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

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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, President Trump on May 6, 2020, asked rhetorically, “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.”[2] 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.”[3] 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 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 that restrict economic activity 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.

Using the model calibrated to the COVID-19 pandemic, I show that when governments only use stay-at-home orders (lockdowns) to mitigate the virus, saving more lives leads to reduced output, generating a tradeoff between lives and the economy. As an alternative, when the government pays individuals to stay at home (and not work) by offering stay-at-home subsidies, it is possible to save lives and increase output, relative to no mitigation policy. In fact, relative to no mitigation, a weekly subsidy of $350 can increase output by nearly 2 percent and reduce deaths by nearly 20 percent. Larger subsidies can reduce deaths by up to 50 percent without any corresponding reduction in output.

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

[3] See https://twitter.com/nygovcuomo/status/1242264009342095361?lang=en.

How can a policy that subsidizes individuals to reduce their labor supply lead to increased output? The increase is the result of two opposing effects. The first is the *direct effect*: The subsidy provides an incentive to not work (holding fixed the severity of the pandemic), which leads to less output. This effect is small for subsidies less than $500 per week because they only change the behavior of very 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, leading to better economic and health outcomes. This is possible because the labor from low-wage workers is almost exclusively "outside," implying that most of the reduction in hours contribute to mitigating the severity of the pandemic.

To quantify these effects and analyze optimal mitigation policies, 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 activities such as outside consumption and outside labor affect the spread of COVID-19, and conversely, the virus affects economic decisions. The model also features incomplete markets, endogenous labor with the option to work from home, and hospital capacity constraints.

The model has two main sources of externalities. The first is static and is generated by *currently infected* individuals who do not take into account how their economic activities may transmit the virus to susceptible individuals. The second externality is dynamic and is generated by *currently susceptible* individuals who understand how their economic activities affect their own probability of getting infected, but do not take into account how those activities could transmit the virus if they become infected. This latter externality is exacerbated by the fact that COVID-19 fatality risk varies across age groups.

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.

The first main finding is that, **in the absence of mitigation policies, private mitigation by individuals is 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 dynamic externality explained above: Young low wage–low wealth (susceptible) workers engage in too much economic activity, relative to the social optimum, leading to higher infections and deaths in the aggregate. Additionally, low-wage workers' reduction of outside consumption and hours by less than their high-wage counterparts is qualitatively consistent with the fact that higher income locations had larger declines in spending and mobility than lower income locations (Chetty et al. 2020). It is also consistent with high-income individuals reducing their outside labor more than their low-income counterparts, documented using individual-level survey data provided by Bick et al. (2020).

These externalities give rise to the possibility of welfare-improving government interventions. In the third part of the paper, I study the effects of 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 for individuals who do not work. The subsidy is fully funded by a tax on consumption. I study the optimal configuration of these policies, by varying 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 different intensities. Here, I utilize high performance computing to solve for over 40,000 transition paths, including sensitivity analyses.

The second main finding is that **the stay-at-home subsidy is superior to the stay-at-home order**. 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 can be Pareto improving. 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.

The third main finding is that **it is possible to simultaneously improve public health and economic outcomes**. 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 is also Pareto improving. Larger subsidies can reduce deaths by up to 50 percent without a corresponding reduction in output. Finally, I find that the best Pareto improving policy—which involves a weekly subsidy of $1050, a duration of 7 months, and no lockdown—reduces deaths by nearly 60 percent, while reducing output by less than 2 percent, relative to no mitigation. Note that these policies are Pareto improving even though the subsidies are fully funded with a consumption tax.

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 very large. 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), Baqaee 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. Other papers that study the trade-off between health and economic outcomes include Acemoglu et al. (2020), Assenza et al. (2020), Hall et al. (2020), and Mendoza et al. (2020).[4]

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 targeted lockdowns in a life-cycle model with heterogeneity across age, health, income, and wealth. They find that lockdowns targeted toward individuals with greater risk to COVID-19 can improve economic outcomes relative to lockdowns that are random. To my knowledge, Nakajima (2020) is the only other paper that uses a quantitative economic-epidemiological model that features heterogeneity across age, income, and wealth. Nakajima (2020) focuses on evaluating US policies, while my paper 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 heterogeneous behavior of these subgroups. 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.[5] 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 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 discusses the properties of optimal policies. Finally, section 6 concludes.

[4]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.

[5]I show that accounting for differences in fatality risk across ages is quantitatively important for the main policy implications (Appendix D).

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 a heterogeneous-agent overlapping-generations model with an economic-epidemiological model that resembles that used in Eichenbaum et al. (2020). The economy is inhabited by overlapping generations of stochastically aging individuals. Time is discrete and indexed by $t = 0, ..., \infty$. Workers face idiosyncratic 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.[6] The transition between health states builds on the widely used SIR model, originally developed by Kermack and McKendrick (1927).[7] Susceptible individuals get infected with probability π_{It}, which depends on individual outside consumption and outside labor (c_o, ℓ_o) and the aggregate measure of infected individuals (μ_{It}) and their outside consumption and outside labor (C^o_{It}, L^o_{It}).[8] Formally,

$$\pi_{It}(c_o, \ell_o; Z_t) = \beta_c c_o C^o_{It} + \beta_\ell \ell_o L^o_{It} + (\beta_e + \epsilon_t)\, \mu_{It}, \tag{1}$$

where ϵ_t captures time-varying transmissibility (e.g. seasonal factors) and $Z_t \equiv \{\mu_{It}, C^o_{It}, L^o_{It}, \epsilon_t\}$. This framework allows the virus to be contracted from consumption-related activities, labor-related activities, and from other settings. It also allows a feedback between disease progression and economic activities as in Eichenbaum et al. (2020), Glover et al. (2020), and Jones et al. (2020). Relative to these papers, however, the richer heterogeneity in this model

[6] One could easily extend the model to have shorter durations of immunity.

[7] 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).

[8] This distinction between inside and outside activities is based on whether or not there is infection risk and not based on physical location.

allows for infection probabilities to be very different across the distribution.

