I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13265

An Economic Model of the COVID-19 Epidemic: The Importance of Testing and Age-Specific Policies

Luiz Brotherhood
Philipp Kircher
Cezar Santos
Michèle Tertilt

MAY 2020

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13265

An Economic Model of the COVID-19 Epidemic: The Importance of Testing and Age-Specific Policies

Luiz Brotherhood
Universitat de Barcelona

Philipp Kircher
EUI and IZA

Cezar Santos
Banco de Portugal, FGV EPGE and CEPR

Michèle Tertilt
Universitat Mannheim and IZA

MAY 2020

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

An Economic Model of the COVID-19 Epidemic: The Importance of Testing and Age-Specific Policies*

This paper investigates the role of testing and age-composition in the Covid-19 epidemic. We augment a standard SIR epidemiological model with individual choices regarding how much time to spend working and consuming outside the house, both of which increase the risk of transmission. Individuals who have flu symptoms are unsure whether they caught Covid-19 or simply a common cold. Testing reduces the time of uncertainty. Individuals are heterogeneous with respect to age. Younger people are less likely to die, exacerbating their willingness to take risks and to impose externalities on the old. We explore heterogeneous policy responses in terms of testing, confinements, and selective mixing by age group.

JEL Classification: E17, C63, D62, I10, I18

Keywords: COVID-19, testing, social distancing, age-specific policies

Corresponding author:
Philipp Kircher
EUI
Villa la Fonte
Via della Fontanelle
50014 San Dominco
Florence
Italy

E-mail: philipp.kircher@eui.eu

* This is a preliminary version of an evolving project—feedback highly appreciated. Financial support from the German Science Foundation (through CRC-TR-224 (project A3) and the Gottfried Wilhelm Leibniz-Prize), the European Research Council (through ERC grant 818859), the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior—Brasil (CAPES)—Finance Code 001 and Faperj is gratefully acknowledged. We thank Michele Belot for many insights and suggestions, and Suzanne Bellue and Jan Sun for excellent research assistance. The views expressed in this article are those of the authors and do not necessarily represent those of Banco de Portugal or the Eurosystem.

1 Introduction

In the ongoing Covid-19 epidemic three features seem striking. First, countries that have dealt more successfully with the crisis seem to undertake massive testing programs. Second, Covid deaths are more concentrated among older individuals, who have much lower chance of surviving Covid-related hospitalization. Third, even when faced with the same laws requiring social distancing, young individuals seem to distance themselves less.[1] That suggests that individuals have some form of choice in the face of existing regulation, and the need to earn a living and the lower health consequences can induce young individuals to take more risks. The risks that young people take might spill over onto the old: negatively through increased transmission but maybe positively by reaching the point of herd immunity more quickly. Even some form of altruism and quarantining does not prevent the negatives if individuals do not know their status, giving importance to testing.

In this paper we aim to account for these elements in a calibrated economic model of the epidemic that features *age heterogeneity* and *individual choice* regarding risky labor and leisure activities. Initial symptoms leave individuals and the government with *incomplete information* whether they have Covid or not, rendering testing valuable. We study the equilibrium interaction between age groups, and we analyze policies such as *confinement*, *testing*, *quarantining*, and *limited mixing* to curb the spread of the disease and its costs. We also explore to which extent age-specific policies are promising.

As a note of caution: despite an older theorical literature on the economics of infectious diseases - reviewed below - we are only aware of a small pre-existing literature that calibrates individual prevention efforts in epidemiological contexts to build on (Greenwood et al 2019, 2017, 2013 consider responses to policies in the HIV/AIDS epidemic; Chan, Hamilton, and Papageorge (2016) structurally estimate responses to value medical innovations in that context; Keppo et al. (2020) have a long-standing agenda to study this in the context of the Swine Flu

[1] Examples like parties among college students in the 2020 "spring break" in the US abound. See, e.g., NBC News, March, 19. 2020 "Coronavirus comes for spring break: Local officials close Florida beaches after governor refuses to".

and, now, Covid-19). While age heterogeneity, selective mixing between groups and incomplete information were present already in these early papers, the current epidemic differs in many dimensions from the HIV/AIDS context including modes of transmission and disease progression. Therefore, it is still a research program in an early stage, and the implications of this work as well as those of the recent literature on Covid reviewed below need further validation. We discuss limitations and important extensions in more details in the conclusion.

Underlying our quantitative assessment is a basic SIR epidemiological model into which we embed behavioral choices and age heterogeneity, as well as some imperfect information about infection status. Individuals in the model will be either healthy, have a fever (which could be due to Covid-19 or the common cold/flu), or known to be infected. Of those known to be infected, some will develop serious symptoms, others recover and some will eventually die. We add testing to the model, which reveals to those in the fever state whether they are infected with Covid-19 or not. The economic side and behavioral choices are modeled as follows. Individuals derive utility from consuming three types of goods: regular consumption, a composite leisure good and leisure at home. Correspondingly, individuals choose to allocate their time between working (outside the home), social activities (outside), leisure inside the home, and teleworking. The infection risk increases with time outside the house (both work and leisure time), so that the higher the infection risk is, the more people will voluntarily reduce their work and outside leisure hours. Yet, there is a cost in that teleworking is assumed less productive than regular work. Similarly, leisure at home (such as reading a book or resting) is no perfect substitute for leisure outside the house (such as bars, fitness center), so we account for them separately and capture the financial costs in the latter through a composite good involving time and money.

Covid-19 spreads in the model through human contact. Infection risk is thus a function of one's own time outside the house and the time that others with Covid-19 infection spend outside their houses. The model features two age groups – the young and the old. The difference is two-fold: (i) the young are less likely to develop serious symptoms and die from Covid-19 than the old and (ii) only the young can work, while the old get a fixed retirement income. Thus, the old naturally spend less time outside the house, even when the Covid-19 infection

risk is zero.

