked to reduce their probability of infection. While this is a common feature in economic-epidemiological models, such as [Eichenbaum et al. \(2020\)](#), the rich heterogeneity in my model allows for additional new insights. All else equal, private mitigation is stronger for older individuals, who face higher death rates if infected; for higher-wage workers, who are more likely to work from home; and for wealthier individuals, who can afford to sustain prolonged time away from work. This highlights the key externality: young low wage–low wealth workers engage in too much economic activity, relative to the social optimum, leading to higher infections and deaths in the aggregate. Additionally, the fact that low-wage workers reduce their outside consumption and hours by less than their high-wage counterparts is also qualitatively consistent with the fact documented by [Chetty et al. \(2020\)](#) that higher income locations had larger declines in spending and mobility than lower income locations.

2. **The stay-at-home subsidy is superior to the stay-at-home order along all the relevant dimensions.** Relative to the lockdown policy alone, the subsidy policy alone delivers a higher average welfare gain and reduces deaths by more and output by less. In the case of the lockdown, older individuals experience a welfare gain because of the reduced infection and death probability, but these gains are mostly offset by the welfare losses of low-wage workers, who face a large decline in their income. In contrast, the stay-at-home subsidy benefits all individuals, making it a Pareto improvement. This contrast arises because while both policies result in reduced economic activities of young, low-wage/low-wealth workers, the subsidy policy provides the incentives to do so and the lockdown does not. Neither policy has a direct effect on the labor supply of high-wage individuals, who choose to work mostly from home during the pandemic.
3. **Optimal policies involve larger and longer duration subsidies compared with current US policy.** I refer to the constrained optimum as the policy configuration that delivers the highest average welfare gain, conditional on full support (i.e. Pareto improvements). The constrained optimum involves a larger subsidy (\$1050 per week), longer duration (7 months), and no lockdown, compared with the configuration that most resembles US policy. The constrained optimum reduces deaths by nearly 60 percent, but reduces 2-year output by 2 percentage points, compared with no mitigation.

4. **It is possible to simultaneously improve public health and economic objectives.** The output maximizing policy, which involve a weekly subsidy of \$350, a duration of 13 months, and no lockdown, *reduces* deaths by nearly 20 percent and *increases* two-year output by nearly 2 percentage points, compared with no mitigation. Furthermore, this policy also benefits all individuals. The increase in output is the result of two opposing effects. The first is the *direct effect*: The subsidy provides an incentive to reduce hours (holding fixed the severity of the pandemic), which leads to less output. This effect is negligible for subsidies less than \$600 per week because they only change the behavior of low-wage workers. The second is the *indirect effect*: The mitigation policy attenuates the pandemic, leading to increased economic activity. For mitigation policies with moderate subsidy amounts, the indirect effect dominates, improving both economic and health objectives. This is possible because the labor from low-wage workers is almost exclusively “outside,” implying that almost of all of the reduction in hours contribute to mitigating the severity of the pandemic. For larger subsidy amounts, the direct effect can dominate the indirect effect, leading to a decline in output.

**Related literature.** The epidemiological part of the model borrows from the SIR model of disease transmission, originally developed by [Kermack and McKendrick \(1927\)](#). [Atkeson \(2020\)](#) was one of the first papers to use the SIR model in an economics context. The literature that uses the SIR framework in an economic context is already very large and rapidly expanding. [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. \(2020\)](#), [Baqae 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. [Argente et al. \(2020\)](#) and [Azzimonti et al. \(2020\)](#) enrich the SIR model with city structure and contact networks, respectively. [Bognanni et al. \(2020\)](#) develop a SIR model with multiple regions and estimate it on daily county-level US data and [Fernández-Villaverde and Jones \(2020\)](#) estimate a SIR model for

many cities, states, and countries. [Aum et al. \(2020\)](#) study the effects of lockdowns in a model with heterogeneous age, skill, and occupation choice and [Brotherhood et al. \(2020\)](#) study age-specific testing and quarantine policies.<sup>5</sup>

This paper is most related to [Bairoliya and Imrohoroglu \(2020\)](#), [Glover et al. \(2020\)](#), [Kaplan et al. \(2020\)](#), and [Nakajima \(2020\)](#). [Bairoliya and Imrohoroglu \(2020\)](#) study quarantine policies in a life-cycle model with heterogeneity across age, health, income, and wealth. They primarily focus on the effects of selective quarantines based on age and health. Relative to my paper, [Bairoliya and Imrohoroglu \(2020\)](#) study the disease progression at a lower frequency (yearly) and do not incorporate the economic-epidemiological feedback channel. To my knowledge, [Nakajima \(2020\)](#) is the only other paper that uses a quantitative economic-epidemiological feedback that features heterogeneity across age, income, and wealth. [Nakajima \(2020\)](#) focuses on evaluating US policies, while my paper additionally focuses on characterizing optimal mitigation policies. [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 their work, my paper features heterogeneity across not only age, but also income and wealth, and complements [Glover et al. \(2020\)](#) by analyzing mitigation policies specifically targeting the behavior of these groups. [Kaplan et al. \(2020\)](#) do not model heterogeneity by age, but include heterogeneity across income, wealth, sector, and occupation. Like my paper, they focus on policies that improve not only average outcomes but also account for the distributional consequences of mitigation policies. Relative to [Kaplan et al. \(2020\)](#), my paper addresses the externalities that are generated by the differential effects of COVID-19 by age.<sup>6</sup> It also explicitly accounts for the value of life so that individual welfare changes directly reflect economic as well as expected health outcomes and proposes a specific set of policies that can improve aggregate outcomes in a Pareto improving sense.

This paper is structured as follows. The next section presents the model. Section 3 describes the calibration of the model’s economic and epidemiological parameters and discusses the model’s fit. In Section 4, the calibrated model is used to investigate the role of private mitigation and the welfare consequences of the pandemic and mitigation policies. Section 5

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<sup>5</sup>Given the rapidly expanding literature, this is likely not an exhaustive list. I refer the reader to [Brodeur et al. \(2020\)](#) and [Hur and Jenuwine \(2020\)](#) for reviews of this literature.

<sup>6</sup>I show that accounting for differences in fatality risk across ages is quantitatively important for the main policy implications (Appendix D).

discusses the properties of optimal policies. Finally, section 6 concludes.

## 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 economic-epidemiological model that resembles those used in [Eichenbaum et al. \(2020\)](#). The economy is inhabited by overlapping generations of stochastically aging individuals. Time is discrete and indexed by  $t = 0, \dots, \infty$ . Workers face idiosyncratic efficiency shocks and borrowing constraints within an incomplete market setting. I now describe the model in more detail.

### 2.1 Individuals

**Epidemiological block.** 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.<sup>7</sup> The transition between health states builds on the widely used SIR model, originally developed by [Kermack and McKendrick \(1927\)](#).<sup>8</sup> Susceptible individuals get infected with probability  $\pi_{It}$ , which depends on individual outside consumption and outside labor  $(c_o, \ell_o)$  and the aggregate measure of infected individuals  $(\mu_{It})$  and their outside consumption and outside labor  $(C_{It}^o, L_{It}^o)$ .<sup>9</sup> Formally,

$$\pi_{It}(c_o, \ell_o; Z_t) = \beta_c c_o C_{It}^o + \beta_\ell \ell_o L_{It}^o + (\beta_e + \epsilon_t) \mu_{It}, \quad (1)$$

where  $\epsilon_t$  captures time-varying transmissibility (e.g. seasonal factors) and  $Z_t \equiv \{\mu_{It}, C_{It}^o, L_{It}^o, \epsilon_t\}$ . This framework allows the virus to be contracted from consumption-related activities, labor-

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<sup>7</sup>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.

<sup>8</sup>A popular variant of the SIR model is the SEIR model, which adds a category of individuals that have been *exposed* to the virus, and may or may not be infectious without symptoms. This distinction is more relevant for studying disease dynamics at an even higher frequency, and particularly for those that study testing and quarantine such as [Berger et al. \(2020\)](#).

<sup>9</sup>This distinction between inside and outside activities is based on whether or not there is infection risk and not based on location.



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. \(2020\)](#). Relative to these papers, however, the richer heterogeneity in this model allows for infection probabilities to be very different across the distribution.

Infected individuals exit the infection with probability  $\pi_{Xt}$ , and upon exit, they recover with probability  $1 - \delta_{jt}(\mu_{It})$  and die with probability  $\delta_{jt}(\mu_{It})$ , where  $j$  is the individual's age. The fatality rate depends on the individual's age and on the aggregate measure of infected individuals, reflecting hospital capacity constraints. Finally, susceptible individuals may transition directly to the recovered state with probability  $\pi_{jRt}$ , for example, by a vaccine. Then the transition matrix between health states is given by

$$\Pi_{jhh't}(c_0, \ell_0; Z_t) = \tag{2}$$

	$S$	$I$	$R$	$D$
$S$	$1 - \pi_{It}(c_0, \ell_0; Z_t) - \pi_{jRt}$	$\pi_{It}(c_0, \ell_0; Z_t)$	$\pi_{jRt}$	$0$
$I$	$0$	$1 - \pi_{Xt}$	$\pi_{Xt}(1 - \delta_{jt}(Z_t))$	$\pi_{Xt}\delta_{jt}(Z_t)$
$R$	$0$	$0$	$1$	$0$
$D$	$0$	$0$	$0$	$1$

**Economic block.** Individuals of age  $j \in J \equiv \{1, 2, \dots, \bar{J}\}$  face conditional aging probabilities given by  $\{\psi_j\}$ , with mandatory retirement at age  $j = J_R$ .<sup>10</sup> Workers ( $j < J_R$ ) face uninsurable wage risk: Each period, workers receive idiosyncratic efficiency shocks  $\varepsilon \in E$ , which follow a Markov process, with transition matrix  $\Gamma$ . Their labor income is given by  $w_t \eta_{jh} \varepsilon \ell$ , where  $w_t$  is the efficiency wage,  $\eta_{jh}$  is the health- and age-profile of efficiency units, and  $\ell$  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 efficiency. Retirees ( $j \geq J_R$ ) are assumed to receive a fixed income of  $s$  each period.<sup>11</sup> Retirement income is funded by taxes on labor income,  $\tau_{\ell t}$ . Individuals can accumulate non-contingent assets  $k$ , which deliver a net return of  $r_t$ .

<sup>10</sup>Given that the model will be used to analyze disease progression at a high (bi-weekly) frequency, the assumption of stochastic aging greatly reduces the state space and computational burden.

<sup>11</sup>This can readily be extended to depend on lifetime earnings as in [Hur \(2018\)](#).

**Mitigation policies.** Individuals take as given a sequence of taxes, subsidies, and other restrictions on quantities that are designed to mitigate the severity of the pandemic.

1. Stay-at-home subsidies: Individuals receive a subsidy of  $T_t$  each period in which they supply zero hours of total labor.
2. Stay-at-home order (lockdown): Lockdowns restrict the quantity of outside labor to at most  $\bar{\ell}_{ot}$ .
3. Taxes: In the baseline model, I consider taxes on consumption  $\tau_{ct}$ . These taxes serve two purposes: a) They can be used to fund the stay-at-home subsidies and b) they reduce economic activities that contribute to the spread of the virus. In an extension of the model, I also consider smarter Pigouvian taxes that more directly target outside consumption.

**Individuals' recursive problem.** Given the sequence of prices  $\{r_t\}$ , 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 inside and outside consumption  $\{c_i, c_o\}$  and savings  $k'$  to solve:

$$\begin{aligned}
v_{jt}^R(k, h) = & \max_{c_i, c_o, k' \geq 0} u(c_i, c_o) + \bar{u} + \hat{u}^h & (3) \\
& + \beta \psi_j \sum_{h' \in \{S, I, R\}} \Pi_{hh't}(c_o, 0) v_{j+1, t+1}^R(k', h') \\
& + \beta(1 - \psi_j) \sum_{h' \in \{S, I, R\}} \Pi_{hh't}(c_o, 0) v_{j, t+1}^R(k', h') \\
\text{s.t. } & (1 + \tau_{ct})c + k' \leq s + k(1 + r_t)
\end{aligned}$$

where  $\beta$  is the time discount factor,  $u(c_i, c_o)$  is the utility derived from inside and outside consumption,  $c = c_i + c_o$  is total consumption, and  $\bar{u}$  and  $\hat{u}_h$  govern the flow value of being alive and being in health state  $h$ , respectively. Solving this yields retiree policy functions  $\{c_{ijt}^R(k, h), c_{oijt}^R(k, h), k_{ijt}^{R'}(k, h)\}_{j \geq J_R}$  for inside and outside consumption and savings, respectively. I normalize the value of death to zero and set  $v_{j+1, t}^R = 0$ . Thus, agents in the last stage of life ( $j = \bar{J}$ ) may die due to stochastic aging (with probability  $\psi_j$ ) and, if infected, because of the virus (with probability  $\Pi_{ID}$ ).