Infected individuals exit the infection with probability π_{Xt}, and upon exit, they recover with probability $1 - \delta_{jt}(\mu_{It})$ and die with probability $\delta_{jt}(\mu_{It})$, 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 π_{jRt}, for example, by a vaccine when it becomes available. Then the transition matrix between health states is given by

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

$$\begin{array}{c|cccc} & S & I & R & D \\ \hline S & 1 - \pi_{It}(c_0, \ell_0; Z_t) - \pi_{jRt} & \pi_{It}(c_0, \ell_0; Z_t) & \pi_{jRt} & 0 \\ I & 0 & 1 - \pi_{Xt} & \pi_{Xt}(1 - \delta_{jt}(Z_t)) & \pi_{Xt}\delta_{jt}(Z_t) \\ R & 0 & 0 & 1 & 0 \\ D & 0 & 0 & 0 & 1 \end{array} .$$

Economic block. Individuals of age $j \in J \equiv \{1, 2, .., \overline{J}\}$ face conditional aging probabilities given by $\{\psi_j\}$, with mandatory retirement at age $j = J_R$.[9] 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 Γ. Their labor income is given by $w_t \eta_{jh} \varepsilon \ell$, where w_t is the efficiency wage, η_{jh} is the health- and age-profile of efficiency units, and ℓ is total hours worked. Workers may choose to work up to a fraction $\bar{\theta}_j(\varepsilon)$ of their labor hours from home, where $\bar{\theta}_j(\varepsilon)$ is allowed to vary by age and efficiency. Retirees ($j \geq J_R$) are assumed to receive a fixed income of s each period.[10] 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.

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.

[9]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.

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

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 τ_{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 extensions of the model, I also consider taxes on labor income and smarter Pigouvian taxes that 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:

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

where β 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 $\{c_{ijt}^R(k,h), c_{ojt}^R(k,h),\ k_{jt}^{R\prime}(k,h)\}_{j \geq J_R}$ for inside and outside consumption and savings, respectively. I normalize the value of death to zero and set $v_{\bar{J}+1,t}^R = 0$. Thus, agents in the last stage of life ($j = \bar{J}$) may die due to stochastic aging (with probability ψ_j) and, if infected, because of the virus (with probability Π_{jIDt}).

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

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

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 $\{c_{ijt}(k,\varepsilon,h), c_{ojt}(k,\varepsilon,h), \ell_{ijt}(k,\varepsilon,h), \ell_{ojt}(k,\varepsilon,h), k'_{jt}(k,\varepsilon,h)\}_{j<J_R}$ for inside and outside consumption, inside and outside labor, and savings, respectively. Additionally, let $c_{ijt}(k,\varepsilon,h) = c_{ijt}^R(k,h)$, $c_{ojt}(k,\varepsilon,h) = c_{ojt}^R(k,h)$, and $k'_{jt}(k,\varepsilon,h) = k_{jt}^{R'}(k,h)$ 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

$$Y_{ft} = K_{ft}^{\alpha} L_{ft}^{1-\alpha}. \tag{5}$$

Taking prices as given, the firm solves

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

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

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

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

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 Π is the identity matrix (with no vaccine). I set aside all mitigation policies by assuming that $\tau_c = 0$ and $T = 0$ and setting $\bar{\ell}_o$ 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 σ-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 ω, 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:
   (a) $Y_f = \int_X \sum_{j\in J} \left(c_{ij}(k,\varepsilon,h) + c_{oj}(k,\varepsilon,h) + \delta k\right) d\mu_j(k,\varepsilon,h)$,
   (b) $L_f = \int_X \sum_{j<J_R} \eta_{jh}\varepsilon \left(\ell_{ij}(k,\varepsilon,h) + \ell_{oj}(k,\varepsilon,h)\right) d\mu_j(k,\varepsilon,h)$,
   (c) $K_f = \int_X \sum_{j\in J} k d\mu_j(k,\varepsilon,h)$.
4. The government budget constraint holds:
$$\tau_\ell w \int_X \sum_{j<J_R} \eta_{jh}\varepsilon \left(\ell_{ij}(k,\varepsilon,h) + \ell_{oj}(k,\varepsilon,h)\right) d\mu_j(k,\varepsilon,h) = s\int_X \sum_{j\geq J_R} d\mu_j(k,\varepsilon,h). \qquad (9)$$
5. For any subset $(\mathcal{K},\mathcal{E},\mathcal{H}) \in \mathcal{B}$, the invariant measure μ_j satisfies, for $j > 1$,
$$\begin{aligned}\mu_j(\mathcal{K},\mathcal{E},\mathcal{H}) = &\int_X \psi_{j-1}\mathbb{1}_{\left\{k'_{j-1}(k,\varepsilon,h)\in\mathcal{K}\right\}} \sum_{\varepsilon'\in\mathcal{E}}\sum_{h'\in\mathcal{H}} \Gamma_{\varepsilon\varepsilon'}\Pi_{hh'} d\mu_{j-1}(k,\varepsilon,h) \\ &+ \int_X (1-\psi_j)\mathbb{1}_{\left\{k'_j(k,\varepsilon,h)\in\mathcal{K}\right\}} \sum_{\varepsilon'\in\mathcal{E}}\sum_{h'\in\mathcal{H}} \Gamma_{\varepsilon\varepsilon'}\Pi_{hh'} d\mu_j(k,\varepsilon,h)\end{aligned} \qquad (10)$$
   and
$$\mu_1(\mathcal{K},\mathcal{E},\mathcal{H}) = \int_X (1-\psi_1)\mathbb{1}_{\left\{k'_1(k,\varepsilon,h)\in\mathcal{K}\right\}} \sum_{\varepsilon'\in\mathcal{E}}\sum_{h'\in\mathcal{H}} \Gamma_{\varepsilon\varepsilon'}\Pi_{hh'} d\mu_1(k,\varepsilon,h) + \omega(\mathcal{K},\mathcal{E},\mathcal{H}). \qquad (11)$$

6. The newborn distribution satisfies:

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

Note that I assume that inside and outside consumption and investment use the same good. Similarly, note that inside and outside labor are perfect substitutes in production. I discuss the implications of these assumptions in Section 5.

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 ψ_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.[11]

[11] 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. This issue could be addressed by increasing the number of retired cohorts so that retired individuals draw down more wealth before dying.

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

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

which exhibits constant relative risk aversion over a Cobb-Douglas aggregation of inside and outside consumption. There are two points worth discussing. 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 way to pin down γ, 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, γ 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.[12] 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:

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

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.[13] The parameter that governs the disutility from labor, φ, 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 β is chosen so that the model replicates the US net-worth-to-GDP ratio (2010–2019, *Board of Governors*). Finally, I set risk aversion, σ, to be 2, and the

[12] 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).

[13] 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.

Frisch elasticity, $1/\nu$, to be 0.5—commonly used values in the literature (for example, see Heathcote et al. 2014 and Storesletten et al. 2004 for risk aversion and Chetty et al. 2011 and Kaplan et al. 2018 for the Frisch elasticity).

Technology and income. The capital elasticity in the production function, α, is set to match the aggregate capital income share of 0.36. The labor income tax τ_ℓ and retirement income s are chosen so that retirement income is 30 percent of average labor earnings in the model and the government budget constraint is satisfied. The depreciation rate of capital, δ, is set at an annualized rate of 5 percent per year, a standard value used in the literature (for example, see Kehoe et al. 2018 and Chari et al. 2007). The stay-at-home subsidy and consumption tax are set to zero in the pre-pandemic steady state.