The model clearly features a negative externality that has been pointed out in the theoretical literature on the economics of infectious diseases (see, e.g., Kremer (1996), Quercioli and Smith (2006), Toxvaerd (2019), Toxvaerd (2020)): spending more time outside increases not only one's own risk (which people will rationally take into account when choosing their time allocation), but it also increases the risk down the road that they will infect others. This cost on society is not taken into account when people make decisions about their leisure and work time allocation. This externality is made worse by the information problem and the age heterogeneity in death rates. At a given point in time, the low health consequences of the young lead them to take less precautions in terms of "social distancing," which increases the exposure for the old. Partial altruism and government quarantine measures increases social distancing for the infected, but those with a fever in the early stages of the disease attribute the fever most likely to other causes unless they are tested.

The underlying epidemiological model also features a hidden "positive" externality in the presence of heterogeneous agents that has been largely absent from the theoretical literature on the economics of infectious diseases: The disease dies out once enough people are infected, i.e., once herd immunity is reached. When the young engage in more risky behavior, they reduce the time until herd immunity is reached. The young then take a larger share in the infections needed for herd immunity, which is amplified if the old can shield themselves for short periods by voluntarily engaging in stronger social distancing.

Our calibrated benchmark indicates that the positive externality is indeed present in the absence of a vaccine/cure. This can limit and sometimes negate the effects policies such as temporary shelter-at-home policies. It also indicates that its strength is limited, as it is quickly overpowered through other channels, for example in extensions with scarce hospital beds which the risk-taking young exhaust through their behavior. The interactions by age indicate that it is an important margin to consider, that the effects are not trivial, and that age-specific policies might be warranted.

We use the model to analyze potential government policies – both in terms of

their effectiveness to reduce Covid-19 but also in terms of their effect on GDP and welfare. We report both total deaths and deaths within the first year; the latter is important if one believes that a vaccine might be developed in this time frame. Note that these three outcomes do not always move in the same direction. GDP does not take "saved lives" into account, while simply counting "deaths" ignores the economic costs. Welfare captures yet another effect beyond GDP and lives saved through the shift of leisure time from outside to inside, which is not a perfect substitute.

The main policies of interest are the following, ordered by the fraction of the economy that is affected by the policies: (i) quarantines for those confirmed to be infected, (ii) stay-at-home orders for everyone. These might differ by age. Another important margin that interacts with the above is testing. In the extreme case in which everyone is perfectly tested, (i) dominates (ii) as it targets the real cases and avoids negative economic costs on the others. Testing can have positive effects even in the absence of further quarantines because of the partial altruism of the population. On the other extreme, if no tests are available, then (i) becomes infeasible and (ii) is a natural point for disease prevention, but at the same time the economic costs apply to everyone and are therefore much higher. These costs can be reduced if one can restrict the policies to particular age groups, such as only the old or the young.

Qualitatively, the economy with behavioral adjustment features roughly half of the deaths compared to a model where individuals do not adjust their behavior. The old in particular refrain from public life during the peak of the epidemic. We find that the recklessness of the young actually reduces overall transmission onto the old as they bear the burden of the disease before herd immunity is reached. But if hospital beds are scarce, they block scarce recovery options for the old, and their recklessness increases deaths for the old and overall. In terms of policies, continual large-scale testing reduces deaths, especially when coupled with some quarantines for those found to be infected. Testing the young is key for this. Also, shelter-at-home policies that constrain only the old for at least half a year reduce aggregate deaths by avoiding spill-overs onto them before the disease dies out (though these policies also reduce the welfare of the old). General shelter-at-home policies for everyone or only for the young have very little effect on overall

death rates if shorter than half a year – it only delays the deaths. Those that are severe and last 26 or 35 weeks reduce death significantly in the first year, which might be helpful if a cure/vaccine should be available at that point. But in the longer run without such relief, shelter at home for everyone or the young has very little effect on deaths. And mild versions of this policy can backfire and increase deaths by restricting mainly the young, delaying herd immunity and thereby exposing more of the old. These insights carry over to a scenario where hospital beds are scarce, except that now shorter shelter-at-home policies of 8 to 12 weeks are already effective in curbing deaths within the first year, though again no shelter-at home policies curb them in the long run without availability of cure/vaccine. Another difference is that backfiring no longer occurs for the policies we study as restricting the young now additionally frees hospital beds. Finally, we analyze selective mixing in which the outside activities of the two age groups is partially separated. This decreases the overall death toll, but has differential effects on the two groups: deaths among the old decrease whereas the number among the young rises.

This paper is organized as follows. The next section discusses the related literature. Section 3 describes the model environment and Section 4 discusses the calibration of its parameters. Section 5 discusses our baseline results. Section 6 provides results for policy experiments under the baseline parameters and Section 7 discusses alternative scenarios. Section 8 offers some concluding remarks.

2 Literature Review

This paper contributes to the literature that combines epidemiological models with equilibrium behavioral choice. Theory work on this has long pointed out the negative externality of too little prevention by self-interested agents that do not internalize the costs of transmission to others; see, e.g., Kremer (1996) for SI models, Quercioli and Smith (2006) for SIR models, and more recently Toxvaerd (2019) or Toxvaerd (2020). This literature has mostly abstracted from externalities between heterogeneous groups, though Kremer (1996) shows that an increased engagement of people who have a higher proclivity for prevention can

lead to disappearance of a disease (in the context of HIV/AIDS) by suppressing the aggregate reproductive number among active people.[2] This depends on their transmission function where more engagements by low activity people reduces infection rates for others. This is not present in our transmission function for Covid, where more activity by others always increases the infection rate. While our model has differences in prevention (as the old do not work), the main driver for the positive externality mentioned earlier is the difference in death rates.