Given the sequence of prices  $\{w_t, r_t\}$ , fiscal policies  $\{\tau_{ct}, \tau_{lt}, T_t, \bar{\ell}_{ot}\}$ , and aggregate states  $\{Z_t\}$ , a worker with age  $j < J_R$ , wealth  $k$ , efficiency  $\varepsilon$ , and health  $h$  in period  $t$  chooses

inside and outside consumption  $\{c_i, c_o\}$ , inside and outside labor  $\{\ell_i, \ell_o\}$ , and savings  $k'$  to solve:

$$\begin{aligned}
v_{jt}(k, \varepsilon, h) = & \max_{c_i, c_o, \ell_i, \ell_o, k' \geq 0} u(c_i, c_o) - g(\ell) + \bar{u} + \hat{u}^h & (4) \\
& + \beta \psi_j \sum_{\varepsilon' \in E} \sum_{h' \in H} \Gamma_{\varepsilon \varepsilon'} \Pi_{hh't}(c_o, \ell_o) v_{j+1, t+1}(k', \varepsilon', h') \\
& + \beta (1 - \psi_j) \sum_{\varepsilon' \in E} \sum_{h' \in H} \Gamma_{\varepsilon \varepsilon'} \Pi_{hh't}(c_o, \ell_o) v_{j, t+1}(k', \varepsilon', h') \\
\text{s.t. } & (1 + \tau_{ct})c + k' \leq w_t \eta_j^h (1 - \tau_{\ell t}) \varepsilon \ell + k(1 + r_t) + T_t(\ell) \\
& \ell_i \leq \bar{\theta}_j(\varepsilon) \ell, \quad \ell_o \leq \bar{\ell}_{ot}
\end{aligned}$$

where  $\ell = \ell_i + \ell_o$  is total labor,  $g(\ell)$  is the disutility of labor, and  $v_{jt}(k, \varepsilon, h) = v_{jt}^R(k, h)$  for  $j \geq J_R$  and  $\varepsilon \in E$ . Solving this yields worker policy functions  $\{c_{ijt}(k, \varepsilon, h), c_{ojt}(k, \varepsilon, h), \ell_{ijt}(k, \varepsilon, h), \ell_{ojt}(k, \varepsilon, h), k'_j(k, \varepsilon, h)\}_{j < J_R}$  for inside and outside consumption, inside and outside labor, and savings, respectively. Additionally, let  $c_{ij}(k, \varepsilon, h) = c_{ij}^R(k, h)$ ,  $c_{oj}(k, \varepsilon, h) = c_{oj}^R(k, h)$ , and  $k'_j(k, \varepsilon, h) = k_j^{R'}(k, h)$  for  $j \geq J_R$  and  $\varepsilon \in E$ .

## 2.2 Production

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

$$Y_{ft} = K_{ft}^\alpha L_{ft}^{1-\alpha}. \quad (5)$$

Taking prices as given, the firm solves

$$\max_{L_{ft}, K_{ft}} Y_{ft} - w_t L_{ft} - (r_t + \delta) K_{ft}, \quad (6)$$

where  $\delta$  is the depreciation rate of capital. Optimality conditions are given by

$$w_t = (1 - \alpha) K_{ft}^\alpha L_{ft}^{-\alpha}, \quad (7)$$

$$r_t = \alpha K_{ft}^{\alpha-1} L_{ft}^{1-\alpha} - \delta. \quad (8)$$

## 2.3 Equilibrium

We are ultimately interested in studying disease dynamics and mitigation policies along a transition path. However, because most of the model parameters are calibrated to an

initial pre-pandemic steady state, it is useful to first define a stationary equilibrium in which  $\mu_I = 0$ . In this case, aggregate outside consumption and outside labor of infected individuals is trivially zero. Furthermore, if we set the time-varying transmissibility parameter  $\epsilon_t = 0$ , then  $Z = (0, 0, 0, 0)$  and  $\Pi$  is the identity matrix (with no vaccine). Furthermore, I assume that  $\tau_c = 0$  and  $T = 0$  and set  $\bar{\ell}_o$  sufficiently large such that it is not binding for any individual. Finally, retirement income is financed by labor income taxes and accidental bequests from death are distributed to newborns each period. Define the state space over wealth, efficiency, and health as  $X = K \times E \times H$  and let a  $\sigma$ -algebra over  $X$  be defined by the Borel sets,  $\mathcal{B}$ , on  $X$ .

**Definition.** A *stationary recursive competitive equilibrium*, given fiscal policies  $\{\tau_\ell, s\}$ , is a set of value functions  $\{v_j\}_{j \in J}$ , policy functions  $\{c_{ij}, c_{oj}, \ell_{ij}, \ell_{oj}, k'_j\}_{j \in J}$ , prices  $\{w, r\}$ , producer plans  $\{Y_f, L_f, K_f\}$ , the distribution of newborns  $\omega$ , and invariant measures  $\{\mu_j\}_{j \in J}$  such that:

1. Given prices and fiscal policies, retirees and workers solve (3) and (4), respectively.
2. Given prices, firms solve (6).
3. Markets clear:

$$\begin{aligned} \text{(a)} \quad Y_f &= \int_X \sum_{j \in J} (c_{ij}(k, \varepsilon, h) + c_{oj}(k, \varepsilon, h) + \delta k) d\mu_j(k, \varepsilon, h), \\ \text{(b)} \quad L_f &= \int_X \sum_{j < J_R} \eta_{jh} \varepsilon (\ell_{ij}(k, \varepsilon, h) + \ell_{oj}(k, \varepsilon, h)) d\mu_j(k, \varepsilon, h), \\ \text{(c)} \quad K_f &= \int_X \sum_{j \in J} k d\mu_j(k, \varepsilon, h). \end{aligned}$$

4. The government budget constraint holds:

$$\tau_\ell w \int_X \sum_{j < J_R} \eta_{jh} \varepsilon (\ell_{ij}(k, \varepsilon, h) + \ell_{oj}(k, \varepsilon, h)) d\mu_j(k, \varepsilon, h) = s \int_X \sum_{j \geq J_R} d\mu_j(k, \varepsilon, h). \quad (9)$$

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

$$\begin{aligned} \mu_j(\mathcal{K}, \mathcal{E}, \mathcal{H}) &= \int_X \psi_{j-1} \mathbb{1}_{\{k'_{j-1}(k, \varepsilon, h) \in \mathcal{K}\}} \sum_{\varepsilon' \in \mathcal{E}} \sum_{h' \in \mathcal{H}} \Gamma_{\varepsilon \varepsilon'} \Pi_{hh'} d\mu_{j-1}(k, \varepsilon, h) \\ &\quad + \int_X (1 - \psi_j) \mathbb{1}_{\{k'_j(k, \varepsilon, h) \in \mathcal{K}\}} \sum_{\varepsilon' \in \mathcal{E}} \sum_{h' \in \mathcal{H}} \Gamma_{\varepsilon \varepsilon'} \Pi_{hh'} d\mu_j(k, \varepsilon, h) \end{aligned} \quad (10)$$

and

$$\mu_1(\mathcal{K}, \mathcal{E}, \mathcal{H}) = \int_X (1 - \psi_1) \mathbb{1}_{\{k'_1(k, \varepsilon, h) \in \mathcal{K}\}} \sum_{\varepsilon' \in \mathcal{E}} \sum_{h' \in \mathcal{H}} \Gamma_{\varepsilon \varepsilon'} \Pi_{hh'} d\mu_1(k, \varepsilon, h) + \omega(\mathcal{K}, \mathcal{E}, \mathcal{H}). \quad (11)$$

6. The newborn distribution satisfies:

$$\int_X k d\omega(k, \varepsilon, h) = \int_X \psi_{\bar{j}} k'_{\bar{j}}(k, \varepsilon, h) d\mu_{\bar{j}}(k, \varepsilon, h). \quad (12)$$

### 3 Calibration

In this section, I begin by calibrating some of the model’s parameters to the pre-pandemic steady state and discuss how other parameters that require solving for the transition path are set. I then discuss the model’s fit by examining both targeted and non-targeted moments in the steady state and during the course of the pandemic. The parameters are summarized in Tables 1 and 2. See Appendix C for details regarding the computation and calibration strategy.

#### 3.1 Calibration of the pre-pandemic steady state

**Environment and demographics.** 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+ (retired). The worker aging probability  $\psi_1 = \psi_2$  is set so that workers spend, on average, 20 years in each age cohort. The aging (death) probability of retired individuals  $\psi_3$  is set so that the retired account for 20 percent of the 25+ population. The wealth of deceased individuals is given 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.<sup>12</sup>

**Preferences.** The utility function is assumed to take the form:

$$u(c_i, c_o) = \frac{(c_i^\gamma c_o^{1-\gamma})^{1-\sigma}}{1-\sigma}, \quad (13)$$

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<sup>12</sup>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. One way to address this issue would be to increase the number of retired cohorts so that retired individuals draw down more wealth before dying.

which exhibits constant relative risk aversion over a Cobb-Douglas aggregation of inside and outside consumption. There are two points worth mentioning here. First, the distinction between inside and outside consumption in the model is purely based on whether there is risk of infection. There is not such a clear distinction in the data. Thus, as a starting point, I assume that household expenditures on goods and housing and utility services represent expenditures that are relatively safe, which constitute 51 percent of total household expenditures on goods and services (2019, *Bureau of Economic Analysis*). Accordingly,  $\gamma$  is set to 51 percent to match this share. I then show in Appendix D that the main findings of the paper are robust to alternative values of this parameter. Second, I am assuming a unitary elasticity of substitution between inside and outside consumption.<sup>13</sup> I show later in this section that the model generates reasonable time series of total and outside consumption in response to the pandemic.

The disutility from labor is given by:

$$g(\ell) = \varphi \frac{\ell^{1+\nu}}{1+\nu} + \mathbb{1}_{\{\ell=0\}}\tilde{u}, \quad (14)$$

where  $\tilde{u}$  represents the disutility from not working (e.g. administrative costs, stigma, or any other costs not modeled explicitly here). I set  $\tilde{u}$  so that not working is associated with a 2.5 percent reduction in the flow value of life. This generates a 19 percent reduction in employment during the transition path described in Section 3.2, matching the decline reported by Bick et al. (2020) based on survey data.<sup>14</sup> The parameter that governs the disutility from labor,  $\varphi$ , is set so that the model generates an average of 34.4 hours worked per week (2019, *Bureau of Economic Analysis*).

The time discount factor  $\beta$  is chosen so that the model replicates the US net-worth-to-GDP ratio (2010–2019, *Board of Governors*). Finally, I set risk aversion,  $\sigma$ , to be 2, and the Frisch elasticity,  $1/\nu$ , to be 0.5, which are standard values in the literature.

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<sup>13</sup>A unitary elasticity is somewhat consistent with estimates for the elasticity of substitution between market and home goods, which range between 0.8 (Duernecker and Herrendorf 2018) and 2.2 (Dotsey et al. 2014). However, these estimates are only partially informative since many market goods can be purchased online and consumed safely at home (e.g. consumer electronics).

<sup>14</sup>Sensitivity analysis (Appendix D) demonstrates that the main results are robust to a higher utility cost, which generates a lower reduction in employment that is closer to the 15 percent reduction reported by the Bureau of Labor Statistics.

**Technology and income.** The capital elasticity in the production function,  $\alpha$ , is set to match the aggregate capital income share of 0.36. The labor income tax  $\tau_\ell$  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,  $\delta$ , is set at an annualized rate of 5 percent per year. The stay-at-home subsidy and consumption tax are set to zero in the pre-pandemic steady state.

The age-profile of efficiency units,  $\eta_{jS}$ , 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 those of susceptible individuals,  $\eta_{jR} = \eta_{jS}$ .<sup>15</sup> The fraction of labor that can be 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 \(2020\)](#).<sup>16</sup> Thus,  $\bar{\theta}_j(\varepsilon)$  is set to 0.03 for individuals in the bottom 20 percent of the wage distribution, 0.21 for the second quintile, 0.32 for the third quintile, 0.47 for the fourth quintile, and 0.66 for those in the top 20 percent of the wage distribution, where the wage is defined as  $w\eta_{jS}\varepsilon$ .

The labor efficiency shocks  $\varepsilon$  are assumed to follow an order-one autoregressive process as follows:

$$\log \varepsilon_t = \rho_\varepsilon \log \varepsilon_{t-1} + v_t, \quad v_t \sim N(0, \sigma_v^2). \quad (15)$$

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  $\sigma_v = 0.19$ .<sup>17</sup> 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 \(2010\)](#).

**Clinical and epidemiological parameters.** The exit rate,  $\pi_X$ , 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, I use data from South Korea’s Ministry of

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<sup>15</sup>It is too early to conclude about the potentially long-lasting consequences of COVID-19. That said, these assumptions can easily be modified if evidence dictates.

<sup>16</sup>See [Appendix A.1](#) for details.

<sup>17</sup>The wages are constructed similarly to [Floden and Lindé \(2001\)](#) and the sample selection and estimation procedures closely follow [Krueger et al. \(2016\)](#). See [Appendix A.2](#) for details.

Table 1: Calibration of economic parameters

Parameters	Values	Targets / Source
Discount factor, annualized, $\beta$	0.97	Wealth-to-GDP: 4.8
Risk aversion, $\sigma$	2	Standard value
Inside consumption share, $\gamma$	0.51	Expenditure share
Disutility from labor, $\varphi$	22.64	Average weekly hours: 34.4
Frisch elasticity, $1/\nu$	0.50	Standard value
Death probability, annualized, $\psi_3$	0.10	65+ share of population 25+: 0.2
Aging probability, annualized, $\psi_1 = \psi_2$	0.05	Expected duration: 20 years
Efficiency units, $\eta_{1S} = \eta_{1R}$	1.00	Wage ratio of age 45-64 workers
$\eta_{2S} = \eta_{2R}$	1.35	to age 25-44 workers
Factor elasticity, $\alpha$	0.36	Capital share
Capital depreciation, annualized, $\delta$	0.05	Standard value
Retirement income, $s$	1.00	30% of average earnings per worker
Labor income tax, $\tau_\ell$	0.07	Government budget constraint
Persistence, annual, $\rho_\varepsilon$	0.94	Author estimates
Standard deviation, annual, $\sigma_\nu$	0.19	Author estimates



Health and Welfare (accessed August 4, 2020) to compute a fatality rate of 8.47 percent for ages 65–84, 0.85 percent for ages 45–64, and 0.08 percent for ages 25–44. I use South Korean data because testing has been abundant since the outbreak began<sup>18</sup>, the in-sample 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.<sup>19</sup>

Next, I discuss the hospital capacity constraints and how they affect death rates. Following [Pigullem and Shi \(2020\)](#), I use the functional form

$$\delta_j(\mu_I) = \delta_j^u \min \left\{ 1, \frac{\kappa}{\mu_I} \right\} + \delta_j^c \max \left\{ 0, 1 - \frac{\kappa}{\mu_I} \right\} \quad (16)$$

where  $\delta_j^u$  and  $\delta_j^c$  denote the unconstrained and untreated death rates and  $\kappa$  denotes the measure 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.<sup>20</sup> Since not all infected cases require hospitalization, I use a generous capacity constraint,  $\kappa$ , of 1 percent.<sup>21</sup> The unconstrained death rates,  $\delta_j^u$ , are set to match those documented for South Korea, and the untreated death rates are set as  $\delta_j^c = 2\delta_j^u$ , following [Pigullem and Shi \(2020\)](#). I later show that infections peak at 1.2 percent, implying a 13.6 percent increase in fatality rates at the peak (e.g. the middle-age fatality rate increases from 0.85 percent to 0.97 percent).