The age-profile of efficiency units, η_{jS}, is normalized to one for healthy young workers and healthy middle-age workers are assumed to be 35 percent more efficient, to match the wage ratio in the data (2014, *Panel Survey of Income Dynamics*). I assume that the efficiencies of recovered individuals are the same as those of susceptible individuals, $\eta_{jR} = \eta_{jS}$.[14] 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).[15] 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 ε are assumed to follow an order-one autoregressive process as follows:

$$\log \varepsilon_t = \rho_\varepsilon \log \varepsilon_{t-1} + \upsilon_t,\ \upsilon_t \sim N\left(0, \sigma_\upsilon^2\right). \tag{15}$$

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 $\sigma_\upsilon = 0.19$.[16] 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

[14]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.

[15]See Appendix A.1 for details.

[16]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, β	0.97	Wealth-to-GDP: 4.8
Risk aversion, σ	2	Heathcote et al. (2014)
Inside consumption share, γ	0.51	Expenditure share
Disutility from labor, φ	22.64	Average weekly hours: 34.4
Frisch elasticity, $1/\nu$	0.50	Chetty et al. (2011)
Death probability, annualized, ψ_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, α	0.36	Capital share
Capital depreciation, annualized, δ	0.05	Kehoe et al. (2018)
Retirement income, s	1.00	30% of average earnings per worker
Labor income tax, τ_ℓ	0.07	Government budget constraint
Persistence, annual, ρ_ε	0.94	Author estimates
Standard deviation, annual, σ_υ	0.19	Author estimates

Suen (2010).

Clinical and epidemiological parameters. The exit rate, π_X, is set to 14/18 so that the expected duration of the infection is 18 days, as in Atkeson (2020) and Eichenbaum et al. (2020). For the unconstrained case fatality rates, I use data from South Korea's Ministry of 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[17], 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

[17] 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.

of the population.[18]

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

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

where δ_j^u and δ_j^c denote the unconstrained and untreated death rates, respectively, and κ 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.[19] Since not all infected cases require hospitalization, I use a generous capacity constraint, κ, of 1 percent. The unconstrained death rates, δ_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 Piguillem 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).[20]

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.[21] By the law of large numbers, equation (1) implies that new infections in a given period are given by

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

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. By substituting $L_S/\mu_S = L_I/\mu_I$ and $C_S^o/\mu_S = C_I^o/\mu_I$, taking $\mu_S \to 1$, and setting $\epsilon_t = 0$, the basic reproduction number is given

[18] 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/.

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

[20] In Appendix D, I show that the main findings are robust to assuming that there is no capacity constraint.

[21] It is worth noting that the more recent Delta variant is more infectious than the original strain. In Appendix D, I show that the main results are robust to a higher value for the basic reproduction number.

by

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

Thus, given values for the basic reproduction number, R_0, the exit rate, π_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 β_c, β_ℓ, and β_e. Evidence on how COVID-19 is transmitted is thus far 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.[22] 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, by setting $\hat{u}_I$ so that the average infected individual suffers a 50 percent decline. In any case, the main results are not sensitive to this parameter value, 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.

[22] 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, π_X	0.78	Expected infection duration: 18 days
Unconstrained death rate,		Fatality rates in South Korea
$\delta_1^u \times 100$	0.08	
$\delta_2^u \times 100$	0.85	
$\delta_3^u \times 100$	8.47	
Untreated death rate, δ_j^c	$2\delta_j^u$	Piguillem and Shi (2020)
Hospital capacity, κ	0.01	See discussion above
Transmission parameters,		Basic reproduction number, $R_0 = 2.2$,
consumption-related, β_c	0.23	and initial transmission equally
labor-related, β_ℓ	9.46	likely through three channels
other, β_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, η_{jI}	$0.5\eta_{jS}$	See discussion above

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 ϵ_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.[23] 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 is 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 (τ_ℓ) are fixed at their pre-pandemic steady state levels.[24] 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 counterfactual mitigation policies are the focus of the next sections, here I need to specify them to closely mimic mitigation policies implemented in the United States for calibration purposes. I focus on the set of policies implemented at the

[23] 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.

[24] 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). One could also make the argument that wages did not change much during the pandemic after accounting for composition effects (for example, see Rouse and Gimbel 2021).

federal, state, and local levels 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 27, 2020, to July 27, 2020, and the $300 supplement in effect between December 26, 2020, and September 6, 2021 (Consolidated Appropriations Act and American Rescue Plan Act). 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.[25]

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 at $t = 21$ (January 1, 2021) and ends at $t = 38$ (September 9, 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, implying that the subsidy is debt-financed. 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. The duration and intensity varied substantially across locations and many areas began reopening in early May. One caveat is that the stay-at-home orders affected workers differently 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.

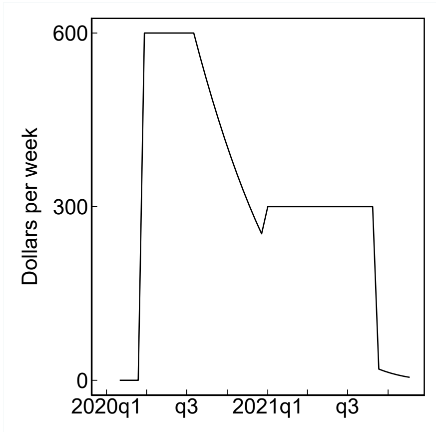
The model lockdown is implemented by restricting outside labor supply to less than $\bar{\ell}^o$

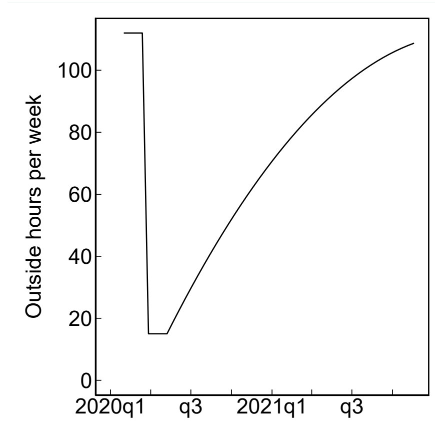
[25] To a lesser extent, the subsidy is also related to the Paycheck Protection Program (PPP), part of which was used by firms adversely impacted by the pandemic and mitigation policies to pay furloughed workers.