Among the early quantitative economic models of disease transmission, Greenwood et al. (2019) develop a heterogeneous-agent choice-theoretic equilibrium model for the HIV/AIDS epidemic and use it to analyze different mitigation policies. Within this framework, Greenwood et al. (2017) explore particular channels of selective mixing by relationship type, while Greenwood et al. (2013) allow for incomplete information in infection status. In these works, the behavioral response of agents is crucial for the results of different policies. Chan, Hamilton, and Papageorge (2016) argue in a structurally estimated model that behavioral adjustments quantitatively matter for the valuation of medical innovations. Keppo et al. (2020)'s agenda expands Quercioli and Smith (2006) to a calibrated homogeneous-agent epidemiological model and argues that a substantial behavioral elasticity is necessary to match the Swine Flu and, now, the Covid-19 epidemic.

In the great influx of recent economics papers studying different aspects of the Covid-19 epidemic some papers look for optimal containment policies that trade off economic well-being of living individuals versus lost lives. Alvarez, Argente, and Lippi (2020) solve an optimal control problem to find the optimal containment policy in the presence of the Covid-19. Unlike our model, there is no behavioral response in their analysis. Eichenbaum, Rebelo, and Trabandt (2020a) solve computationally for the optimal containment policy in a model that does feature agents' optimization. Garobaldi, Moen, and Pissarides (2020) characterize theoretically the discrete-time equilibrium and planning problem with a more general matching function, and show in a calibration that the equilibrium attains the low-

[2]See also Galeotti and Rogers (2012) who consider two identical populations but with non-random mixing patterns, and shows that government immunization efforts depend on the mixing pattern. Galeotti and Rogers (2015) consider protection efforts in a network model where individuals differ with respect to their degree.

est level of herd immunity. Farboodi, Jarosch, and Shimer (2020) and McAdams (2020) provide the theoretical differential equations in continuous time, and the former calibrates an immediate, mild and long-lasting policy. Unlike our work, these models so far feature homogeneous agents and no age heterogeneity, and agents either have perfect information or no information whether they are currently infected.[3] This reduces the control variable of the policy maker to a single one, but omits considerations of across-group externalities and improvements through testing, which are qualitatively and quantitatively important in our analysis. The sheer number of policy variables in our model (how much to test, to shelter-at-home for the healthy, to quarantine if infected, for the young or old) as well as the fact that some costs are outside the model (e.g., the cost of extending testing capacity) complicates the search for the optimal policy. This version of the paper therefore aims to inform about the effects of stylized representations of the most common intervention policies; the optimal time-variant mix remains to be computed.

Some recent papers also take into account the potential uncertainty about one's infection status and the role for testing, e.g. Berger, Herkenhoff, and Mongey (2020). von Thadden (2020) explicitly introduces asymptomatic infections, leading to a role for testing. Piguillem and Shi (2020) solve an optimal control problem to find the best testing policy in an SIR model without behavior. Eichenbaum, Rebelo, and Trabandt (2020b) account also for behavioral adjustments like in our paper, though in their setting infected individuals become more reckless if tested which makes testing optimal only when combined with quarantines. Neither paper considers individuals with different ages (and, consequently, different risk groups). In our model individual optimization makes the infected more cautious if tested (because of partial altruism), the others less cautious because the environment gets safer, and these reactions are heterogeneous by age and shape the response to testing.

Our paper features a key heterogeneity across individuals: different ages and, hence, different risk groups. Other papers have also explored heterogeneity

[3]This also holds for Kapicka and Rupert (2020) who model the interaction between the pandemic and individual choices through a labor search model. Farboodi, Jarosch, and Shimer (2020) have heterogeneity in death risk as an extension to be done.

across different dimensions. Kaplan, Moll, and Violante (2020) focus on the different effects of the epidemic across agents that are heterogeneous regarding their occupation and their asset holdings. They do not model different age groups as we do. Glover et al. (2020) have different age groups in their model and they solve for the optimal containment policy within a parametric class and compare them to the age-preferred policy. Acemoglu et al. (2020) consider the unrestricted optimal lock-down policy, include a more general transmission function, and allow the planner differential lock-down of tested individuals. Favero, Ichino, and Rustichini (2020) allow for rich age and sector specific transmissions and analyze the effect of stylized policies to end the lockdown in Italy. Gollier (2020) discusses which age group should carry the population to herd immunity, but does not consider whether individuals incentives are sufficient to bring the economy to the optimal solution or whether the old actually prefer to be sheltered more. This is a general point: these papers assume that the transition matrix under a given policy is constant and do not consider individual behavior, i.e., to which extent people individually try to avoid getting infected and how much they dislike confinement, while our model predicts a strong decline in transmission to the elderly as they protect themselves especially during the peak and further confinement of just the old tends to lower their welfare. Except for Acemoglu et al. (2020) these papers do not consider uncertainty about the infection status nor testing.

Fernández-Villaverde and Jones (2020) analyze possible reopening scenarios in a SIRD model of many countries and cities. While there are no explicit economic choices, behavioral adjustments are captured through an exogenous contact function which changes over time as the disease spreads.

On a more empirical side Kuhn and Bayer (2020) propose the differences in the interaction between old and young as a possible explanation for the cross-country differences in death rates across countries. Reducing the spread through separation of old and young, e.g., through different times for shopping, has also been part of the current debate.[4] We take up this idea about selective mixing as part

[4]Different shopping times feature in many countries - for the UK see for example the article "These are the supermarket opening times for the elderly: when Tesco, Aldi, Sainsbury's and more are open just for over-70s during lockdown" in the Edinburgh Evening News, April 23rd 2020, https://www.edinburghnews.scotsman.com/lifestyle/shopping/these-are-supermarket-

of the policy analysis where we plan to analyze the effects of separating the old and the young more - see Section 7.3.

Finally, even though we analyze the impact of the epidemic and different policies on output, we do not focus on macroeconomic stabilization policies. This is the focus of some recent papers, such as Faria-e Castro (2020) and Guerrieri et al. (2020) for example.