There is some 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. Most estimates range between 2.2 and 3.1 (see for example, [Wang et al. 2020](#) and [Fauci et al. 2020](#)), so I use a conservative estimate of 2.2.<sup>22</sup> By the law of large numbers, equation (1) implies that new infections in a given period are given by

$$T_t = \beta_c C_{St}^o C_{It}^o + \beta_\ell L_{St}^o L_{It}^o + (\beta_e + \epsilon_t) \mu_{St} \mu_{It}. \quad (17)$$

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<sup>18</sup>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.

<sup>19</sup>Prior to the second wave in December of 2020, active infection cases in South Korea had peaked at 7,362 on March 11, 2020, according to <https://www.worldometers.info/coronavirus/country/south-korea/>

<sup>20</sup>See <https://www.aha.org/statistics/fast-facts-us-hospitals>.

<sup>21</sup>In Appendix D, I show that the main findings are robust to assuming that there is no capacity constraint.

<sup>22</sup>The main results are robust to a higher value for the basic reproduction number (Appendix D).

where  $C_{ht}^o$  and  $L_{ht}^o$  denote aggregate outside consumption and labor, respectively, of individuals with health  $h$  in period  $t$ . 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 efficiency 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  $C_S^o/\mu_S = C_I^o/\mu_I$ , then by taking  $\mu_S \rightarrow 1$  and setting  $\epsilon_t = 0$ , the basic reproduction number is given by<sup>23</sup>

$$R_0 = \frac{\beta_c(C_S^o)^2 + \beta_\ell(L_S^o)^2 + \beta_e}{\pi_X}. \quad (18)$$

Thus, given values for the basic reproduction number,  $R_0$ , the exit rate,  $\pi_X$ , the steady state values for aggregate outside consumption and labor,  $C_S^o$  and  $L_S^o$ , we need to assign values to the fractions of new infections occurring through consumption activities, work activities, and other settings to pin down the values for  $\beta_c$ ,  $\beta_\ell$ , and  $\beta_e$ . 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.

I set the flow value of life  $\bar{u}$  so that the model generates an average value of statistical life (VSL) of \$7.4 million in 2006—the value recommended by [U.S. Environmental Protection Agency \(2020\)](#)—corresponding to 6,226 times biweekly consumption per capita in 2006.<sup>24</sup> See Appendix C.1.1 for the derivation of VSL in the model. 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  $\hat{u}_I$  so that the average infected individual suffers a 50 percent decline. The results

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<sup>23</sup>These assumptions allow the calibration of these epidemiological parameters using steady state values. These are also plausible assumptions, given that both susceptible agents and the very first infected individuals may not change their behavior given the lack of information regarding the pandemic in the early stages.

<sup>24</sup>As a robustness check, I use a higher VSL used by [Greenstone and Nigam \(2020\)](#) and [Glover et al. \(2020\)](#) of \$11.5 million, or 6,772 times biweekly consumption per capita (see Appendix D). The main results of the paper are robust to this higher value.

Table 2: Clinical and epidemiological parameters

Parameters	Values	Targets / Source
Infection exit rate, $\pi_X$	0.78	Expected infection duration: 18 days
Unconstrained death rate, $\delta_1^u \times 100$	0.08	Fatality rates in South Korea
$\delta_2^u \times 100$	0.85	
$\delta_3^u \times 100$	8.47	
Untreated death rate, $\delta_j^c$	$2\delta_j^u$	<a href="#">Piguillem and Shi (2020)</a>
Hospital capacity, $\kappa$	0.01	See discussion above
Transmission parameters, consumption-related, $\beta_c$	0.23	Basic reproduction number, $R_0 = 2.2$ , and initial transmission equally
labor-related, $\beta_\ell$	9.46	likely through three channels
other, $\beta_e$	0.57	
Flow value of life, $\bar{u}$	25.91	Value of statistical life: \$7.4 million (2006)
Flow value of infection, $\hat{u}_I$	-12.48	50 percent reduction in flow utility value of average agent
Disutility from not working, $\tilde{u}$	0.62	19 percent reduction in employment during pandemic
Efficiency units, $\eta_{jI}$	$0.5\eta_{jS}$	See discussion above

are robust to a 30 percent reduction in the flow value of life, as shown in Appendix D.

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 efficiency, I assume that infected individuals suffer a 50 percent loss in efficiency. Sensitivity analysis in Appendix D reveals that the main results are robust to assuming, alternatively, a 30 percent loss in efficiency.

### 3.2 Calibration of the transition path

In this subsection, I start by discussing the initial conditions, the timing of a vaccine and cure, and transition path assumptions. I then discuss how the mitigation policies are set to

align with mitigation policies that have been implemented in the United States. Finally, I discuss how the time-varying transmissibility parameter  $\epsilon_t$  is set.

**Initial conditions and timeline.** The economy starts in the pre-pandemic steady state in period  $t = 0$ . Then, in period  $t = 1$  (March 27, 2020), the virus is introduced into the model so that 0.5 percent of the population is infected.<sup>25</sup> I assume that a vaccine becomes available in  $t = 20$  (December 18, 2020), after which individuals over the age of 45 transit to the recovered state with a probability of 10 percent every two weeks (5 percent for young individuals). This implies an expected wait time of 20 and 40 weeks for older and younger individuals, respectively. I assume that a cure is available in  $t = \hat{t} \equiv 53$  (March 25, 2022), when all remaining susceptible and infected individuals transit to the recovered state with probability 1.

While the steady state analysis was done in general equilibrium, the transition path analysis is done in partial equilibrium. In other words, factor prices ( $w, r$ ), retirement income ( $s$ ), and the labor income tax ( $\tau_\ell$ ) are fixed at their pre-pandemic steady state levels.<sup>26</sup> Furthermore, the measure of newborns and their wealth distribution is also assumed to be constant throughout the transition. I provide a formal definition of the equilibrium with transition in Appendix B.

**Mitigation policies.** While the mitigation policies are the focus of the main counterfactual exercises in the next sections, here I need to specify them to closely mimic mitigation policies implemented in the United States. I focus on the set of fiscal policies implemented at the federal, state, and local level that are relevant for virus mitigation. For example, I do not consider tax credit payments that may have been important for distributional consequences but otherwise irrelevant for mitigating the virus.

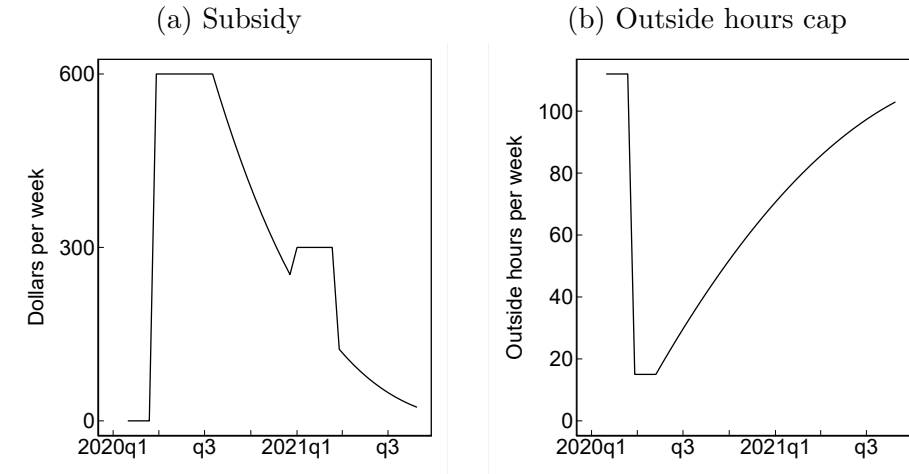
The stay-at-home subsidy most closely resembles the \$600 supplement to unemployment benefits (Federal Pandemic Unemployment Compensation, FPUC) that was in effect March

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<sup>25</sup>In the US, there were 17,982 COVID-19 related deaths during the 14-day period from March 27, 2020, to April 9, 2020, according to <https://www.worldometers.info/coronavirus/country/us/>. An initial infected rate of 0.5 percent generates deaths in the model ( $t = 1$ ) that are consistent with the data.

<sup>26</sup>While these assumptions have been made for computational tractability, there are also other considerations. For instance, social security benefits and contribution rates do not typically respond to recessions at a high frequency (and did not during the pandemic).

Figure 1: Mitigation policies



27, 2020, to July 27, 2020 and the \$300 supplement in effect between December 26, 2020, and March 14, 2021. While the stay-at-home subsidy has similarities to the FPUC unemployment supplement, one important difference is that unemployment benefits typically require involuntary unemployment, while the model subsidy is based on voluntary nonemployment. However, this difference is mitigated by the Pandemic Unemployment Act (PUA), which expanded the eligibility guidelines to include any individual out of work because of the pandemic, including self-employed and gig workers, whose labor supply decisions are likely more voluntary.<sup>27</sup>

Based on the timeline of the FPUC, the model subsidy of \$600 per week begins at  $t = 1$  (March 27, 2020), with a gradual reduction after  $t = 9$  (July 30, 2020). There is a second subsidy of \$300, which begins  $t = 21$  (January 1, 2021) and ends  $t = 26$  (March 25, 2021). Figure 1 (panel a) plots the model subsidy amount over time. For the purpose of calibration, I set the consumption tax  $\tau_c = 0$ , since there was no associated tax increase in the data. In the counterfactual exercises in Section 5, I use the consumption tax as a means to fund the stay-at-home subsidy.

The model stay-at-home order (lockdown) most closely resembles the local- and state-level stay-at-home orders, which began in most states between March 23 and April 1, but the duration and intensity varied substantially across locations and many areas began re-opening in early May. One caveat is that the stay-at-home orders affected workers differently

<sup>27</sup>To a lesser extent, the subsidy is also related to the Paycheck Protection Program (PPP), which allowed firms adversely impacted by the pandemic and mitigation policies to pay furloughed workers.

based on whether or not their place of work was essential (grocery stores) or social-intensive (restaurants and bars). By abstracting from sectors and occupations, the model cannot speak directly to these differences. However, to the extent that social-intensive occupations tend to have lower wages as documented by [Kaplan et al. \(2020\)](#), the model indirectly captures these differences since the lockdown disproportionately affects lower-wage individuals.

The model lockdown is implemented by restricting outside labor supply to less than  $\bar{\ell}^o = 0.13$ , equivalent to 15 hours per week, beginning  $t = 1$  (March 27, 2020), and gradually phasing out after  $t = 4$  (May 8, 2020). In equilibrium, the cap is no longer binding for any individual after September 24, 2020. [Figure 1](#) shows the time series of both the stay-at-home subsidy and the hours cap implemented in the model. Since the lockdowns implemented in the US differed across sectors and localities in scope and intensity, the model lockdown should be interpreted as the average effect.

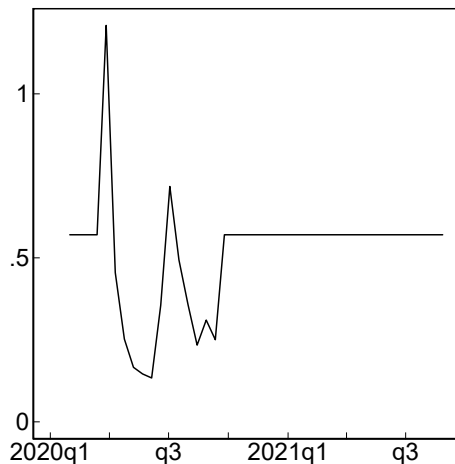
**Time-varying transmissibility.** Finally, I discuss how the time-varying parameter that governs the virus transmission outside of consumption and work,  $\epsilon_t$ , is set.

Because the progression of the pandemic in the data is a function of activities endogenous to the model but also a host of other factors that are not in the model, I use the time-varying parameter to parsimoniously capture all of those other factors, which allows the model to generate exactly the time series of deaths observed in the United States. I use the first six months of data on biweekly deaths in the United States (March 27–September 24, 2020) to calibrate  $\epsilon_t$ . I then set  $\epsilon_t = 0$  for  $t \geq 14$  (after September 25, 2020). [Figure 2](#) plots path of  $\beta_e + \epsilon_t$ , which governs the transmission of the virus other than through outside consumption and labor. It shows that the fitted  $\epsilon_t$  is consistent with a) a seasonal variation in which the transmissibility declines during the summer months and b) changes in behavior not in the model such as increased transmission around holidays such as July 4, 2020.<sup>28</sup> I show in the next subsection that the model generates a times series of deaths that is consistent with that in the United States, even out of sample (after September 24, 2020).

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<sup>28</sup>See, for example, [Grassly and Fraser \(2006\)](#) for a discussion of what causes seasonality in infectious diseases. One factor that may contribute to higher transmissibility in the winter is lower humidity, which increases the survival of the influenza virus in air. Another factor is seasonal changes in human behavior, such as those affected by summer vacation as well as by the tendency of family gatherings over the November and December holidays.

Figure 2: Time-varying transmissibility



### 3.3 Model validity

In this subsection, I investigate the model’s fit by examining both targeted and non-targeted moments in the steady state and during the course of the pandemic. The goal is to assess whether we can plausibly use the model as a laboratory to run counterfactual experiments.

**Pre-pandemic steady state.** Table 3 reports some steady state moments that illustrate the calibration’s overall performance. In addition to successfully matching the targeted moments, the model also generates non-targeted moments that are reasonably close to the data. For example, the model generates a gini for disposable labor income that is very close to that in the data and a consumption gini that is also reasonably close. The model balances a wealth gini that is somewhat lower than in the data with a 75-to-25 ratio that is somewhat higher than in the data. There are two points to make regarding the wealth distribution. On the one hand, the model inherits the limitations in generating a sufficiently skewed wealth distribution that are common in standard incomplete market models. On the other hand, for the context of this paper, this limitation is mitigated by the fact that the behavior of wealthy individuals in this class of models is not very different from those of extremely wealthy individuals.