Figure 1: Mitigation policies

(a) Subsidy

(b) Outside hours cap





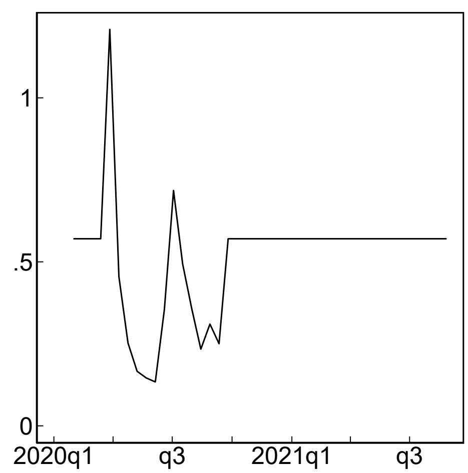
$= 0.13$, equivalent to 15 hours per week, beginning at $t = 1$ (March 27, 2020), and gradually phasing out after $t = 4$ (May 8, 2020). In equilibrium, the cap is no longer binding for any individual after September 24, 2020. Figure 1 shows the time series of both the stay-at-home subsidy and the hours 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 capturing an average effect.

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

Because the progression of the pandemic in the data is a function of activities endogenous in the model and 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 ϵ_t.[26] I then set $\epsilon_t = 0$ for $t \geq 14$ (after September 25, 2020) to examine the out-of-sample fit. Figure 2 plots the 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 ϵ_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

[26]See Appendix C.2 for details on the computation of the transition path, including how the path of ϵ_t is found.

Figure 2: Time-varying transmissibility



such as July 4, 2020.[27] I show in the next subsection that the model generates a time series of deaths that is consistent with that in the United States, even out-of-sample (after September 24, 2020).

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

[27] 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 a greater likelihood of family gatherings over the November and December holidays.

Table 3: Targeted and non-targeted moments

	Data	Model
Targeted moments		
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
Non-targeted moments		
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

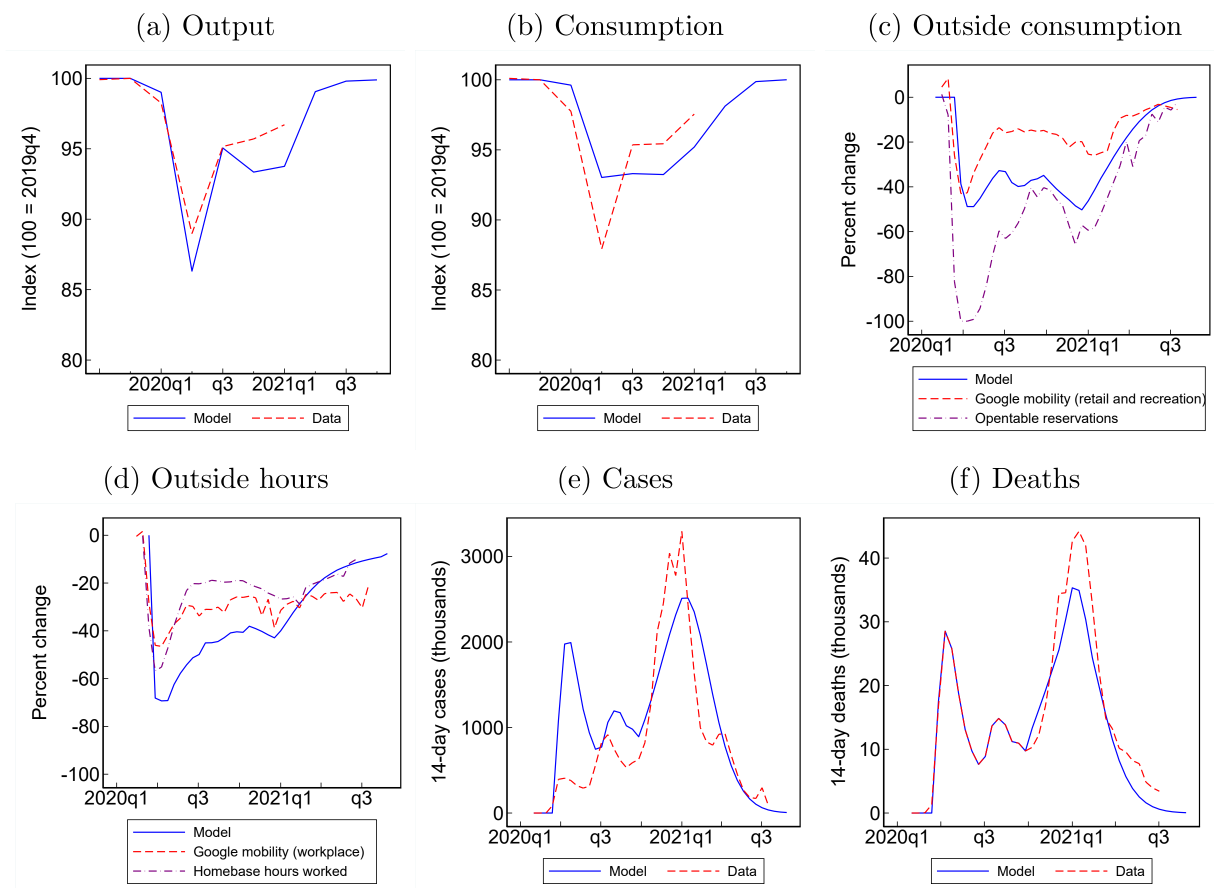
Notes: Statistics related to the disposable earnings, consumption, and wealth distribution in the data are computed on a per capita basis. See Appendix A.1 for details.

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. Another test of 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 performs reasonably 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

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.

relative to the data in the second quarter and rebounds less strongly in the third quarter.[28] Model consumption stalls in the fourth quarter and begins recovering in early 2021, as in the data. 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.

[28]One reason that model consumption declines less sharply than in the data may be that the model lockdown is implemented as a cap on outside hours, without a corresponding cap on outside consumption. In reality, business closures implied less opportunities for both outside labor and outside consumption.

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 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 (f) of Figure 3 plot the times series of cases and deaths, respectively. Recall that the time-varying transmissibility parameter ϵ_t was calibrated to fit the death series from March 27 to September 24, 2020, so it is not surprising that the within-sample time series for deaths generated by the model line up exactly with that in the data. Somewhat surprisingly, however, the model cases and deaths increased in the fourth quarter of 2020, peaking in January of 2021, as in the 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 humidity). 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.[29]

[29]Note that the model projects a monotonic decline in cases and deaths from January 2021 onward. This outlook can change for a variety of reasons, including, but not limited to, the spread of more transmissible variants such as the Delta variant, the efficacy of the vaccines against these variants, and vaccine hesitancy.

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 the heterogeneous mitigation efforts across the distribution and examine optimal policies in the next two sections.