3 Model

The general setup of our model is in discrete time. The economy is populated by a continuum of ex-ante identical agents of two types: young y and old o, so that age $a \in \{y, o\}$. Agents work, enjoy leisure outside the home and home hours. In the presence of the coronavirus, denote the agent's status by j. A healthy agent is denoted by $j = h$. By spending time outside the house, the agent may catch a disease, which may be Covid-19 or a common cold. Both lead to mild "fever" symptoms. These agents can be tested for coronavirus with probability $\xi_p(a)$, where the subscript denotes that this is a "policy" choice of the government, which could be time-dependent. With complementary probability they are not tested and are therefore unsure about the source of their symptoms. Call this fever state $j = f$. A tested individual knows for sure whether they are infected by Covid-19. For simplicity, we also assume that infected individuals get to know their status after one period of uncertainty in case they are not tested. If the agent knows he has Covid-19, denote this by $j = i$. Conditional on being infected, they can develop more serious symptoms associated with Covid-19, a status denoted by $j = s$. This happens with probability $\alpha(a)$. If the agent develops symptoms, he can die with probability $\delta_t(a)$, on top of the natural death probability $\overline{\delta}(a)$ in the absence of the epidemic.[5] The Covid death rate is time-dependent because the death rate for individuals who obtain a bed in an intensive care unit ($\tilde{\delta}_1(a)$)

opening-times-elderly-when-tesco-aldi-sainsburys-and-more-are-open-just-over-70s-during-lockdown-2502462.

[5]We do not add a birth process to the model as this is unlikely to be important over the time-frame of the epidemic. The death rate is mainly included to account for differences in effective discount factors between the young and the old.

is lower than the death rate for those who do not ($\tilde{\delta}_2(a)$), and intensive care bed shortages depend on the state of the epidemic. The agent can recover from the disease with probability $\phi(j = s, a)$. If the agent recovers, he becomes immune (or resistant) to future infections, a status denoted by $j = r$. Thus, $j \in \{h, f, i, s, r\}$.[6] Agents discount the future at a common factor $\tilde{\beta}$, but since the natural survival probability $\Delta(a) = 1 - \overline{\delta}(a)$ is age-specific, their effective discount factor is $\beta(a) = \tilde{\beta}\Delta(a)$.

For production and leisure each agent is endowed with one unit of time per period. This can be divided into work hours n, teleworking hours ν, leisure outside the house ℓ and hours at home (in your "dwelling") d. The agent time constraint is thus given by:

$$n + \nu + \ell + d = 1 \tag{1}$$

The agent enjoys utility from consumption c, a composite leisure good when it leaves home g, and hours spent at home d. The good g is produced using hours ℓ and buying "intermediate" goods x according to $g = g(x, \ell)$. We normalize the utility after death to zero and capture the bliss from being alive through parameter b. The utility function is given by:

$$\begin{aligned} u(c, g, d, \nu; j, a, p) &= \ln c + \gamma \ln g + \lambda_d \ln(d) + b \\ &\quad + [\lambda(j) + \lambda_p(j, a)] \ln(d + \nu). \end{aligned}$$

The term $\lambda(j)$ expresses an additional preference for staying at home when being infected, and is a crude way of capturing altruism. We assume two levels: $\lambda(s) = \lambda(i) = \lambda_a$ and $\lambda(r) = \lambda(h) = 0$, so that individuals who transmit the virus are altruistic and the others have no need for that. Individuals in the fever state are unsure whether the are infected or not, and $\lambda(f)$ is a weighted average of these two levels, with weights equal to their belief of being infected with Covid. We suppress the dependence on the belief for notational convenience. $\lambda_p(j, a)$ has a similar role, but from the point of view of the government. This captures simple policies that confine everyone to staying at home ($\lambda_p(j, a) = \bar{\lambda}_p$) but can also capture age-dependent confinements ($\lambda_p(j, a) = \bar{\lambda}_p(a)$) and could even condition

[6] Variables with an underscore "p" are policy instruments that can be used by the government. With a slight abuse of notation, let p_t denote the set of policies the government undertakes at period t.

on infection status.

Each unit of time that the agent spends working outside the home is paid the wage $w(a, j, n)$. The hourly wage for teleworking is $\tau w(a, j, n)$, where $\tau < 1$. This is given by:

$$w(a, j, n, \nu) = \begin{cases} w(j)(n + \tau\nu) & \text{if } a = y \\ \overline{w} & \text{if } a = o \end{cases}$$

The budget constraint of the agent is thus given by:

$$c + x = w(a, j, n, \nu) \tag{2}$$

Infections happen to healthy people ($j = h$) when they leave their house. The longer they spend outside, the riskier it gets. Per hour outside the house, the transmission risk $\Pi_t(a)$ is time-varying and depends on the number of infected people and how much time these people spend outside, as discussed later. So the probability of getting infected this period is

$$\pi(n + \ell, \Pi_t(a)) = (n + \ell)\Pi_t(a).$$

Now, an agent might also catch a common cold, which happens with probability

$$\pi^*(n + \ell) = (n + \ell)\Pi^*.$$

The probability that the agents catches either disease is

$$\pi_f(n + \ell, \Pi_t(a)) = \pi(n + \ell, \Pi_t(a)) + \pi^*(n + \ell),$$

which implicitly assumes that these are mutually exclusive events.[7] If this happens and the agent is not tested (probability $1 - \xi_p(a)$), the agent is in the fever state $j = f$ for one period in which he cannot distinguish between the common cold and Covid-19. He assigns probability $\Pi_t(a)/(\Pi_t(a) + \Pi^*)$ to having Covid-19. If he is tested (probability $\xi_p(a)$), he will know the immediately whether he is

[7]This is a good approximation when the probability of either event is sufficiently small, in which the chance of getting both becomes negligible.

infected ($j = i$) or not ($j = h$). Otherwise he will learn at the end of the period whether the fever symptoms were due to coronavirus or not.