**Transition path with pandemic.** So far, we have confirmed that the model generates a reasonable starting point for the pandemic along the relevant margins. The real test of

Table 3: Targeted and non-targeted moments

	Data	Model
<i>Targeted moments</i>		
wealth/GDP	4.8	4.8
average weekly hours	34.4	34.4
average VSL (multiples of annual consumption per capita)	238.8	238.8
<i>Non-targeted moments</i>		
disposable earnings gini	0.37	0.36
consumption gini	0.33	0.25
wealth gini	0.74	0.59
wealth p75/p25	11.9	13.2

Notes: Statistics related to the disposable earnings, consumption, and wealth distribution in the data are computed on a per capita basis. See Appendix A.1 for details.

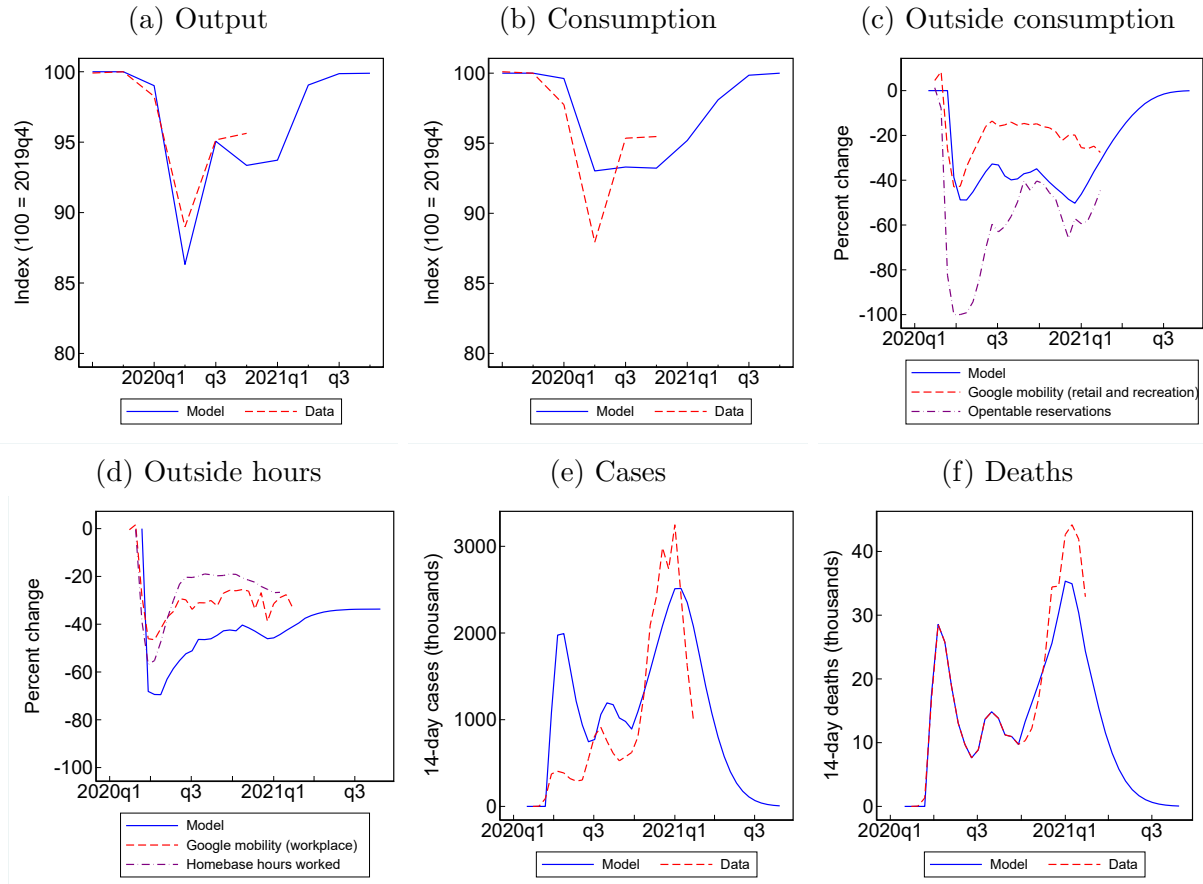
the model lies in its performance along the transition path when COVID-19 is introduced. Figure 3, which plots the time series of relevant variables for the model and data, shows that the model does well in this dimension.

Panel (a) of Figure 3 shows that output contracts sharply in the second quarter with a strong recovery in the third quarter (as in the data). From there, the model deviates slightly from the data in generating a slight decline in output in the fourth quarter whereas the data features a slight increase. Panel (b) shows that consumption contracts less sharply relative to the data in the second quarter and rebounds less strongly in the third quarter. Model consumption stalls in the fourth quarter (as in the data) and begins recovering in early 2021. Overall, the model generates dynamics for aggregate output and consumption that are reasonably similar to the data.

Panels (c) and (d) of Figure 3 show the time series of outside consumption and labor. For each of these series, there is not a perfect data counterpart because of data limitations. Having said that, the model generated series for outside consumption lies between the data series for Google mobility (retail and recreation) and OpenTable reservations. These are imperfect yet informative measures of consumption activities that are risky in the sense that



Figure 3: Aggregates during the pandemic



Notes: Both output and consumption in the data are linearly detrended at 2 percent per year. Outside consumption and hours in the model are relative to the pre-pandemic steady state. Google mobility and OpenTable reservations are year-over-year percent changes. Homebase hours are percent changes relative to the median for each day of the week during the January 4–31, 2020.

they involve leaving the house and potentially getting the disease from or passing it onto others. Similarly, the model generated series for outside hours tracks fairly closely the data series for Google mobility (workplace) and Homebase hours worked, which reports changes in hours worked for hourly employees that mostly work in contact-intensive sectors (e.g. restaurants, retail, health care, and other services). These measures are also imperfect but provide information regarding the changes in work-related activities that are risky because they take place outside of one’s house. The model decline in outside hours is larger than the data counterparts: Most of this can be accounted for by the fact that the pre-pandemic steady state assumes that no labor is done from home, whereas in the data, there was at least some labor done from home before the pandemic. Nonetheless, the dynamics for both outside consumption and labor are very similar to the data with large contractions in March followed by a strong recovery and a fourth-quarter decline that persisted into early 2021.

Finally, panels (e) and (d) of Figure 3 plot the times series of cases and deaths, respectively. Recall that the time-varying transmissibility parameter  $\epsilon_t$  was calibrated to fit the death series from March 27–September 24, 2020, so it is not surprising that the time series for deaths generated by the model line up exactly with that in the data. Somewhat surprisingly, however, cases and deaths increased in the fourth quarter of 2020, peaking in January of 2021 (both model and data). In the model, the increase is primarily driven by the higher transmissibility that kicks in after September 25, 2020 (Figure 2)—potentially reflecting seasonal factors that contribute to virus survival (e.g. lower humidity) and to increased risky activity (e.g. holiday gatherings)—and the decrease can be attributed to the \$300 subsidy that takes effect January 1, 2021, the vaccinations that begin December 18, 2020, and the reduction in the measure of susceptible individuals as a result of both infections and vaccinations (i.e. herd immunity). Note that the data series for cases is well below the model generated series in the early part of the pandemic, possibly reflecting the widely reported lack of testing in early stages of the pandemic in the United States.<sup>29</sup>

Overall, the model generates times series for relevant variables that are reasonably similar to the data. Having established that the model can plausibly be used as a laboratory for running counterfactual experiments, I quantify the effects of the pandemic and implemented

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<sup>29</sup>Note that the model projects a monotonic decline in cases and deaths going forward. This outlook can change for a variety of reasons, including, but not limited to, the spread of more transmissible variants and the efficacy of the vaccines against these variants.

mitigation policies and examine optimal policies in the next sections.

## 4 Quantitative exercises

This section uses the calibrated model to investigate the distributional consequences of the pandemic and mitigation policies. First, I study the properties of private mitigation by comparing the baseline model with endogenous transmission (one in which economic interactions change the spread of the virus) and an exogenous transmission model (one in which the spread of the virus only depends on the number of susceptible and infected agents). Second, I will quantify the effects of the mitigation policies that mimic those implemented in the US. In particular, I contrast the *stay-at-home order* (lockdown) and the *stay-at-home subsidy*. While both policies reduce infections and deaths, the subsidy policy delivers a higher welfare gain and is favored by all individuals in the economy, whereas the lockdown benefits older individuals at the expense of low-wage workers.

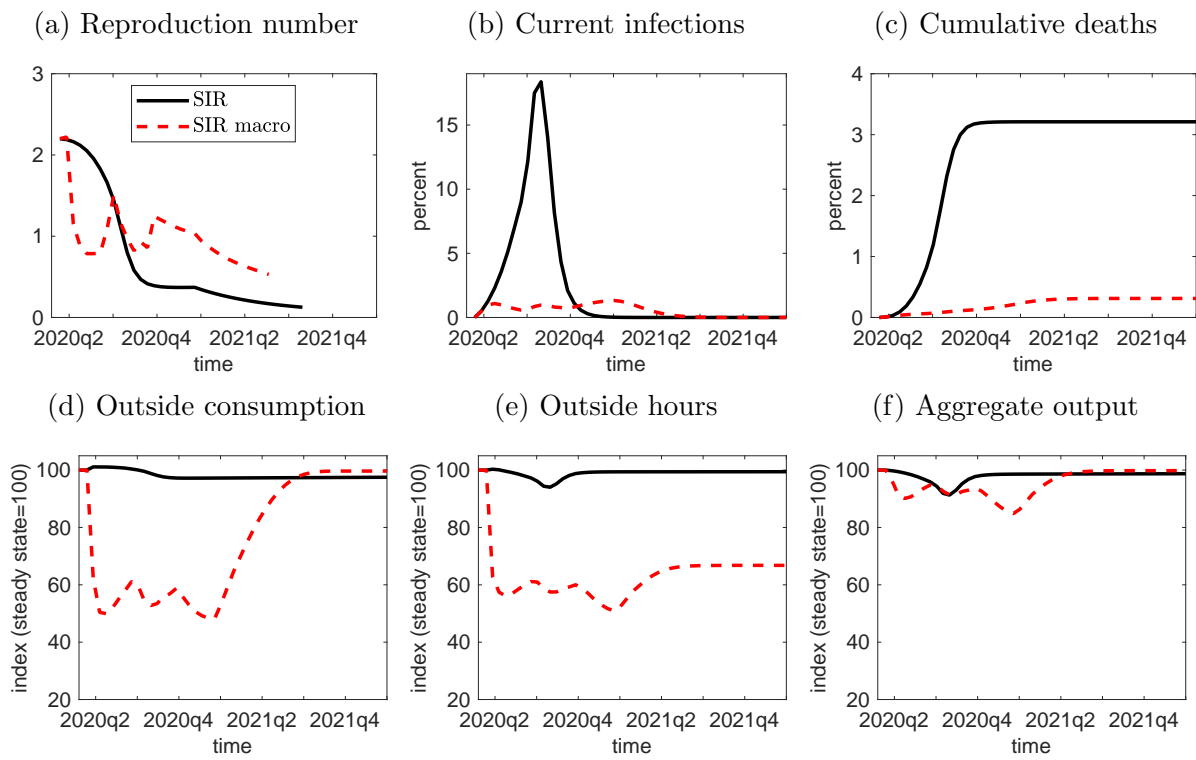
### 4.1 Private mitigation

To better understand the role of private mitigation, I contrast the baseline model—the “SIR Macro” model with endogenous transmission—with the alternative “SIR” model with exogenous transmission, where  $\beta_c = \beta_\ell = 0$ . In the SIR model, I 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. In both versions, I turn off all mitigation policies and feed in the same calibrated values of  $\epsilon_t$ .

Figure 4 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 outside consumption and hours dramatically, leading to a large decline in output, as can be seen in panels (d)–(f). Note that the small decline in outside hours and output in the SIR model is not due to mitigation efforts but rather due to the pandemic-induced decline in healthy workers.

Taking a closer look at private mitigation in the baseline model, consider the policy functions for outside consumption and labor of susceptible agents across the age, income,

Figure 4: Engendous vs. exogenous transmission (no mitigation)



and wealth distribution (Figure 5). The decline in outside consumption and hours is broad based. However, the decline in outside consumption is much greater for middle-aged and old agents than for young agents (panels a–c), and the decline in outside hours is much larger for middle-aged workers than for young workers (panels d–e). This reflects the lower fatality risk for young agents. Moreover, within each age cohort, the declines in outside consumption and hours are the smallest for low-wage/low-wealth workers. There are three reasons. First, while high-wage workers can switch to mostly working from home, low-wage workers are unable to do so. Second, the fact that middle-aged low-wage/high-wealth workers effectively sit out the labor market during the pandemic suggests that the lack of precautionary savings prevents low-wage/low-wealth workers from reducing their labor supply by more. Finally, high-wage and high-wealth individuals are more willing to curtail activities that increase infection risk because they have higher expected continuation values that are derived from higher expected future consumption and leisure.<sup>30</sup> Overall, young workers experience a much larger increase in infections, as shown in panel (f).

## 4.2 Welfare consequences of COVID-19 and mitigation policies

The previous subsection highlighted the externalities at work: Young workers do not reduce their outside 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 contribute to higher infections among older individuals, who face higher fatality rates. In this subsection, I quantify the distributional effects of the pandemic and implemented mitigation policies.