4 Quantitative exercises

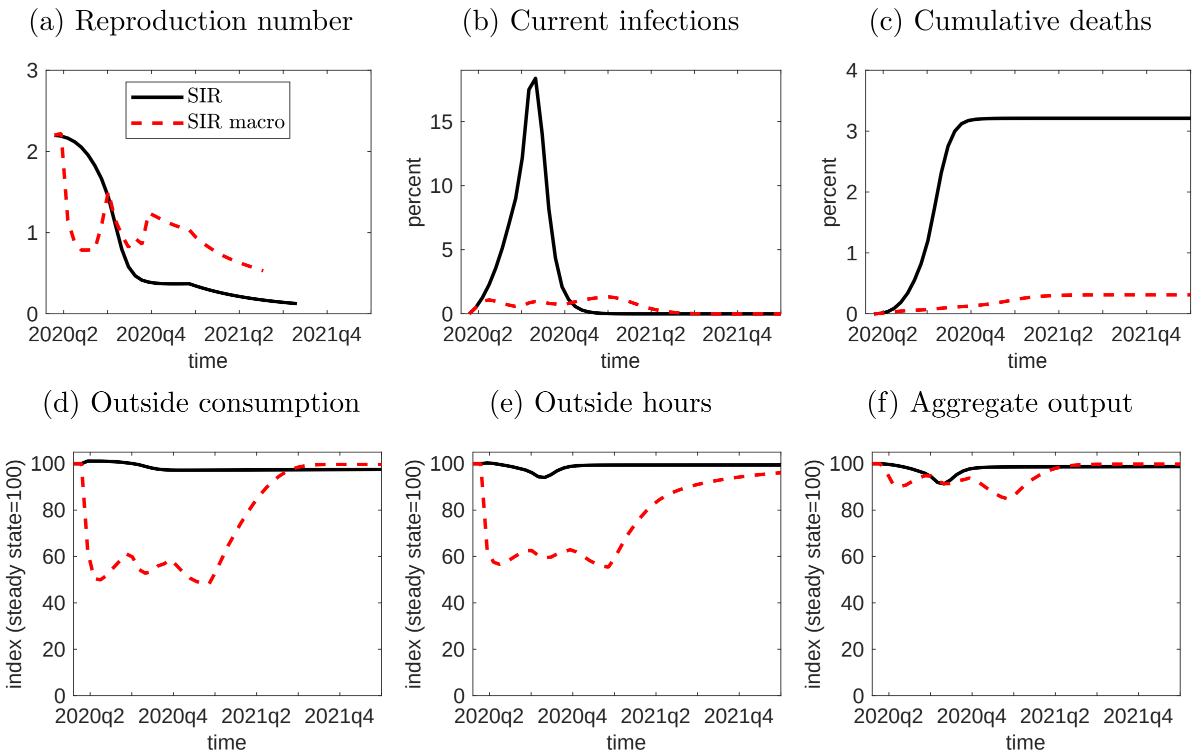
This section uses the calibrated model to investigate the properties of private mitigation and the distributional consequences of the pandemic and mitigation policies. First, I study the properties of private mitigation by contrasting the model with endogenous transmission (one in which economic interactions change the spread of the virus, as in the baseline) and no mitigation policies to an exogenous transmission model (one in which the spread of the virus only depends on the number of susceptible and infected agents), also without mitigation policies. Second, I will quantify the effects of the pandemic and the mitigation policies that resemble 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 cases, I turn off all mitigation policies, keeping unchanged all other parameters.

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 much smaller number of infections (panel b) and deaths (panel c). This is because, in response to the pandemic, individuals in the SIR Macro model reduce their outside consumption and hours significantly, leading to a large decline in

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



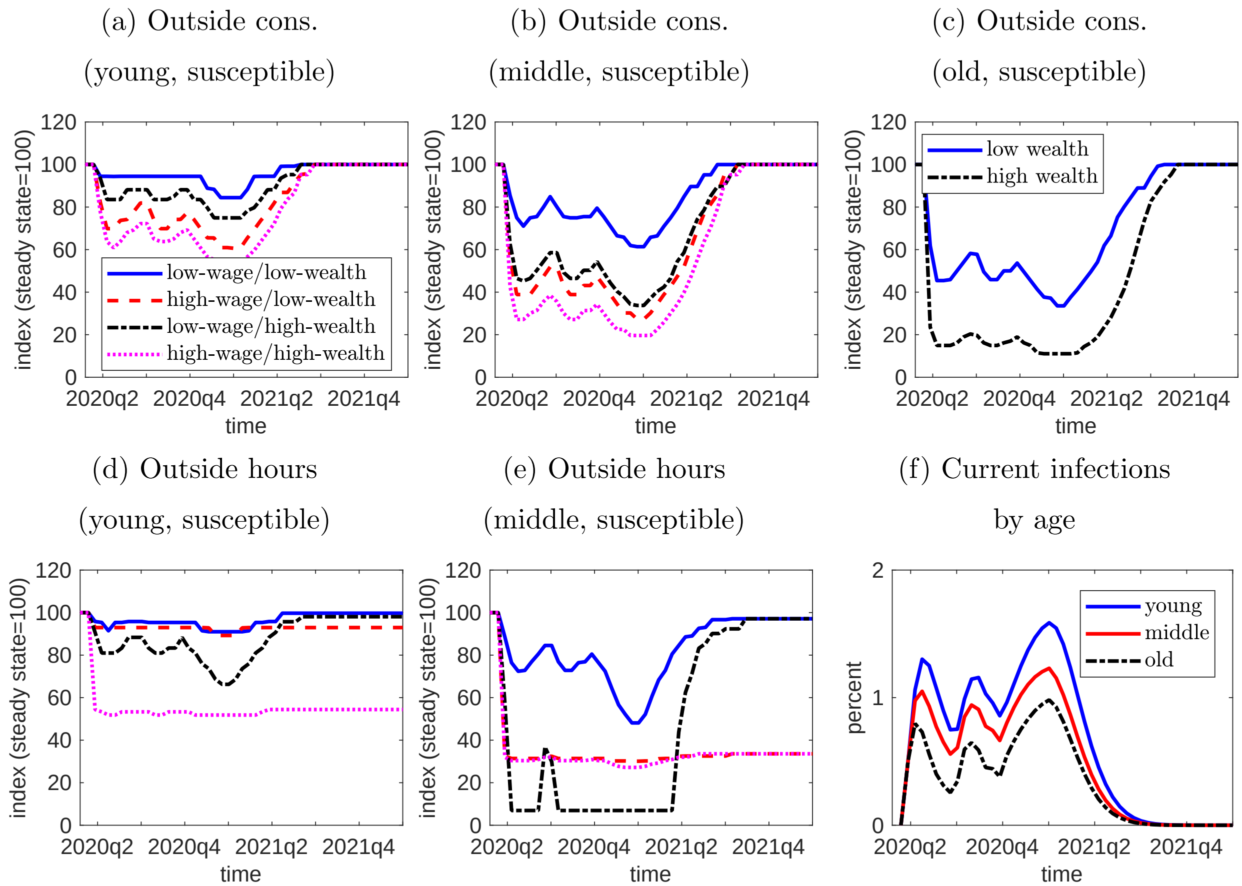
output, as can be seen in panels (d)–(f). Note that the small decline in outside hours and output in the SIR model is not due to mitigation efforts but rather to the pandemic-induced decline in healthy workers.