The value functions for healthy agents that are susceptible to future infections is given by:

$$\begin{aligned} V_t(h,a) = \max_{c,x,n,\nu,\ell,d} & u(c, g(x,\ell), d, \nu; h, a, p_t) + \\ & \beta(a)[1 - \pi_f(n+\ell, \Pi_t(a)) + \pi^*(n+\ell, \Pi_t(a))\xi_{p_t}(a)]V_{t+1}(h,a) + \\ & \beta(a)\xi_{p_t}(a)\pi(n+\ell, \Pi_t(a))V_{t+1}(i,a) + \\ & \beta(a)(1-\xi_{p_t}(a))\pi_f(n+\ell, \Pi_t(a))V_{t+1}(f,a) \\ & \text{s.t. (1) and (2).} \end{aligned} \tag{3}$$

The first line captures the utility from consumption and leisure. If the agent has no fever or has fever but is tested and healthy, he continues into the next period as a healthy person, captured in the second line. The third line captures the continuation for a feverish person who gets tested and had been infected, and the fourth line the symptoms for someone with in the fever state (with fever symptoms and no test).

The value function for an agent who knows that he is infected with coronavirus but has not developed severe symptoms is given by:

$$\begin{aligned} V_t(i,a) = \max_{c,x,n,\nu,\ell,d} & u(c, g(x,\ell), d, \nu; i, a, p_t) + \beta(a)\phi(0,a)V_{t+1}(r,a) + \\ & \beta(a)(1-\phi(0,a))\alpha(a)V_{t+1}(s,a) \\ & \beta(a)(1-\phi(0,a))(1-\alpha(a))V_{t+1}(i,a) \\ & \text{s.t. (1) and (2).} \end{aligned} \tag{4}$$

The last term in the first line captures the case in which the agent recovers from the disease and becomes resistant to the virus. The second line gives the value for the case in which the agent does not recover and develops symptoms. The third line is the case in which the agent does not recover and does not develop severe symptoms and, thus, remains infected.

To define the value for an agent in the fever state, it is convenient to denote by

$\tilde{V}_t(c, x, n, \nu, \ell, d; h, a)$ the term within the max operator on the right hand side of (3), and by $\tilde{V}_t(c, x, n, \nu, \ell, d; i, a)$ the corresponding term in (4). They represent the continuation value conditional on choices made this period, both for the healthy and the infected. Those in the fever state simply get the weighted average of these continuation values, weighted by their belief of being infected with Covid:

$$V_t(f, a) = \max_{c,x,n,\nu,\ell,d} \frac{\Pi^* \, \tilde{V}_t(c, x, n, \nu, \ell, d; h, a)}{\Pi_{t-1}(a) + \Pi^*} + \frac{\Pi_{t-1}(a) \, \tilde{V}_t(c, x, n, \nu, \ell, d; i, a)}{\Pi_{t-1}(a) + \Pi^*} \quad (5)$$
$$\text{s.t. (1) and (2).}$$

For individuals with severe symptoms we set the flow utility equal to that of death (i.e., to zero) to account for the harsh nature of the disease at this stage and the induced coma during ventilator treatment. Obviously they can recover and enjoy the utility of normal life again if they recover. These agents provide no labor ($n = \nu = 0$) but we assign an exogenous level of outside time ($\ell = \bar{\ell}_s$) to account for the infection burden that they impose onto their carers. The value function for a person with symptoms is:

$$V_t(s, a) = \beta(a) \left[\phi(1, a) V_{t+1}(r, a) + (1 - \phi(1, a))(1 - \delta_t(a)) V_{t+1}(s, a)\right] \quad (6)$$
$$\text{s.t. (1) and (2).}$$

The expression captures the case of recovery as well as the chance of remaining with severe symptoms, and the continuation value after dying is set permanently to zero.

Finally, an agent who has already recovered and is resistant to the virus enjoys utility:

$$V_t(r, a) = \max_{c,x,n,\nu,\ell,h} u(c, g(x, \ell), d, \nu; r, a, p_t) + \beta(a) V_{t+1}(r, a) \quad (7)$$
$$\text{s.t. (1) and (2).}$$

To define the laws of motion, denote the measure of agents of each type j of age a in period t by $M_t(j, a)$. Let $\mathcal{M}_t$ be the set of these for all j and a. Further, let $n_t(j, a)$ and $\ell_t(j, a)$ denote their times spend outside the house in equilibrium, and $\nu_t(j, a)$

their time teleworking. Let $\mathcal{N}_t$ be the set of these equilibrium time allocations in period t for all j and a. The law of motion is a mapping from the state vector and equilibrium actions and the infection rates in period t into the number of agents of each type $\mathcal{M}_{t+1}$ in the next period. Call this map T, so that

$$\mathcal{M}_{t+1} = T(\mathcal{M}_t, \mathcal{N}_t, \Pi_t(o), \Pi_t(y)). \tag{8}$$

It simplifies the accounting to introduce two separate sub-states of the fever state: $j = f_h$ for those with fever who are healthy (called fever-healthy) and $j = f_i$ for those who are infected (called fever-infected). Agents do not know their sub-state, obviously, and therefore act identically in both states. We continue to denote by state $j = f$ all agents who have a fever, which encompasses those in f_i and f_h.

As an example of the laws of motion for this economy, consider the number of healthy agents next period, which is given by

$$\begin{aligned} &M_{t+1}(h,a) \qquad (9)\\ &= M_t(h,a)\Delta(a)\left[1-\pi_f(n_t(h,a)+\ell_t(h,a),\Pi_t(a))+\pi^*(n_t(h,a)+\ell_t(h,a),\Pi_t(a))\xi_{p_t}(a)\right]\\ &+ M_t(f_h,a)\Delta(a)\left[1-\pi_f(n_t(f,a)+\ell_t(f,a),\Pi_t(a))+\pi^*(n_t(f,a)+\ell_t(f,a),\Pi_t(a))\xi_{p_t}(a)\right] \end{aligned}$$

where the second line captures all situations in which healthy individuals from last period remain alive and healthy, as explained in connection to value function (3). The third line resembles the second except that it uses the time allocations of those in the fever state. It accounts for those who entered the period fever-healthy and continue to remain healthy during this period. The right hand side of (9) gives the map T_h for the healthy agents. Appendix A provides the analogous laws of motions T_j for agents in the other states $j = f_h, f_i, f, i, s, r$, and for completeness also for Covid deaths and new infections. The aggregate mapping T is then the vector of the T_j for all states j and ages a.