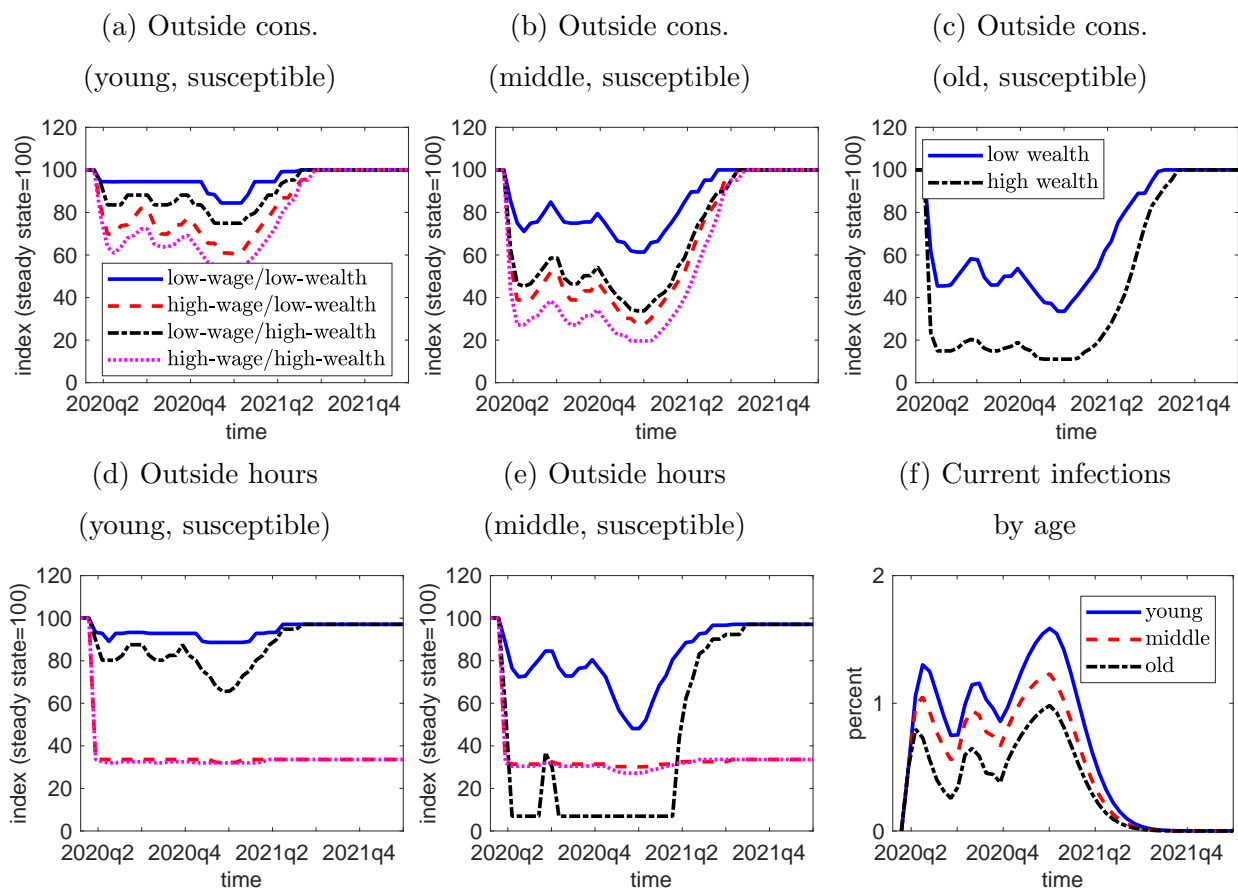
Table 4 shows the welfare, economic, and health outcomes of the pandemic and mitigation policies, decomposed by the effects of the subsidy policy and the lockdown policy. The first column shows that even without mitigation policies, the contraction of output is large, amounting to a nearly 5 percent loss in two-year output. The welfare consequences of the pandemic—measured as permanent consumption equivalents—are large across the distribution, but largest for retirees, who face a higher fatality risk.

Mitigation policies implemented in the US (described in Section 3.2) have had a positive impact by reducing deaths and even increasing output slightly, relative to no mitigation

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<sup>30</sup>For example, the model-implied VSL for low-wage/low-wealth individuals is 67 times annual consumption per capita, compared to 405 for high-wage/high-wealth individuals.

Figure 5: Response to pandemic (no mitigation)



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

Table 4: Welfare consequences of pandemic and mitigation policies

	no mitigation	US mitigation	subsidy only	lockdown only
welfare	-8.0	-6.4	-6.4	-7.8
working-age	-4.9	-3.8	-3.8	-4.9
retired	-20.4	-16.8	-16.9	-19.8
low-wage	-3.1	-2.2	-2.2	-3.2
high-wage	-6.8	-5.4	-5.4	-6.5
low-wealth	-6.0	-4.6	-4.6	-6.0
high-wealth	-10.0	-8.2	-8.2	-9.7
policy support		100.0	100.0	81.4
2-year output	95.6	95.8	96.6	95.0
deaths per 10k	20.6	16.0	16.2	19.8

Notes: Low- and high-wage correspond to below and above the median wage, respectively. Low- and high-wealth corresponds to below and above the median wealth, respectively. Welfare refers to permanent consumption equivalents, in percent. Blue and red colors denote groups with welfare gains and losses from the mitigation policies, respectively. Policy support refers to the percent of the initial population that benefits from the mitigation policy. Output refers to output from  $t = 1$  (March 27, 2020) to  $t = 52$  (March 24, 2022), compared with the analogous 52-period output in the steady state, indexed at 100.

(second column of Table 4). I defer the discussion about how mitigation policies can increase output to the next section, which examines the properties of optimal and output maximizing policies. Notice that all individuals benefit from the mitigation policy (i.e. the policy is a Pareto improvement).

The third and fourth columns of Table 4 decompose the effects of the subsidy and lockdown separately. Both policies improve average welfare and reduce deaths. However, in terms of welfare, the lockdown policy is vastly inferior: Whereas the subsidy policy reduces the average welfare loss from the pandemic by 1.6 percentage points, the lockdown policy reduces the average welfare loss by only 0.2 percentage points. 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 low-wage workers for whom the lockdown policy is most binding. Overall, the lockdown policy is favored by only 81.4 percent of the initial population. In contrast, the subsidy policy is favored by all individuals in the economy. I show in the next section that lockdowns generally are a very inefficient means to save lives.

## 5 Optimal mitigation policies

I investigate the properties of optimal mitigation policies over a limited set of policy instruments. In particular, I solve for the transition paths for 3,800 combinations of policy parameters, which vary along the weekly subsidy amount,  $T$  (\$0–\$1,200), the duration (4–14 months), and the speed at which the subsidy phases out<sup>31</sup>, with and without lockdowns of varying intensities (10, 15, and 20 weekly hour limits on outside labor). In all cases with a positive subsidy, I solve for a consumption tax that clears the government budget constraint in present value, making all configurations budget-neutral. All other parameters, including the time-varying transmissibility,  $\epsilon_t$ , are kept the same as described in Section 3.

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<sup>31</sup>Specifically, the duration of the subsidy is characterized by  $\bar{t}$ , which denotes the period at which the phase out begins. Then, the subsidy amount follows

$$T_t = \begin{cases} T & \text{if } 1 \leq t \leq \bar{t} \\ T \left(1 - \frac{t - \bar{t}}{\hat{t} - \bar{t}}\right)^x & \text{if } \bar{t} < t < \hat{t} \\ 0 & \text{otherwise.} \end{cases} \quad (19)$$

where  $x \in \{1, 2, 4, 8\}$  determines the speed of phase out. The consumption tax and lockdowns, where applicable, are phased out in an analogous manner.

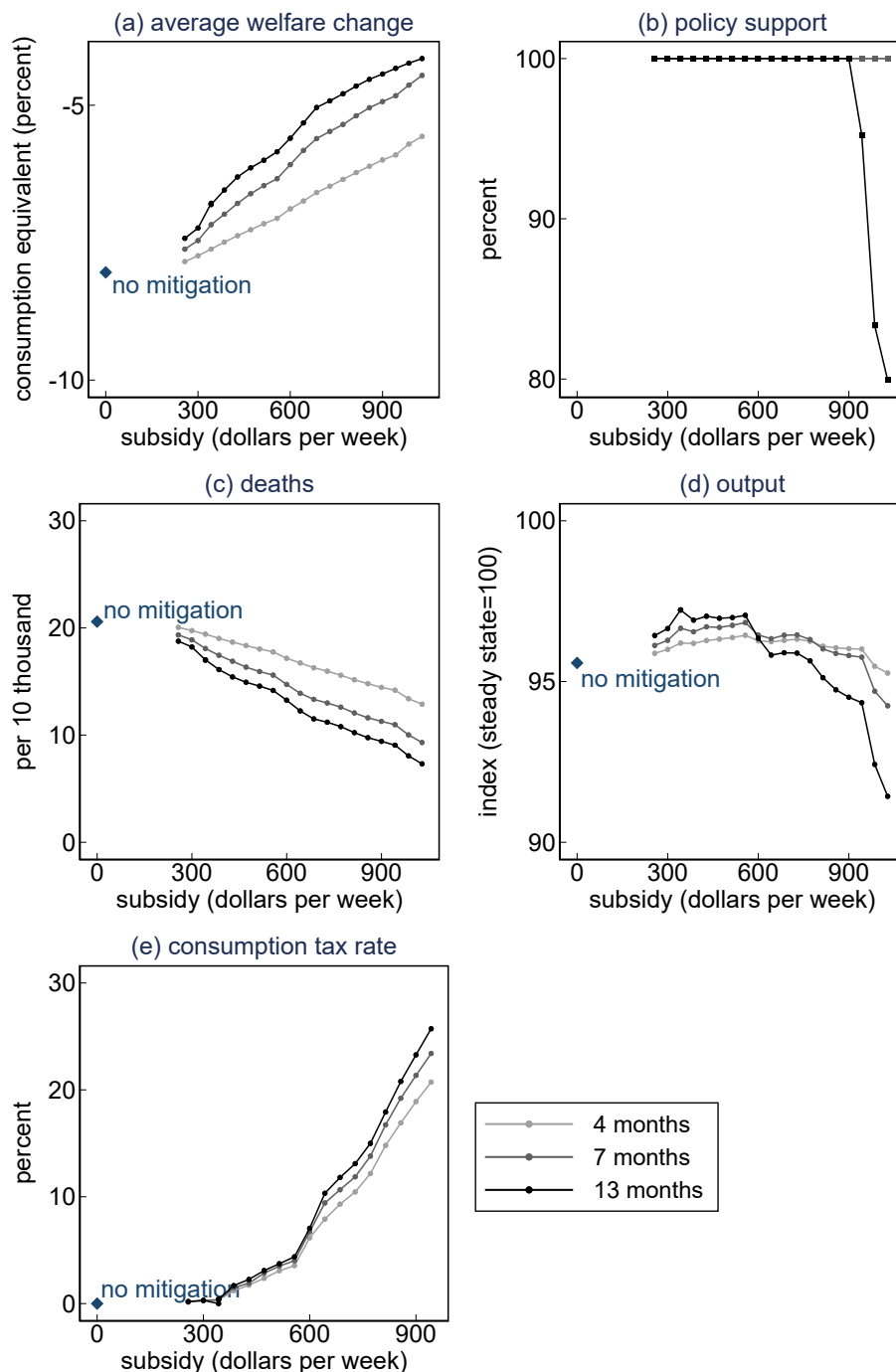


Figure 6 plots the effects of varying subsidy amounts and duration, keeping fixed the speed at which the subsidy phases out and no lockdown. Panel (a) shows that average welfare is increasing in both the subsidy amount and duration and panel (b) shows that for subsidies that are not too large or long, support for the mitigation policy is unanimous. Falling support for the policy is due to the higher consumption tax rate associated with larger and longer duration subsidies (panel e). Panel (c) demonstrates that deaths are decreasing in both the subsidy amount and duration.

Interestingly, the effects of the subsidy amount on output are nonmonotonic (panel d). In particular, for moderate subsidy amounts, the mitigation policy actually increases output relative to the case with no mitigation. This is due to two opposing effects. The first is the *direct effect* of the subsidy reducing labor supply, holding fixed the severity of the pandemic. Moderate subsidies (less than \$600 per week) induce only low-wage workers to reduce their hours, leading to a small decline in output. The second is an *indirect effect* of the subsidy that increases labor supply, by attenuating the pandemic. Specifically, because the labor from low-wage workers are almost exclusively “outside,” almost all of the reduction in hours contribute to mitigating the virus, making it safer to engage in more economic activities. Moreover, taxes used to fund the subsidy also contribute to mitigating the virus, allowing additional economic activity. At moderate subsidy amounts, the indirect effect can dominate the direct effect, leading to an increase in output relative to the no-mitigation scenario.

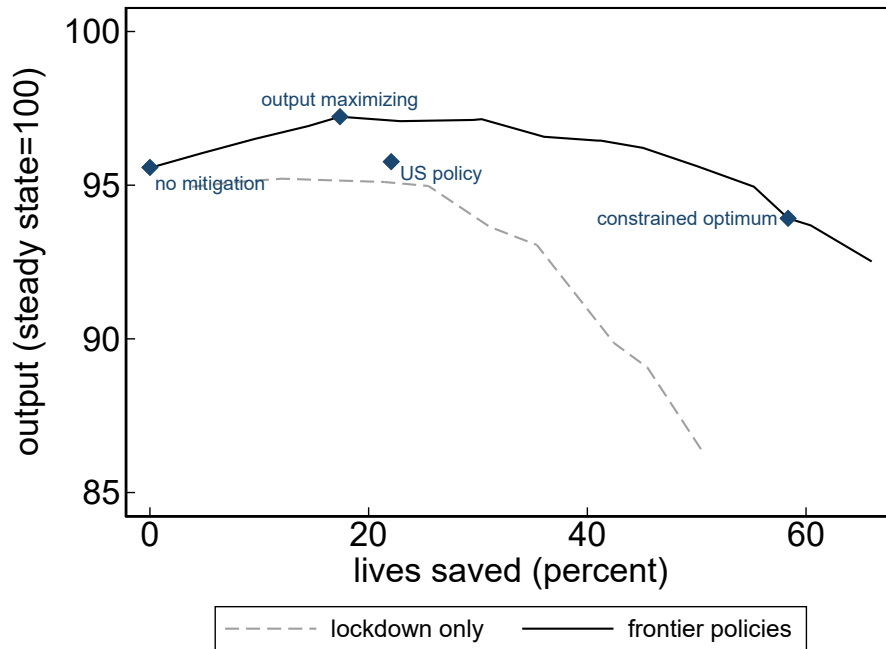
Mitigation policies have often been portrayed in the context of a tradeoff between output and health. Figure 7 illustrates the relation between two-year output and lives saved: The solid line depicts the best mix of policies that maximize output for each level of lives saved during the pandemic and the dashed line is the analogous line that does so with only lockdowns. We can see that, when exclusively relying on lockdowns to save lives, there is indeed a tradeoff between output and lives saved: higher lives saved is associated with lower output. The same is true for the frontier policies, which use a mix of subsidies and taxes, when saving more than 20 percent of lives. However, we can also see that there are policy configurations that simultaneously increase output and save more lives relative to the no mitigation case. As reference points, I include the constrained optimum, which maximizes welfare conditional on full support; the output maximizing configuration; and the configuration that most closely resembles US policy as described in Section 3.2. The policy parameters of the optimal and output maximizing configurations are summarized in Table 5 (top panel).