To study the properties of private mitigation in the baseline model, consider the policy functions for outside consumption and labor of susceptible agents across the age, income, 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). As a result, young workers experience a much larger increase in infections, as shown in panel (f).[30]

Additionally, within each age cohort, the declines in outside consumption and hours are the smallest for low-wage/low-wealth workers. The reasons are threefold. First, while high-wage workers can switch to mostly working from home, low-wage workers are unable

[30]Despite the higher infection rates, because young individuals face a lower fatality risk, they account for less than 3 percent of all COVID deaths, as in the data.

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.

to do so. Second, low-wealth workers are not able to weather prolonged time away from work. The fact that low-wage/high-wealth workers significantly reduce their outside hours during the pandemic (even in the absence of mitigation policies) suggests that the lack of precautionary savings prevents low-wage/low-wealth workers from similarly reducing their labor supply. 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.[31]

These properties are consistent with the data. Using the Real-Time Population Survey

[31] 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.

(RPS), an individual-level nationwide survey developed by Bick et al. (2020), I document that, from February 2020 to May 2020, low-income individuals reduced their outside labor (days commuted) by 36 percent, which is significantly less than the 47 percent reduced by their high-income counterparts. These properties are 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.

4.2 Welfare consequences of COVID-19 and mitigation policies

The previous subsection highlighted the externalities at work: Young susceptible workers—especially those that are low-wage and low-wealth—do not reduce their outside consumption and labor as much as their older counterparts and incur higher rates of infection. 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 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 that most closely resemble mitigation policies implemented in the US (described in Section 3.2) reduce deaths and slightly increase output, relative to no mitigation (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). This is not surprising given that the benefits of the subsidy are provided without a corresponding cost. In the next section, however, I show that Pareto improving policies are possible even when the subsidies are fully financed with a consumption tax.

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. The lockdown

Table 4: Welfare consequences of pandemic and mitigation policies

	no mitigation	US mitigation	subsidy only	lockdown only
welfare	–8.0	–6.4	–6.4	–7.9
working-age	–4.9	–3.8	–3.8	–4.9
retired	–20.4	–16.8	–17.0	–19.8
low-wage	–3.1	–2.2	–2.2	–3.3
high-wage	–6.8	–5.3	–5.4	–6.5
low-wealth	–6.0	–4.5	–4.6	–6.0
high-wealth	–10.0	–8.2	–8.2	–9.7
policy support		100.0	100.0	81.2
2-year output	95.6	95.8	96.6	94.9
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.

policy is favored by only 81.4 percent of the initial population. This is because the lockdown 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. In terms of output, the subsidy alone increases output relative to no mitigation, whereas the lockdown is contractionary. 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[32], 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—levied over the same period as the subsidy—that clears the government budget constraint in present value, making all configurations budget-neutral. All other parameters, including the time-varying transmissibility, ϵ_t, are kept the same as described in Section 3.

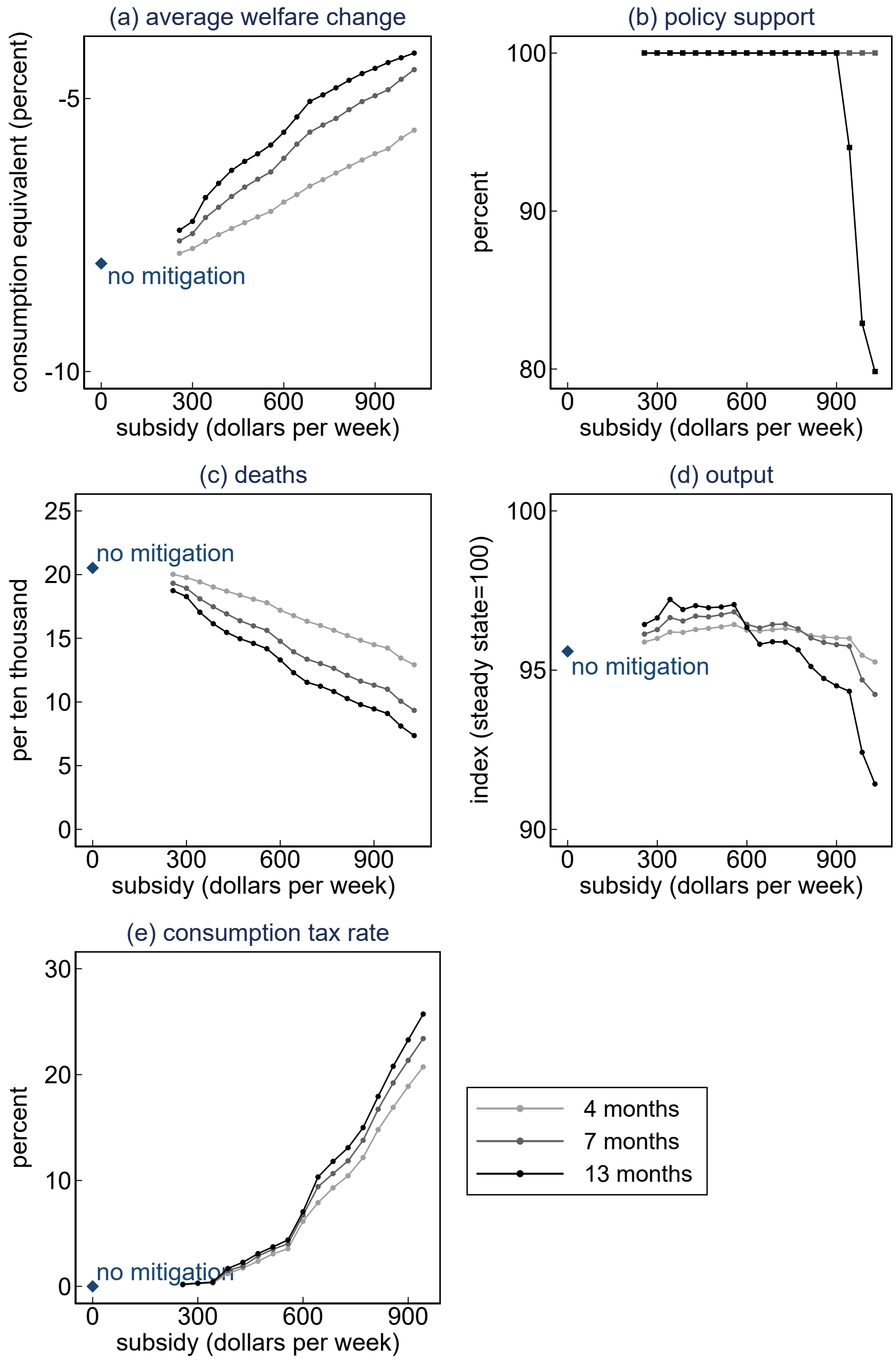
Figure 6 plots the effects of varying subsidy amounts and duration, keeping fixed the speed at which the subsidy phases out and no lockdown. Panel (a) shows that average welfare is increasing in both the subsidy amount and duration and panel (b) shows that for subsidies that are not too large or long, 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.