Aggregation: output, infectiousness, and death: Aggregate output in the economy in a given period is given by the time individuals spend at work (physically or

teleworking) in equilibrium multiplied by their wage rate:

$$Q_t = \sum_j w(j)[n_t(j,y) + \tau\nu_t(j,y)]M_t(j,y). \tag{10}$$

For many of the exercises we add these weekly output measures to get overall GDP measures for the full time period (e.g. year).

To calculate the aggregate probability of getting infected per fraction of the period spent outside, observe that the number of infected people times their average time spent outside the house times an exogenous susceptible-infected transmission rate Π_0 yields a rate of infection of:

$$\hat{\Pi}_t(a) = \Pi_0 \sum_{\tilde{a},j\in\{f_i,i,s\}} \left(n_t(j,\tilde{a}) + \ell_t(j,\tilde{a})\right) M_t(j,\tilde{a}) \tag{11}$$

which we assume to be age-independent in light of no evidence to the contrary. This can be rationalized by assuming a unit amount of common space in which agents are distributed uniformly, so that within each subunit of space an individual encounters the number of infected people represented by the sum in (11), and each transmits the virus at the exogenous rate. Expression (11) then corresponds to the probability of getting infected when this number is close to zero, which happens if either the time-weighted number of infected people or the exogenous transmission rate is low. A low number of infected people happens in particular early in an epidemic. To match the initial reproductive number, calibrations tend to keep Π_0 high, which can push (11) to exceed unity once infection levels peak. This arises because (11) does not take into account the probability of getting infected multiple times within a period, which is irrelevant if this rate is low but becomes important at the peak. Shortening the period length is counterproductive in our setting as this would also reduce the length of uncertainty of fever individuals in our model.

Therefore we explicitly account for multiple infections within a period in a way that keeps belief updating simple but keeps our infection probabilities in line with other epidemiological models. Assume that the time outside the house represents the probability of entering a common space where one can get infected, and with the complementary probability the person is outside but in a safe space,

but the individual does not know which space he is in. If in the common space, interpret (11) as a rate of encountering infections as in continuous time epidemiological models. Conditional on being in common space, one can integrate to a (weekly) unit of time the probability of having at least one encounter that leads to infection:

$$\Pi_t(a) = 1 - e^{-\hat{\Pi}_t(a)}. \tag{12}$$

When $\hat{\Pi}_t(a)$ is small, this reduces approximately to $\Pi_t(a) \approx \hat{\Pi}_t(a)$. This is constructed under the standard random mixing assumption where everyone meets everyone else with equal probability. In the policy analysis we study government interventions that separate parts of the outside activities by age group, leading to selective mixing and age-specific infection risk.

The probability that an agent with serious symptoms ($j = s$) dies of Covid-19, $\delta_t(a)$, can vary over time. This may happen as the recovery probability depends on the supply of hospital resources (e.g. ICU beds) versus the demand for treatment (number of patients with serious symptoms). Let Z denote the total number of hospital beds and $M_t(s)$ the total number of agents with serious symptoms in period t. Recall that $\tilde{\delta}_1(a)$ denotes the probability of dying if one is allocated a hospital bed and $\tilde{\delta}_2(a)$ if not. Assume hospital beds are allocated randomly to patients. Hence, the probability of dying $\delta_t(a)$ is given by:

$$\delta_t(a) = \tilde{\delta}_1(a) \min\left\{\frac{Z}{M_t(s)}, 1\right\} + \tilde{\delta}_2(a) \max\left\{\frac{M_t(s) - Z}{M_t(s)}, 0\right\}. \tag{13}$$

A rational-expectations equilibrium in this economy with initial number of agents $M_0(j, a)$ consists of a sequence of infection and death rates $\{\Pi_t(a), \delta_t(a)\}_{t=0}^{\infty}$ and equilibrium time allocations $\{n_t(j, a), \ell_t(j, a), \nu_t(j, a)\}_{t=0}^{\infty}$ such that these time allocations are part of the solutions to the individual optimization problems (3) to (7), and the resulting law of motion (8) and their aggregation in (12) and (13) indeed give rise to the sequence $\{\Pi_t(a), \delta_t(a)\}_{t=0}^{\infty}$.

4 Calibration

This section describes how we discipline the parameters of the model. Let the time period be one week. Regarding demographics, suppose the old people (who do not work in the model) are those above 65 years old. According to the US Census Bureau, this fraction is 0.16.[8]

We start with the calibration of health-related parameters. Start with the common cold. According to Heikkinen and Järvinen (2003), the average American has between two and four colds every year (children have between six and eight). Suppose an agent in our model has an average of three colds per year. This implies a weekly infection rate of 0.058.[9] In the model, this implies $\Pi^* = 0.107$.

The parameter Π_0 controls how infectious COVID-19 is. We pick Π_0 in order to match the basic reproduction number (R_0) of Covid-19. R_0 represents the average number of new infections that a random person who gets infected at the outstart of the epidemic is expected to generate over the course of his disease. In our model, this is closely related to Π_0.[10] We thus pick this parameter to generate an R_0 of 2.5. This falls within the range of values that Atkeson (2020) uses. Zhang et al. (2020) estimates a value of 2.28 and Remuzzi and Remuzzi (2020) reports values between 2.76 and 3.25. The corresponding parameter value is then $\Pi_0 = 11.56$.