Figure 6: Effects of subsidy amount and duration



Notes: The graphs show the effects of varying subsidy amounts and duration, keeping fixed the pace at which the subsidy phases out and no lockdown. Average welfare change reports the population-weighted average of individual consumption equivalents. Policy support refers to the percent of the initial population that benefits from the mitigation policy. Output refers to output from  $t = 1$  (March 27, 2020) to  $t = 52$  (March 24, 2022), compared to the analogous 52-period output in the steady state, indexed at 100.

Figure 7: Output and lives



Notes: The solid line depicts the best mix of policies that maximize output for each level of lives saved during the pandemic and the dashed line is the analogous line that does so with only lockdowns. Output refers to output from  $t = 1$  (March 27, 2020) to  $t = 52$  (March 24, 2022), compared to the analogous 52-period output in the steady state. Lives saved are relative to no mitigation.

Relative to no mitigation, Table 5 shows that a subsidy of \$1050 per week for 7 months can lead to a substantial reduction in deaths without steeply reducing output. Similarly, a subsidy of \$350 per week for 13 months can increase output and save lives. Neither the constrained optimal nor the output maximizing policy features a lockdown. The middle panel of Table 5 shows the welfare consequences of the mitigation policies across the distribution. In particular, the second and third columns reveal that the welfare gains from both the output maximizing and constrained optimal policies are large and widely shared. The last two columns of Table 5 decompose the effects of the optimal subsidy and tax separately (I omit the analogous decomposition for the output maximizing policy as the effects of the tax are minuscule in that case). The majority of the lives saved and the welfare gains from the optimal policy are due to the subsidy. However, the consumption tax also contributes to saving lives and increasing output (by making it safer to work); it also results in a welfare gain for older and wealthy households who put a larger value in containing the virus. Finally, in Appendix D, I show that using a smarter Pigouvian tax on outside consumption is even more effective in saving lives and improving welfare.

## 6 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 and to investigate the properties of optimal mitigation policies. Using the calibrated model, I show that private mitigation plays a substantial role in reducing deaths and output during the pandemic, but there is large heterogeneity in the intensity of private mitigation across individuals. In particular, reductions in economic activities that contribute to the spread of COVID-19 are larger for individuals that are older, have higher wages, or have higher wealth. I also show that stay-at-home subsidies are superior to stay-at-home orders in that they reduce deaths by more and output by less. Furthermore, the stay-at-home subsidy delivers a higher average welfare gain than the stay-at-home order and benefits all individuals. Finally, it is possible to simultaneously improve economic and public health outcomes, though the constrained optimal policy leans toward saving more lives while causing a slightly lower output relative to no mitigation.

While vaccines may soon put the pandemic in the rear-view mirror in the United States

Table 5: Optimal mitigation policies

	no mitigation	maximizing policy	optimal policy	subsidy only	tax only
subsidy (\$/week)	0	350	1050	1050	0
duration (months)	0	13	7	7	7
cons. tax (percent)	0	0.4	36.5	0	36.5
lockdown	no	no	no	no	no
welfare	-8.0	-6.8	-4.2	-4.3	-8.1
working-age	-4.9	-4.1	-2.3	-2.1	-5.3
retired	-20.4	-17.7	-11.8	-13.4	-19.6
low-wage	-3.1	-2.5	-0.8	-0.1	-3.7
high-wage	-6.8	-5.7	-3.9	-4.0	-6.8
low-wealth	-6.0	-4.9	-2.7	-2.2	-6.4
high-wealth	-10.0	-8.6	-5.7	-6.4	-9.8
policy support		100.0	100.0	100.0	37.9
2-year output	95.6	97.2	93.9	93.7	96.0
deaths per 10k	20.6	17.0	8.6	12.0	18.0

Notes: Average welfare change reports the population-weighted average of individual consumption equivalents. Output refers to output from  $t = 1$  (March 27, 2020) to  $t = 52$  (March 24, 2022), relative to the analogous 52-period output in the steady state, indexed at 100.

and other developed economies, the policy implications raised in this paper are still valuable not only for pandemics in the future, but also for other countries where vaccines may take longer to be implemented on a wide scale.

## References

- ALVAREZ, F., D. ARGENTE, AND F. LIPPI (2020): “A Simple Planning Problem for COVID-19 Lockdown,” *Covid Economics*, 14, 1–32, <https://doi.org/10.3386/w26981>.
- ARGENTE, D. O., C.-T. HSIEH, AND M. LEE (2020): “The Cost of Privacy: Welfare Effect of the Disclosure of COVID-19 Cases,” Tech. rep., National Bureau of Economic Research, <https://doi.org/10.3386/w27220>.
- ATKESON, A. (2020): “What will be the economic impact of COVID-19 in the US? Rough estimates of disease scenarios,” Tech. rep., National Bureau of Economic Research, <https://doi.org/10.3386/w26867>.
- AUM, S., S. Y. T. LEE, AND Y. SHIN (2020): “Inequality of fear and self-quarantine: Is there a trade-off between GDP and public health?” *Covid Economics*, 14, 143–174, <https://doi.org/10.3386/w27100>.
- AZZIMONTI, M., A. FOGLI, F. PERRI, AND M. PONDER (2020): “Pandemic Control in ECON-EPI Networks,” Tech. rep., National Bureau of Economic Research, <https://doi.org/10.3386/w27741>.
- BAIROLIYA, N. AND A. IMROHOROGLU (2020): “Macroeconomic Consequences of Stay-At-Home Policies During the COVID-19 Pandemic,” *Covid Economics*, 13, 71–90, [https://www.marshall.usc.edu/sites/default/files/bairoliy/intellcont/macroeffects\\_of\\_corona-1.pdf](https://www.marshall.usc.edu/sites/default/files/bairoliy/intellcont/macroeffects_of_corona-1.pdf).
- BAQAEE, D., E. FARHI, M. J. MINA, AND J. H. STOCK (2020): “Reopening Scenarios,” Tech. rep., National Bureau of Economic Research, <https://doi.org/10.3386/w27244>.
- BERGER, D. W., K. F. HERKENHOFF, AND S. MONGEY (2020): “An SEIR infectious disease model with testing and conditional quarantine,” *Covid Economics*, 13, 1–30, <https://doi.org/10.3386/w26901>.
- BICK, A., A. BLANDIN, AND K. MERTENS (2020): “Work from home after the COVID-19 Outbreak,” Tech. rep., <https://doi.org/10.24149/wp2017r1>.
- BIRINCI, S., F. KARAHAN, Y. MERCAN, AND K. SEE (2020): “Labor Market Policies during an Epidemic,” Tech. rep., <https://doi.org/10.20955/wp.2020.024>.

- BODENSTEIN, M., G. CORSETTI, AND L. GUERRIERI (2020): “Social distancing and supply disruptions in a pandemic,” *Covid Economics*, 19, 1–52, <https://ssrn.com/abstract=3594260>.
- BOGNANNI, M., D. HANLEY, D. KOLLINER, AND K. MITMAN (2020): “Economic Activity and COVID-19 Transmission: Evidence from an Estimated Economic-Epidemiological Model,” Tech. rep., University of Pittsburgh, <https://doughanley.com/files/papers/COVID.pdf>.
- BRODEUR, A., D. M. GRAY, A. ISLAM, AND S. BHUIYAN (2020): “A Literature Review of the Economics of COVID-19,” Tech. rep., <https://ssrn.com/abstract=3636640>.
- BROTHERHOOD, L., P. KIRCHER, C. SANTOS, M. TERTILT, ET AL. (2020): “An economic model of the Covid-19 pandemic with young and old agents: Behavior, testing and policies,” *University of Bonn and University of Mannheim, Germany, Discussion Paper*, <https://econpapers.repec.org/paper/ptuwpaper/w202014.htm>.
- CARROLL, D. AND S. HUR (2020a): “On the distributional effects of international tariffs,” Tech. rep., Federal Reserve Bank of Cleveland, <https://doi.org/10.26509/frbc-wp-202018>.
- CARROLL, D. R. AND S. HUR (2020b): “On the heterogeneous welfare gains and losses from trade,” *Journal of Monetary Economics*, 109, 1–16, <https://doi.org/10.1016/j.jmoneco.2019.10.009>.
- CHARI, V. V., R. KIRPALANI, AND C. PHELAN (2020): “The hammer and the scalpel: On the economics of indiscriminate versus targeted isolation policies during pandemics,” Tech. rep., National Bureau of Economic Research, <https://doi.org/10.3386/w27232>.
- CHETTY, R., J. N. FRIEDMAN, N. HENDREN, M. STEPNER, ET AL. (2020): “How did covid-19 and stabilization policies affect spending and employment? a new real-time economic tracker based on private sector data,” Tech. rep., National Bureau of Economic Research, <https://doi.org/10.3386/w27232>.
- DINGEL, J. I. AND B. NEIMAN (2020): “How many jobs can be done at home?” *Covid Economics*, 1, 16–24, <https://doi.org/10.3386/w26948>.



- DOTSEY, M., W. LI, AND F. YANG (2014): “Consumption and time use over the life cycle,” *International Economic Review*, 55, 665–692, <https://doi.org/10.1111/iere.12066>.
- DUERNECKER, G. AND B. HERRENDORF (2018): “On the allocation of time—A quantitative analysis of the roles of taxes and productivities,” *European Economic Review*, 102, 169–187, <https://doi.org/10.1016/j.euroecorev.2017.10.025>.
- EICHENBAUM, M. S., S. REBELO, AND M. TRABANDT (2020): “The macroeconomics of epidemics,” Tech. rep., National Bureau of Economic Research, <https://doi.org/10.3386/w26882>.
- FARBOODI, M., G. JAROSCH, AND R. SHIMER (2020): “Internal and external effects of social distancing in a pandemic,” *Covid Economics*, 9, 22–58, <https://doi.org/10.3386/w27059>.
- FAUCI, A. S., H. C. LANE, AND R. R. REDFIELD (2020): “Covid-19—navigating the uncharted,” *New England Journal of Medicine*, 382, 1268–1269, <https://doi.org/10.1056/NEJMe2002387>.
- FERGUSON, N. M., D. A. CUMMINGS, C. FRASER, J. C. CAJKA, P. C. COOLEY, AND D. S. BURKE (2006): “Strategies for mitigating an influenza pandemic,” *Nature*, 442, 448–452, <https://doi.org/10.1038/nature04795>.
- FERNÁNDEZ-VILLAYERDE, J. AND C. I. JONES (2020): “Estimating and Simulating a SIRD Model of COVID-19 for Many Countries, States, and Cities,” Tech. rep., National Bureau of Economic Research, <http://doi.org/10.3386/w27128>.
- FLODEN, M. AND J. LINDÉ (2001): “Idiosyncratic risk in the United States and Sweden: Is there a role for government insurance?” *Review of Economic dynamics*, 4, 406–437, <https://doi.org/10.1006/redy.2000.0121>.
- GARIBALDI, P., E. R. MOEN, AND C. A. PISSARIDES (2020): “Modelling contacts and transitions in the SIR epidemics model,” *Covid Economics*, 5, 1–20, <https://www.carloalberto.org/wp-content/uploads/2020/04/garibaldi.pdf>.

- GLOVER, A., J. HEATHCOTE, D. KRUEGER, AND J.-V. RIOS-RULL (2020): “Health versus Wealth: On the Distributional Effects of Controlling a Pandemic,” *Covid Economics*, 6, 22–64, <https://doi.org/10.1006/redy.2000.0121>.
- GRASSLY, N. C. AND C. FRASER (2006): “Seasonal infectious disease epidemiology,” *Proceedings of the Royal Society B: Biological Sciences*, 273, 2541–2550, <https://doi.org/10.1098/rspb.2006.3604>.
- GREENSTONE, M. AND V. NIGAM (2020): “Does Social Distancing Matter?” Tech. rep., University of Chicago, Becker Friedman Institute for Economics Working Paper, <https://dx.doi.org/10.2139/ssrn.3561244>.
- HUR, S. (2018): “The lost generation of the Great Recession,” *Review of Economic Dynamics*, 30, 179–202, <https://doi.org/10.1016/j.red.2018.05.004>.
- HUR, S. AND M. JENUWINE (2020): “Lessons on the Economics of Pandemics from Recent Research,” *Economic Commentary*, <https://doi.org/10.26509/frbc-ec-202011>.
- JONES, C., T. PHILIPPON, AND V. VENKATESWARAN (2020): “Optimal Mitigation Policies in a Pandemic: Social Distancing and Working from Home,” Tech. rep., <https://doi.org/10.3386/w26984>.
- KAPICKA, M. AND P. RUPERT (2020): “Labor markets during pandemics,” Tech. rep., UC Santa Barbara.
- KAPLAN, G., B. MOLL, AND G. L. VIOLANTE (2020): “The Great Lockdown and the Big Stimulus: Tracing the Pandemic Possibility Frontier for the US,” Tech. rep., National Bureau of Economic Research, <https://doi.org/10.3386/w27794>.
- KERMACK, W. O. AND A. G. MCKENDRICK (1927): “A contribution to the mathematical theory of epidemics,” *Proceedings of the royal society of london. Series A, Containing papers of a mathematical and physical character*, 115, 700–721, <https://doi.org/10.1098/rspa.1927.0118>.
- KOPECKY, K. A. AND R. M. SUEN (2010): “Finite state Markov-chain approximations to highly persistent processes,” *Review of Economic Dynamics*, 13, 701–714, <https://doi.org/10.1016/j.red.2010.02.002>.