[32]Specifically, the subsidy amount follows

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

where $\bar{t}$ denotes the period at which the phase-out begins and $x \in \{1, 2, 4, 8\}$ determines the speed of the phase-out. The consumption tax and lockdowns, where applicable, are phased out in an analogous manner.

Figure 6: Effects of subsidy amount and duration



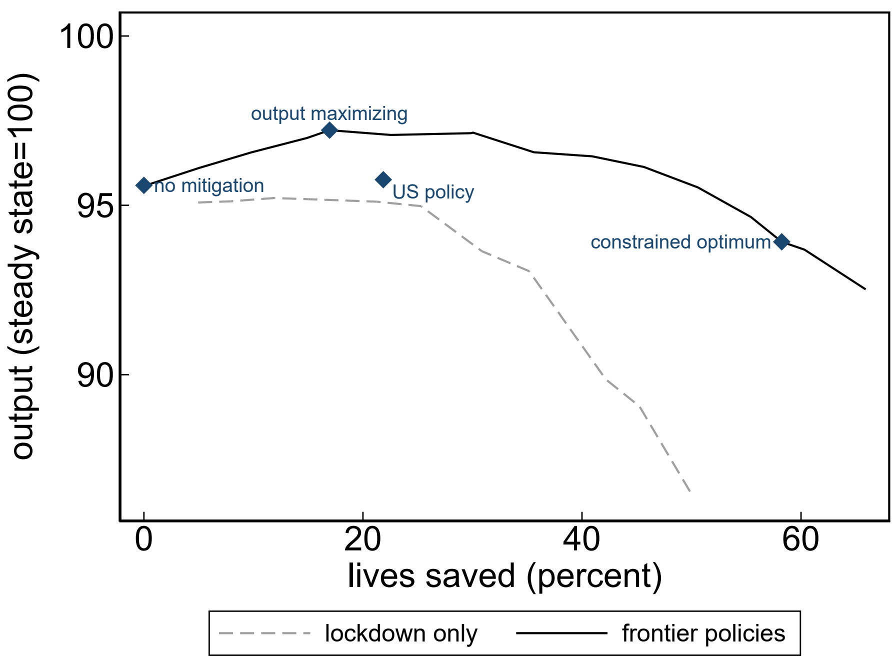
Notes: The graphs show the effects of varying subsidy amounts and duration, keeping fixed the pace at which the subsidy phases out and no lockdown. Average welfare change reports the population-weighted average of individual consumption equivalents. Policy support refers to the percent of the initial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

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 \$500 per week) induce only the very low-wage workers to reduce their hours, leading to a small decline in output. The second is the *indirect effect* of the subsidy attenuating the pandemic, thereby leading to increased labor supply. Specifically, because the labor from low-wage workers is almost exclusively "outside," most 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: A better health outcome is associated with lower output. However, we can also see that there are many policy configurations that simultaneously increase output and save more lives, relative to no mitigation. In fact, Figure 7 shows that COVID-19 deaths can be reduced by as much as 50 percent without any further reduction in output, relative to no mitigation. 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 mitigation policy as described in Section 3.2. The policy parameters of the optimal and output maximizing configurations are summarized in Table 5 (top panel).

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. In addition, a subsidy of \$350 per week for 13 months can simultaneously 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

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 with the analogous 52-period output in the steady state. Lives saved are relative to no mitigation.

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	–8.2
working-age	–4.9	–4.1	–2.3	–2.1	–5.3
retired	–20.4	–17.7	–11.8	–13.4	–19.4
low-wage	–3.1	–2.5	–0.8	–0.1	–3.9
high-wage	–6.8	–5.7	–3.9	–4.0	–6.8
low-wealth	–6.0	–5.0	–2.7	–2.2	–6.5
high-wealth	–10.0	–8.6	–5.7	–6.4	–9.8
policy support		100.0	100.0	100.0	37.8
2-year output	95.6	97.2	93.9	93.7	96.1
deaths per 10k	20.6	17.0	8.6	12.0	17.5

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.

distribution. In particular, the second and third columns reveal that the welfare gains from both the output maximizing and constrained optimal policies (derived by subtracting the first column from the second or third column) are large and widely shared. Importantly, note that these policies are Pareto improvements.

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. In Appendix D, I show that using a smarter Pigouvian tax on outside consumption is even more effective in savings lives and improving welfare.[33]

Discussion. The stay-at-home subsidy, fully funded by a consumption tax, can be Pareto improving because it addresses a key externality: Susceptible individuals understand that outside labor and consumption increases their own risk of infection, but they do not take into account the risk induced by the outside labor and consumption of their future infected selves for other susceptible individuals. As seen in Section 4.1, private mitigation is smallest for young, low-wage, and low-wealth individuals. This subsidy is particularly effective because it provides the incentive for this demographic to stay at home, attenuating the externality and consequently the severity of the pandemic.

When considering the counterfactual in which all age groups face the same case fatality risk from COVID-19, this externality is attenuated: The optimal policy prescribes a smaller weekly subsidy of $400 (compared with $1050 in the baseline), reducing deaths by only 30 percent (compared with 58 percent in the baseline), as shown in Appendix D. This suggests that accounting for age heterogeneity is quantitatively essential.

Might a similar tax-and-subsidy policy be Pareto improving in normal times? When conducting the same optimal policy search over the same limited set of instruments in the absence of a pandemic, I am unable to find any policy that is welfare improving, let alone one that is Pareto improving (see Appendix D). This suggests that the externalities generated by the COVID-19 pandemic are crucial for the possibility of allowing Pareto improving policies.

The main results of the paper are robust to alternative parameter values (see Appendix D). The results could be sensitive, however, to alternative modeling assumptions. For instance, the model assumes that both outside and inside consumption use an identical good, differentiated only in the manner in which that good is consumed (e.g. food at a restaurant versus food at home). If, alternatively, inside and outside consumption were different goods (with limited factor mobility), then changes in the relative demand for these goods would lead to relative changes in prices. Including these price dynamics would likely strengthen the need for mitigation policies, since private mitigation would be reduced as a result of an

[33] I do not consider this for the baseline, however, as implementing such a Pigouvian tax could be difficult, since the relevant margin is not the physical location of consumption but whether the activity is high-risk for transmission. For example, in-home dining can be high-risk if it includes individuals from outside of one's own household.

increase in the relative price of inside consumption goods.