Once the agent is infected with the coronavirus ($j = i$), there is a probability of recovering from the disease ($\phi(0, a)$), and if not recovered, a probability for developing symptoms ($\alpha(a)$). Set $\alpha(a) = 1$ such that an infected agent spends one week with mild symptoms and recovers (probability $\phi(0, a)$) or develops more serious symptoms (probability $1 - \phi(0, a)$). These numbers are close to those reported by Lauer et al. (2020) and Backer, Klinkenberg, and Wallinga (2020) and the WHO.[11] The parameter $\phi(0, a)$ will then control the fraction of agents that recover from mild symptoms or need to move to an ICU. CDC (2020) reports age-specific hospitalization (including ICU) rates for Covid-19 patients. A fraction

[8] See the 2018 Population Estimates by the US Census Bureau (PEPAGESEX).
[9] For details, see Appendix B.2
[10] For details, see Appendix B.3.
[11] See the Report of the WHO-China Joint Mission on Coronavirus Disease 2019 (COVID-19).

of 3.33% of patients aged 20-64 required being moved to an ICU, whereas this number was 9.1% for those above 65 years. This yields an average of 4.56%, a number similar to the one reported by Wu and McGoogan (2020) for Chinese data. Given the potential for under-reporting of cases, we use half these numbers and set $\phi(0, y) = 0.983$ and $\phi(0, o) = 0.954$.

We treat agents with serious symptoms as those that are in an Intensive Care Unit (ICU). As discussed above, we assume they cannot work and do not make any decisions. We impute a flow utility level of 0, i.e. the same as death. These individuals still interact with others (e.g. doctors and nurses) for a fraction $\bar{\ell}_s$ of their time. Butler et al. (2018) estimate that patients in ICUs spend about 7.6 hours a day interacting with other people. As these patients are under carefully controlled environments, we assume their infectiousness is half as much as others. Thus, set $\bar{\ell}_s = (7.6/24)/2 = 0.158$.

Agents with serious symptoms ($j = s$) may die (probability $\delta(a)$) or recover ($\phi(1, a)$). Verity et al. (2020) reports that patients with severe symptoms were discharged after an average of 24.7 days, or 3.52 weeks. This yields $\phi(1, a) = 1/3.52 = 0.284$. CDC (2020) also reports age-specific death rates conditional on being hospitalized in the ICU: 14.2% for those aged 20-64 and 65% for those above 65 years old. Given our time period of one week and the recovery rate, this yields weekly death rates of $\delta(y) = 0.065$ and $\delta(o) = 0.738$.

For older agents, Arias and Xu (2019) report an annual survival rate for individuals above 65 years old of 0.95. Thus, set the weekly survival rate for old agents to $\Delta(o) = 0.95^{1/52} = 0.999$. For younger agents, set $\Delta(y) = 1$.

All of the parameters regarding infections and health discussed above are summarized in Table 1.

Now turn to the preference parameters. Let the leisure goods g be produced according to $g(x, \ell) = [\theta x^\rho + (1 - \theta) l^\rho]^{1/\rho}$. The parameter ρ controls the elasticity of substitution between leisure time outside the home and leisure goods. Set $\rho = -2$, which implies an elasticity of $1/3$ so that goods x and leisure time ℓ are complements. The parameters γ (utility weight of leisure goods g), λ_d (utility weight of leisure time at home) and θ are jointly chosen to match the following

Table 1: Calibration – Disease Parameters

Parameter	Value	Interpretation
	0.16	Fraction of old in Population
Π^*	0.107	Weekly infectiousness of common cold/flu
Π_0	11.56	Infectiousness of Covid-19
α	1	Prob(serious symptoms — no recovery from mild)
$\phi(0, y)$	0.983	Prob of recovering from mild Covid-19, young
$\phi(0, o)$	0.954	Prob of recovering from mild Covid-19, old
$\phi(1, y)$	0.284	Prob of recovering from serious Covid-19, young
$\phi(1, o)$	0.284	Prob of recovering from serious Covid-19, old
$\bar{\ell}$	0.158	Infections through the health care system
$\delta(y)$	0.065	Weekly death rate (among critically ill), young
$\delta(o)$	0.738	Weekly death rate (among critically ill), old
$\Delta(y)$	1	Weekly survival (natural causes), young
$\Delta(o)$	0.999	Weekly survival (natural causes), old

Table 2: Calibration – Economic & Preference Parameters

Parameter	Value	Interpretation
ρ	-2	Elasticity of subst. bw leisure time and goods
θ	0.024	Production of leisure goods
γ	0.636	Rel. utility weight - leisure goods
λ_d	1.56	Rel. utility weight - leisure at home
$\lambda(i)$	1.13	Rel. utility weight - leisure at home (infected)
b	7.5	Value of being alive
$\tilde{\beta}$	$0.96^{1/52}$	Discount factor
w	1	Wage per unit of time
$\overline{w}$	0.214	Retirement income
τ	0	Productivity of telework

Table 3: Moments – Model vs. Data

Moment	Model	Data (ranges)
Common colds per year	3	2-4
R_0, Covid-19	2.5	1.6-4
% of infected in critical care, young	1.66	3.33 (over-reporting?)
% of infected in critical care, old	4.55	9.10 (over-reporting?)
% in critical care that dies, young	14.2	5-24
% in critical care that dies, old	65.0	40-73
Weeks in critical care, young	3.5	3-6
Weeks in critical care, old	3.5	3-6
Hours/day interacting while in ICU	3.8	7.6 (controlled)
Life expectancy (natural), young	∞	79
Life expectancy (natural), old	20	20
Hours of work per week	40	
Hours of outside activities per week	17.3	17.3
% of income on goods outside	12.5	11.1-16.1
% $\uparrow$ in time @ home - outset of Covid-19	5.3	10% (Sweden)
% $\uparrow$ in time @ home - mild symptoms	26	26 (Influenza)
Replacement rate - social security, %	60	46-64

three data targets: i) a 40-hour work week ($n = 40/112 = 0.357$),[12] ii) 17.3 hours spent on non-working outside activities ($\ell = 17.3/112 = .154$),[13] and iii) a fraction of income spent on x equal to 12.5% ($x/wn = .125$).[14] Set the discount factor to $\tilde{\beta} = 0.96^{1/52}$.