- KRUEGER, D., K. MITMAN, AND F. PERRI (2016): “Macroeconomics and household heterogeneity,” in *Handbook of Macroeconomics*, Elsevier, vol. 2, 843–921, <https://doi.org/10.1016/bs.hesmac.2016.04.003>.
- KRUEGER, D., H. UHLIG, AND T. XIE (2020): “Macroeconomic dynamics and reallocation in an epidemic,” *Covid Economics*, 5, 21–55, <https://doi.org/10.3386/w27047>.
- MOSSONG, J., N. HENS, M. JIT, P. BEUTELS, K. AURANEN, R. MIKOLAJCZYK, M. MASSARI, S. SALMASO, G. S. TOMBA, J. WALLINGA, ET AL. (2008): “Social contacts and mixing patterns relevant to the spread of infectious diseases,” *PLoS medicine*, 5, <https://doi.org/10.1371/journal.pmed.0050074>.
- NAKAJIMA, M. (2020): “Consumption and Saving during the Pandemic,” Tech. rep., <https://makotonakajima.github.io/files/paper/cscovid-paper-201030.pdf>.
- FIGUILLEM, F. AND L. SHI (2020): “The Optimal COVID-19 Quarantine and Testing Policies,” Tech. rep., Einaudi Institute for Economics and Finance (EIEF), [http://www.eief.it/eief/images/WP\\_20.04.pdf](http://www.eief.it/eief/images/WP_20.04.pdf).
- U.S. ENVIRONMENTAL PROTECTION AGENCY (2020): “Mortality Risk Valuation,” Tech. rep., <https://www.epa.gov/environmental-economics/mortality-risk-valuation>.
- WANG, H., Z. WANG, Y. DONG, R. CHANG, C. XU, X. YU, S. ZHANG, L. TSAMLAG, M. SHANG, J. HUANG, ET AL. (2020): “Phase-adjusted estimation of the number of coronavirus disease 2019 cases in Wuhan, China,” *Cell Discovery*, 6, 1–8, <https://doi.org/10.1038/s41421-020-0148-0>.

# A Data appendix

## A.1 Details on data construction

- Inside (safe) expenditure share (Table 1): Using 2019 data on personal consumption expenditures (BEA), I compute inside consumption as the sum of expenditures on goods and housing and utilities. The inside expenditure share is then inside consumption divided by the sum of consumption expenditures on goods and household consumption expenditures on services.
- Wage ratio (Table 1): I use annual income data from the PSID core sample (2004–2014), selecting all household heads, ages 25 to 64. 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. The ratio of the average wage for households aged 45–64 to that of households aged 25–44 is 1.35.
- Share of jobs that can be done from home (Section 3.1): Using the data provided by [Dingel and Neiman \(2020\)](#), I first sort occupations by their median wage. Then I place them into wage quintiles, weighted by total employment in each occupation. Finally, within each wage bin, I compute the average share of jobs that can be done from home—provided by [Dingel and Neiman \(2020\)](#)—weighted by total employment.
- Per capita disposable earnings, consumption, and wealth (Table 3): I use annual income data from the PSID core sample (2014) for households whose heads are ages 25 and above. I first compute total household labor income as the sum of the head’s and spouse’s labor income (excluding farm and business income), head’s and spouse’s labor part of business income, and 50 percent of household farm income. I then use TAXSIM9 to estimate household taxes and transfers. Disposable earnings is defined as household labor income minus taxes plus transfers. Consumption is defined as expenditures on child care, clothing, education, food, health care, housing (except expenditures on mortgage, property taxes, and homeowner’s and renter’s insurance), transportation,

vacation and entertainment, and in the case of homeowners, I add owner’s equivalent rent (as in [Carroll and Hur 2020b](#)). Wealth is simply defined as household net worth (total assets minus liabilities). I obtain per capita measures by dividing by two for married households.

## A.2 Estimation of wage processes

The sample selection and estimation procedure closely follows the procedure described in [Krueger et al. \(2016\)](#) and [Carroll and Hur \(2020a\)](#). 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 (15) 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 Definition of equilibrium with transition

In this section, I provide the details regarding the equilibrium with transition. While the steady state analysis was done in general equilibrium, the transition path analysis is done in partial equilibrium. In other words, factor prices  $(w, r)$ , retirement income  $(s)$ , and the labor income tax  $(\tau_\ell)$  are fixed at their steady-state levels. Furthermore, the measure of newborns and their wealth distribution is also assumed to be constant throughout the

transition. While these assumptions have been made for computational tractability<sup>32</sup>, there are also other considerations. For instance, social security benefits and contribution rates do not typically respond to recessions at a higher frequency (and did not during the pandemic). A final note about the environment is that firms are not optimizing along the transition path. Instead, they rent supply-determined labor and capital to produce output and, as a consequence, suffer losses during the transition path.<sup>33</sup> The formal definition is provided below.

**Definition.** A *competitive (partial) equilibrium with transition*, given an initial distribution  $\{\mu_{j1}^*\}_{j \in J}$ , prices  $\{w, r\}$ , and fiscal policies  $\{\tau_{ct}, T_t, \bar{\ell}_t^o, \tau_\ell, s\}_{t=1}^\infty$ , is a sequence of value functions  $\{v_{jt}\}_{j \in J, t=1}^\infty$ , policy functions  $\{c_{ijt}, c_{ojt}, \ell_{ijt}, \ell_{ojt}, k'_{jt}\}_{j \in J, t=1}^\infty$ , producer plans  $\{Y_{ft}, L_{ft}, K_{ft}\}_{t=1}^\infty$ , the distribution of newborns  $\omega$ , and measures  $\{\mu_{jt}\}_{j \in J, t=1}^\infty$  such that, for all  $t \geq 1$ :

1. Given prices, fiscal policies, and aggregate states, retirees and workers solve (3) and (4), respectively.

2. Producer plans satisfy

$$Y_{ft} = K_{ft}^\alpha L_{ft}^{1-\alpha} \quad (20)$$

$$L_{ft} = \int_X \sum_{j < J_R} (\ell_{ijt}(k, \varepsilon, h) + \ell_{ojt}(k, \varepsilon, h)) d\mu_{jt}(k, \varepsilon, h) \quad (21)$$

$$K_{ft} = \int_X \sum_{j \in J} k d\mu_{jt}(k, \varepsilon, h). \quad (22)$$

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<sup>32</sup>It is not that solving for general equilibrium dynamics would be infeasible for given a set of parameters. Calibrating the transition dynamics and solving for optimal policies in a general equilibrium setting would add considerably to the computational burden.

<sup>33</sup>Though not explicitly modeled here, the Paycheck Protection Program can be interpreted as a way to keep firms operating in this environment. An alternative approach would be to assume a small open economy environment, in which capital markets do not clear. In this case, aggregate capital demanded by firms would decline, leading to a larger decline in output. None of the other variables would change under this alternative approach.

3. The government budget for mitigation policies clears in present value:

$$\begin{aligned} & \sum_{t=1}^{\infty} \left\{ (1+r)^{1-t} \tau_{ct} \int_X \sum_{j \in J} (c_{ijt}(k, \varepsilon, h) + c_{ojt}(k, \varepsilon, h)) d\mu_{jt}(k, \varepsilon, h) \right\} \\ &= \sum_{t=1}^{\infty} \left\{ (1+r)^{1-t} T_t \int_X \mathbb{1}_{\{\ell_{ijt}(k, \varepsilon, h) + \ell_{ojt}(k, \varepsilon, h) = 0\}} \sum_{j < J_R} d\mu_{jt}(k, \varepsilon, h) \right\}. \end{aligned} \quad (23)$$

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

$$\begin{aligned} \mu_{jt}(\mathcal{K}, \mathcal{E}, \mathcal{H}) &= \int_X \psi_{j-1} \mathbb{1}_{\{k'_{j-1, t-1}(k, \varepsilon, h) \in \mathcal{K}\}} \sum_{\varepsilon' \in \mathcal{E}} \sum_{h' \in \mathcal{H}} \Gamma_{\varepsilon \varepsilon'} \Pi_{hh'} d\mu_{j-1, t-1}(k, \varepsilon, h) \\ &+ \int_X (1 - \psi_j) \mathbb{1}_{\{k'_{j, t-1}(k, \varepsilon, h) \in \mathcal{K}\}} \sum_{\varepsilon' \in \mathcal{E}} \sum_{h' \in \mathcal{H}} \Gamma_{\varepsilon \varepsilon'} \Pi_{hh'} d\mu_{j, t-1}(k, \varepsilon, h) \end{aligned} \quad (24)$$

and

$$\begin{aligned} \mu_{1t}(\mathcal{K}, \mathcal{E}, \mathcal{H}) &= \int_X (1 - \psi_1) \mathbb{1}_{\{k'_{1, t-1}(k, \varepsilon, h) \in \mathcal{K}\}} \sum_{\varepsilon' \in \mathcal{E}} \sum_{h' \in \mathcal{H}} \Gamma_{\varepsilon \varepsilon'} \Pi_{hh'} d\mu_{1, t-1}(k, \varepsilon, h) \\ &+ \omega(\mathcal{K}, \mathcal{E}, \mathcal{H}). \end{aligned} \quad (25)$$

## C Computational appendix

The solution algorithm broadly consists of two steps:

1. Solve for the pre-pandemic steady state.
2. Solve for pandemic transition path.

In each step, I solve the household problem over an unevenly spaced grid of 120 wealth points,  $k_{coarse}$ . To improve solution accuracy and to save time, I place more points near zero, where the household value function is more concave. I store the equilibrium wealth distribution as a histogram over an unevenly spaced wealth grid of 2000 points,  $k_{fine}$ . I set the maximum wealth level on  $k_{fine}$  much lower than the one on  $k_{coarse}$  and check that this upper bound is not overly restrictive by verifying that the equilibrium distribution has no mass on the highest grid point in the steady state or at any point along the transition.

To calibrate the pre-pandemic steady state, I guess a vector of parameters  $[\beta, \varphi, \bar{u}, s, \tau_\ell]$ . I then solve for the steady state, calculate the model-implied values for the targets, and update the guess using a quasi-Newton method with some dampening.

## C.1 Solving for a steady state

1. Let  $\mu_j^{init}(k, \varepsilon, h)$  be an initialization of the distribution over  $k_{fine}$ ,  $E$ , and  $H$ .

2. Solve for the equilibrium rental rate,  $r^*$ .

(a) Guess  $r^0$ .

(b) Given  $r^0$ , use equations (7) and (8) to get the wage,

$$w^0(r^0) = (1 - \alpha) \left( \frac{r + \delta}{\alpha} \right)^{\frac{\alpha}{\alpha-1}}.$$

(c) Starting at  $j = \bar{J}$ , iterate on the Bellman equation in (3) until the value function converges to find the retiree value and policy functions conditional on prices. Repeat for  $j = \bar{J} - 1, \dots, J^R$  if  $\bar{J} > J^R$ .

(d) Starting at  $j = J^R - 1$ , iterate on the Bellman equation in (4) until the value function converges to find the worker value and policy functions conditional on prices. Repeat for  $j = J^R - 2, \dots, 1$  if  $J^R > 2$ .

(e) Use linear interpolation to map the value and policy functions from  $k_{coarse}$  onto  $k_{fine}$ .

(f) Beginning at  $\mu_j^{init}$ , update the distribution using equations (10)–(11) and the fine-grid decision rules for saving. Repeat until  $\mu_j$  converges to  $\mu_j^*(r^0)$ .

(g) Use  $\mu_j^*$  and the fine-grid decision rules to compute all aggregates.

(h) Find the implied interest rate,  $\bar{r}^0 = \alpha \left( \frac{K^0}{L^0} \right)^{\alpha-1} - \delta$ .

(i) Use Brent's method to solve for  $r^*$  over a fixed interval.

### C.1.1 Value of statistical life

The value of  $\bar{u}$  only affects the level of the value function and does not affect the policy functions in the pre-pandemic steady state. Therefore, the value of  $\bar{u}$  can be found after first calibrating  $[\beta, \varphi, s, \tau_\ell]$ . To calculate an individual's VSL, I take the following steps:

1. I start with the pre-pandemic steady state value function:

$$v_j(k, \varepsilon) = \frac{((c_i^*)^\gamma (c_o^*)^{1-\gamma})^{1-\sigma}}{1-\sigma} - g(\ell_i^* + \ell_o^*) + \bar{u} \\ + \beta \sum_{\varepsilon' \in E} \Gamma_{\varepsilon, \varepsilon'} [\psi_j v_{j+1}(k', \varepsilon') + (1 - \psi_j) v_j(k', \varepsilon')]$$



where  $c_i^*, c_o^*, \ell_i^*, \ell_o^*$  denote the pre-pandemic steady-state policy functions.

2. Then, imposing optimality conditions, I define

$$\begin{aligned} \hat{v}_j(k, \varepsilon) = & \frac{[(c^* + \Delta_c) \gamma^\gamma (1 - \gamma)^{1-\gamma}]^{1-\sigma}}{1 - \sigma} - g(\ell_i^* + \ell_o^*) + \bar{u} \\ & + \beta(1 + \Delta_s) \sum_{\varepsilon' \in E} \Gamma_{\varepsilon, \varepsilon'} [\psi_j v_{j+1}(k', \varepsilon') + (1 - \psi_j) v_j(k', \varepsilon')] \end{aligned}$$

where  $c^* = c_i^* + c_o^*$  is the policy function for total consumption and  $\Delta_c, \Delta_s$  are small one-time deviations to consumption and survival probability.