The model also assumes that inside labor and outside labor are perfect substitutes as factor inputs. What if, alternatively, outside consumption goods were comparatively intensive in outside labor (e.g. restaurant dining requires onsite restaurant staff)? One concern could be that subsidizing low-wage individuals (who work almost exclusively outside) to stay at home would create labor shortages in the production of outside goods. All else equal, this would lead to an increase in the relative cost of outside labor and the relative price of outside goods, the latter of which would be desirable from a policy perspective since it would contribute to reducing the transmission of the virus (it would be akin to a Pigouvian tax on outside consumption). Thus, incorporating limited factor substitutability would also likely strengthen the need for mitigation policies.

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, Pareto improving policies can 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.

Widespread vaccines may soon put the pandemic in the rear-view mirror in the United States and other developed economies, though the advent of variants that bypass existing vaccines still looms. Thus, the policy implications raised in this paper are valuable not only for pandemics in the future, but also in the present, especially for other countries where vaccines may take longer to be widely implemented.

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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 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 (τ_ℓ) 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[34], 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.[35] 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 $\left\{\tau_{ct}, T_t, \bar{\ell}^o_t, \tau_\ell, s\right\}_{t=1}^{\infty}$, 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 ω, 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

$$Y_{ft} = K_{ft}^{\alpha} L_{ft}^{1-\alpha} \tag{20}$$

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

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

[34] 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.

[35] 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 domestic 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 equilibrium quantities would change under this alternative approach.

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

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

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

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

and

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

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, $r^\star$.

   (a) Guess r^0.

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

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

   (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 $j = \bar{J}-1, .., J^R$ 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 $j = J^R - 2, .., 1$ if $J^R > 2$.

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

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

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

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

   (i) Use Brent's method to solve for $r^\star$ 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:

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

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

2. Then, imposing optimality conditions, I define

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

where $c^* = c_i^* + c_o^*$ is the policy function for total consumption and Δ_c, Δ_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

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

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

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 μ_{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 $t = 1,..,\hat{t}$.

3. Starting at μ_{j1}, simulate forward using the policy functions to find the sequence of measures from $t = 1, ..., T$. Along the way, solve for aggregate variables in each period, including $\bar{Z}_t \equiv \{\mu_{It}, C^o_{It}, L^o_{It}, \epsilon_t\}$, where ϵ_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.

Note that, while the solution for $\{Z_t\}$ is not guaranteed to have a unique solution, I have checked that starting the routine with alternative guesses converge to the same solution.

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 (ϵ_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 output maximizing policy simultaneously improves output and reduces deaths. Moreover, both the output maximizing and the constrained optimal policies are Pareto improvements, and neither involve a lockdown, except for the case with a higher reproduction number. 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 in 2020, 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 output maximizing policy saves lives and increases output, and both the constrained optimal and output maximizing policies are Pareto improvements, and 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 similar. 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, leading to a more severe pandemic and a larger 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. The main policy implications are nearly identical to the baseline.

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).

Table 6: Sensitivity analysis

	subsidy amount ($/week)	duration (months)	lock-down	average welfare change (percent)	2-year output (index)	deaths (per 10k)
higher value of statistical life ($VSL = 6772\bar{c}$)						
constrained optimum*	1100	7	no	–4.4	94.0	8.3
output maximizing*	600	10	no	–6.1	97.1	13.6
no mitigation	0	0	no	–8.2	95.4	19.5
smaller utility loss during infection ($\hat{u} = -7.49$)						
constrained optimum*	900	11	no	–4.4	95.1	10.0
output maximizing*	350	13	no	–6.9	97.3	18.1
no mitigation	0	0	no	–8.1	95.7	21.8
smaller efficiency loss during infection ($\eta_{jI} = 0.7\eta_{jS}$)						
constrained optimum*	1100	8	no	–4.3	93.2	8.5
output maximizing*	550	11	no	–6.5	96.4	15.9
no mitigation	0	0	no	–8.6	94.4	22.3
higher disutility of not working ($\tilde{u} = 0.75$)						
constrained optimum*	1000	11	no	–4.4	95.1	9.3
output maximizing*	400	13	no	–6.8	97.1	16.8
no mitigation	0	0	no	–8.0	95.6	20.6
higher basic reproduction number ($R_0 = 2.5$)						
constrained optimum*	1100	11	yes	–6.4	90.8	13.4
output maximizing*	550	9	no	–9.9	95.3	26.9
no mitigation	0	0	no	–12.2	92.1	35.2
higher inside consumption ($\gamma = 0.61$)						
constrained optimum*	950	10	no	–3.8	95.3	8.1
output maximizing*	350	13	no	–5.7	97.7	14.2
no mitigation	0	0	no	–6.9	96.2	17.5

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.

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.

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.

Subsidy funded by tax on labor income. Here, I use a labor income tax to fund the stay-at-home subsidy. The outcome from the output maximizing policy is almost identical to the baseline, because the taxes need to finance the subsidy are minuscule. The main difference is that the optimal subsidy is quite a bit lower (\$550 versus \$1050 in the baseline), reducing deaths to only 13.7 (per 10 thousand), compared to 8.6 in the baseline.

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

Table 7: Sensitivity analysis (2)

	subsidy amount ($/week)	duration (months)	lock-down	average welfare change (percent)	2-year output (index)	deaths (per 10k)
no hospital capacity constraint ($\kappa = 1$)						
constrained optimum*	1100	6	no	–4.3	94.1	8.8
output maximizing*	350	13	no	–6.7	97.3	16.8
no mitigation	0	0	no	–7.8	95.7	19.7
subsidy funded by tax on outside consumption						
constrained optimum*	1000	8	no	–2.8	94.3	4.4
output maximizing*	550	11	no	–5.5	97.3	13.1
no mitigation	0	0	no	–8.0	95.6	20.6
subsidy funded by tax on labor income						
constrained optimum*	550	13	no	–5.7	95.0	13.7
output maximizing*	350	13	no	–6.8	97.1	17.0
no mitigation	0	0	no	–8.0	95.6	20.6
common case fatality rate ($\delta^u = 0.0085$)						
constrained optimum*	400	9	yes	–4.1	94.4	6.1
output maximizing*	400	9	no	–4.3	96.4	6.8
no mitigation	0	0	no	–5.4	94.3	8.7
no pandemic						
constrained optimum	0	0	no	0.0	100.0	0.0
output maximizing	0	0	no	0.0	100.0	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.

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 (30 percent compared to nearly 60 percent in the baseline). This suggests that the externality generated by age 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.