3. Then, the VSL—defined as the marginal rate of substitution between survival and consumption—can be expressed as

$$\begin{aligned} VSL_j(k, \varepsilon) &= \left. \frac{\frac{\partial \hat{v}}{\partial \Delta_s}}{\frac{\partial \hat{v}}{\partial \Delta_c}} \right|_{\Delta_c=0, \Delta_s=0} \\ &= \frac{\beta \sum_{\varepsilon' \in E} \Gamma_{\varepsilon, \varepsilon'} [\psi_j v_{j+1}(k', \varepsilon') + (1 - \psi_j) v_j(k', \varepsilon')]}{(c^*)^{-\sigma} (\gamma^\gamma (1 - \gamma)^{1-\gamma})^{1-\sigma}} \end{aligned}$$

4. Set  $\bar{u}$  such that  $\int_X \sum_{j \in J} VSL_j(k, \varepsilon) d\mu_j(k, \varepsilon, h) = 6226 \int_X \sum_{j \in J} (c_{ij}(k, \varepsilon) + c_{oj}(k, \varepsilon)) d\mu_j(k, \varepsilon, h)$ .

## C.2 Solving for a transition path

Recall that all individuals are assumed to be in the recovered state by  $t = \hat{t}$  (e.g. vaccine and cure). Combined with the assumption that prices are fixed at their initial steady state values throughout the transition path, this implies that, even though the measure  $\mu_{jt}$  takes a very long time to return to its steady state values, value and policy functions only need to be solved for  $t \leq \hat{t}$  since all the relevant variables for solving the individual's optimization problem are constant for  $t > \hat{t}$  (at steady-state levels).

To introduce COVID-19 in the economy, set  $\mu_{j1}(k, \varepsilon, I) = 0.005\mu_{j0}(k, \varepsilon, S)$ ,  $\mu_{j1}(k, \varepsilon, S) = 0.995\mu_{j0}(k, \varepsilon, S)$ , and  $\mu_{j1}(k, \varepsilon, R) = 0$  for  $j \in J$ ,  $k \in K$ , and  $\varepsilon \in E$ . Recall that all agents are susceptible in the pre-pandemic steady state ( $t = 0$ ).

1. Guess the sequence  $\{Z_t, \tau_{ct}\}_{t=1}^{\hat{t}}$ .
2. Set  $v_{j, \hat{t}+1}$  equal to the steady-state value function for  $j \in J$ . Then, starting in period  $\hat{t}$ , solve the Bellman equations in (3) and (4) backward. This produces a sequence of policy functions for periods  $t = 1, \dots, \hat{t}$ .

3. Starting at  $\mu_{j1}$ , simulate forward using the policy functions to find the sequence of measures from  $t = 1, \dots, T$ . Along the way, solve for aggregate variables in each period, including  $\bar{Z}_t \equiv \{\mu_{It}, C_{It}^o, L_{It}^o, \epsilon_t\}$ , where  $\epsilon_t$  is set so that the model generates the same times series of deaths as in the data for  $t < 14$ .
4. Check that the difference between the guess for  $\{Z_t\}$  and the implied value  $\{\bar{Z}_t\}$  (measured under the sup norm) is less than a small tolerance. Additionally, if  $T > 0$ , check that the government budget for mitigation policies in (23) clears in present value. If so, a transition path has been found.
5. If not, update the guess using a dampening method and repeat.

## D Robustness

In this section, I explore the robustness of the results to alternative parameter and modeling choices. In all of the robustness exercises, I keep all other parameters of the model as in the baseline, including the time-varying transmissibility shocks ( $\epsilon_t$ ). I find that although the level of average welfare, deaths, and output can vary substantially, the main policy implications are extremely robust. Under all alternative configurations, the constrained optimal policies involve larger subsidies and longer durations than US policy and the output maximizing policies involve weakly smaller subsidies and longer durations than US policy. Furthermore, the result that both constrained optimal and output maximizing policies involve no lockdown is robust to all alternative configurations, except for the case with a higher reproduction number. Finally, in each configuration, the output maximizing policy leads to lower deaths and higher output than without mitigation. The policy parameters and selected outcomes of the constrained optimal and output maximizing policies under alternative parameter values and modeling choices are summarized in Tables 6–7.

**Higher value of statistical life.** In the baseline calibration, I use a VSL of \$7.4 million in 2006, which corresponds to 6,226 biweekly consumption per capita. As a robustness check, I use an higher VSL used by Greenstone and Nigam (2020) and Glover et al. (2020) of \$11.5 million, or 6,772 times biweekly consumption per capita. By comparing the no mitigation results in Tables 5 and 6, I find that assigning a higher value of statistical life leads to

slightly lower deaths and output and a larger welfare loss as result of the pandemic. The main policy implications remain the same: The constrained optimal policy involves a larger and longer duration subsidy than US policy and the output maximizing policy also involves the same subsidy amount as US policy but for a longer duration. Both configurations feature no lockdowns.

**Smaller utility loss during infection.** I also consider a 30 percent reduction in the flow value of life during infection and compare the results to the 50 percent reduction studied in the baseline. The no mitigation scenarios are nearly identical and the main policy implications are also nearly unchanged. I conclude that the utility loss during infection is not a main driver of the economic or epidemiological dynamics.

**Smaller efficiency loss during infection.** Next, I consider a 30 percent reduction in labor efficiency during infection, compared with the baseline calibration of a 50 percent reduction. Interestingly, comparing the no mitigation scenarios under a 30 percent versus a 50 percent efficiency reduction during infection reveals that welfare and output is actually lower under the 30 percent reduction. This is because the smaller efficiency loss for infected individuals induce these infected individuals to work more, increasing the infection risk of susceptible agents, leading to a decline in economic activity among susceptible agents. The main policy implications are nevertheless unchanged.

**Higher disutility of not working.** The baseline calibration ( $\tilde{u} = 0.62$ ) induces a 19 percent decline in employment that is consistent with the real-time survey data reported by [Bick et al. \(2020\)](#), but higher than that reported by the Bureau of Labor Statistics. As a robustness check, here I consider a higher disutility of  $\tilde{u} = -0.75$ , which generates a 16 percent decline in employment. As can be expected, the no-mitigation case is identical to the baseline. Comparing the US policy outcomes to that in the baseline is useful here. A higher utility of not working implies that less individuals are willing to accept the stay-at-home subsidy, leading to slightly higher deaths (16.7 compared with 16.0 in the baseline). Output is unaffected because of two opposing effects that cancel each other out (up to the first decimal digit). On the one hand, more individuals are working as opposed to staying at home, leading to increased output. On the other hand, because of higher infection risk, there is a reduction in hours, leading to decreased output. The main policy implications are

Table 6: Sensitivity analysis

	subsidy		lock-	average	2-year	
	amount	duration	down	welfare	output	deaths
	(\$/week)	(months)		change	(index)	(per 10k)
				(percent)		
<i>higher value of statistical life (<math>VSL = 6772\bar{c}</math>)</i>						
constrained optimum*	1100	7	no	-4.4	94.0	8.3
output maximizing*	600	10	no	-6.1	97.1	13.6
US policy*	600(300)	4(3)	yes	-6.7	95.7	15.4
no mitigation	0	0	no	-8.2	95.4	19.5
<i>smaller utility loss during infection (<math>\hat{u} = -7.49</math>)</i>						
constrained optimum*	900	11	no	-4.4	95.1	10.0
output maximizing*	350	13	no	-6.9	97.3	18.1
US policy*	600(300)	4(3)	yes	-6.5	95.8	17.1
no mitigation	0	0	no	-8.1	95.7	21.8
<i>smaller efficiency loss during infection (<math>\eta_{jI} = 0.7\eta_{jS}</math>)</i>						
constrained optimum*	1100	8	no	-4.3	93.2	8.5
output maximizing*	550	11	no	-6.5	96.4	15.9
US policy*	600(300)	4(3)	yes	-7.1	94.8	18.1
no mitigation	0	0	no	-8.6	94.4	22.3
<i>higher disutility of not working (<math>\tilde{u} = 0.75</math>)</i>						
constrained optimum*	1000	11	no	-4.4	95.1	9.3
output maximizing*	400	13	no	-6.8	97.1	16.8
US policy*	600(300)	4(3)	yes	-6.6	95.8	16.7
no mitigation	0	0	no	-8.0	95.6	20.6
<i>higher basic reproduction number (<math>R_0 = 2.5</math>)</i>						
constrained optimum*	1100	11	yes	-6.4	90.8	13.4
output maximizing*	550	9	no	-9.9	95.3	26.9
US policy*	600(300)	4(3)	yes	-10.5	93.3	29.5
no mitigation	0	0	no	-12.2	92.1	35.2

Notes: Average welfare change reports the population-weighted average of individual consumption equivalents. Output refers to output from  $t = 1$  (March 27, 2020) to  $t = 52$  (March 24, 2022), compared with the analogous 52-period output in the steady state, indexed at 100. FPUC extension in parentheses. \* denotes Pareto improvements relative to the no mitigation case.

unchanged in that the constrained optimal policy features a larger and longer subsidy than US policy with no lockdown and that the output maximizing policy features a smaller but longer subsidy than US policy with no lockdown.

**Higher basic reproduction number.** I also investigate the implications of assuming a higher basic reproduction number of 2.5, compared to the baseline value of 2.2. As expected, a higher basic reproduction number leads to a larger number of deaths. Nevertheless, the policy implications are similar, except that a lockdown is part of the optimal response, albeit one that is mild (a 20 hours cap on outside hours).

**No hospital capacity constraint.** I also investigate the implications of assuming that there is no hospital capacity constraint. As expected, this leads to fewer deaths and a smaller welfare loss under the no mitigation scenario, compared with the baseline calibration. Nevertheless, the policy prescriptions remain nearly identical: the output maximizing policy parameters are unchanged, while the constrained optimal policy features a slightly larger but shorter subsidy than in the baseline calibration.

**Subsidy funded by tax on outside consumption.** In the baseline calibration, I assumed that the stay-at-home subsidy is funded by a tax on consumption. Here, I consider a Pigouvian tax that specifically targets outside consumption. The main policy implications are similar to that in the baseline. The most significant difference is that the Pigouvian tax is much more effective at bringing down deaths. A nearly identical subsidy (\$1000 versus \$1050 in the baseline) brings down deaths to 4.4 (per 10 thousand), compared to 8.6 in the baseline. This is because the Pigouvian tax more directly targets outside consumption, leading to less infections and deaths.

**Higher inside consumption.** In the baseline calibration, I set the inside consumption preference parameter  $\gamma = 0.51$  to match the expenditure share on goods and housing and utility services in 2019. As I discuss in the main text, an exact mapping between inside (or safe) consumption in the model to the data is not possible due to data limitations. Thus, as a robustness check, I consider a higher value of  $\gamma = 0.61$ . Table 7 shows that the results are nearly identical to those in the baseline, except that the constrained optimal subsidy is slightly smaller but for a longer duration than in the baseline.

Table 7: Sensitivity analysis (2)

	subsidy amount (\$/week)	duration (months)	lock- down	average welfare change (percent)	2-year output (index)	deaths (per 10k)
<i>no hospital capacity constraint (<math>\kappa = 1</math>)</i>						
constrained optimum*	1100	6	no	-4.3	94.1	8.8
output maximizing*	350	13	no	-6.7	97.3	16.8
US policy*	600(300)	4(3)	yes	-6.3	95.8	15.8
no mitigation	0	0	no	-7.8	95.7	19.7
<i>subsidy funded by tax on outside consumption</i>						
constrained optimum*	1000	8	no	-2.8	94.3	4.4
output maximizing*	550	11	no	-5.5	97.3	13.1
US policy*	600(300)	4(3)	yes	-6.4	95.8	16.0
no mitigation	0	0	no	-8.0	95.6	20.6
<i>higher inside consumption (<math>\gamma = 0.61</math>)</i>						
constrained optimum*	950	10	no	-3.8	95.3	8.1
output maximizing*	350	13	no	-5.7	97.7	14.2
US policy*	600(300)	4(3)	yes	-5.3	96.2	13.3
no mitigation	0	0	no	-6.9	96.2	17.5
<i>common case fatality rate (<math>\delta^u = 0.0085</math>)</i>						
constrained optimum*	400	9	yes	-3.8	95.3	8.1
output maximizing*	400	9	no	-4.3	96.4	6.8
US policy*	600(300)	4(3)	yes	-4.2	95.0	6.8
no mitigation	0	0	no	-5.4	94.3	8.7
<i>no pandemic</i>						
constrained optimum	0	0	no	0.0	100.0	0.0
output maximizing	0	0	no	0.0	100.0	0.0
US policy	600(300)	4(3)	yes	0.0	98.2	0.0
no mitigation	0	0	no	0.0	100.0	0.0

Notes: Average welfare change reports the population-weighted average of individual consumption equivalents. Output refers to output from  $t = 1$  (March 27, 2020) to  $t = 52$  (March 24, 2022), compared with the analogous 52-period output in the steady state, indexed at 100. FPUC extension in parentheses. \* denotes Pareto improvements relative to the no mitigation case.

**Common case fatality rate.** Here, I report the results for the counterfactual case in which the case fatality rate is constant across age groups. The no mitigation case is associated with a larger decline in output relative to the baseline, since young workers now also face the same fatality rate as middle-age workers. Deaths overall are lower since retirees now face a lower fatality rate. The result that mitigation policies can improve economic and public health outcomes is robust to this change. Quantitatively, however, the optimal subsidy is much lower and is not associated with a dramatic decline in deaths (22 percent compared to nearly 60 percent in the baseline). This suggests that the externality generated by differences in fatality risk in the baseline calibration is quantitatively important.

**No pandemic.** Given the relatively large, broad, and robust support of the mitigation policies, one might wonder whether such policies would be beneficial in normal times. I find that this is not the case. In fact, in the absence of a pandemic, there is no policy configuration that delivers higher output or an average welfare gain, let alone one with unanimous support.