The parameter $\lambda(i)$ denotes the increase in the marginal utility of staying at home for agents that are infected with Covid. This parameter is related the extra amount of time an individual spends at home *without any influence from the government*. In order to identify this parameter, we turn to how agents behave when they contract influenza. Akazawa, Sindelar, and Paltiel (2003) report that the av-

[12]See McGrattan and Rogerson (2004).

[13]This comprises the average hours per week spent on purchasing goods and services; caring for and helping nonhousehold members; organizational, civic, and religious activities; socializing and communicating; arts and entertainment (other than sports); sports, exercise and recreation; and travel related to leisure and sports. The data for the American Time Use Survey (ATUS) is available at https://www.bls.gov/tus/a1-2018.pdf

[14]This comprises expenditures on food away from home, public transportation, medical services and entertainment. The fraction used comes from Table 1300 the 2018 Consumer Expenditure Survey (CEX).

erage American worker takes 1.3 days of sick leave when infected with influenza. Given a 40-hour work week, this implies an average of 10.4 hours. We assume that the same would happen with Covid.[15] As the disease lasts an average of one week (absent development of serious symptoms), this implies a decline in 26% of work time. Assume that leisure outside declines by the same amount. We then choose $\lambda(i)$ to match an increase in time spent at home by 26%.

In the model, the parameter b represents the value of being alive over and above the value of consumption. This influences how "afraid" agents are of dying. In order to discipline this parameter, we look at how agents changed their behavior at the outset of the epidemic. The issue is that, in most places, this coincides with active policies by the government. In order to isolate this, we use Google mobility data to compare the cases of Sweden and Norway.[16] While Norway implemented several restrictions to movement, Sweden did not. We thus choose a value for b in order to generate the rise in time spent at home in the beginning of the epidemic similar to that observed in Sweden, which was about 10%.

Normalize the hourly wage to $w = 1$. According to Biggs and Springstead (2008), the replacement rate for social security benefits for a median-income household ranges between 46% and 64%. Set the replacement rate in the model to 60%, a value towards the upper bound of the range since households may have savings outside the official social security income. This implies $\overline{w} = .6wn = .6 \times .357 = .214$.

For now, assume that there is no teleworking, i.e. $\tau = 0$. Moreover, for our benchmark set $Z = 1$, such that there are enough ICU beds to treat everyone (but see Section 7.2 for the analysis of bed constraints). All of the parameters regarding preferences and technology are reported in Table 2.

Table 3 summarizes how the model fits the data targets.

[15]The time at home with influenza reflects both a concern not to infect others as well as the inability to work due to one's own sickness. We use the same number though we apply it to early stages where the own sickness might be less. This is likely to be offset by a stronger concern for others due to the severity of the Covid-19 disease. That is why we apply it to people that know they have the disease, and only proportionally to those who are unsure.

[16]For details, see Appendix B.1

Table 4: Non-Targeted Moments – Model vs. Data

Moment	Model	Data (ranges)
Case fatality rate	0.35	0.5-13
Daily growth of infections, outset of Covid-19, %	15	15-50
Deaths, old/all, %	34	≈80

Table 5: Deaths – Old vs. Young

Week	1	2	3	4	5	6	7	8
Deaths, old/all, %	85.44	75.18	69.38	66.73	65.51	64.66	63.48	61.16

5 Baseline Results

Our baseline is an economy with COVID-19 but no policy interventions. We begin with a word of caution. Data on many relevant dimensions of the model is still scarce and, even if they exist, wide ranges are reported. We know especially little about the true case fatality rate because it is unclear what fraction of the population is already infected. We thus did not use some important dimensions as calibration targets. Accordingly, all quantitative results should be interpreted with caution. To give the reader a sense what our model implies along these important dimensions, we start by reporting moments from our baseline model that were not directly targeted and compare to empirical estimates, where available. See Table 4. We expect more and better data to become available over the coming months.

Estimates of case fatality rates very immensely, ranging from 0.56 in Iceland to 13.48 in Italy as of April 27, 2020.[17] We are clearly on the low side here. However, as more antibody tests become available, it may well turn out that many more people were already infected than is currently believed, which will bring the case fatality rate down substantially.

Second, the daily growth rate at the outset of the epidemic in the model is 15%. In the data, these numbers vary greatly. Countries like Australia report an initial daily growth rate of 15%; whereas the counterpart for Spain is around 30%. In

[17] See the University of Oxford's ourworldindata.org website.

Table 6: Benchmark Results

	Benchmark	Epidem.	Age ext. partial	Age ext. general
Wks to peak srsly ill (yng)	15.00	15.00	15.00	16.00
Wks to peak srsly ill (old)	14.00	14.00	14.00	14.00
Srsly ill p/ 1,000 @ peak (yng)	3.22	6.56	1.43	1.18
Srsly ill p/ 1,000 @ peak (old)	0.46	5.32	0.46	0.38
Dead p/ 1,000 1year (yng)	1.56	2.02	1.01	1.16
Dead p/ 1,000 1year (old)	4.18	14.79	4.18	5.06
Dead p/ 1,000 1year (all)	1.98	4.06	1.52	1.78
Dead p/ 1,000 LR (yng)	1.58	2.02	1.04	1.39
Dead p/ 1,000 LR (old)	4.41	14.79	4.40	6.65
Dead p/ 1,000 LR (all)	2.03	4.06	1.58	2.23
Immune in LR (yng), %	66.98	85.29	44.18	58.85
Immune in LR (old), %	12.69	42.21	12.67	19.40
Immune in LR (all), %	58.29	78.39	39.13	52.53
GDP at peak - rel to BM	1.00	1.24	0.44	0.83
GDP 1year - rel to BM	1.00	1.03	0.86	0.89
Cost p/ life saved, million $	0.00	1.03	18.48	35.21
Hrs @ home (yng) - peak	68.56	54.77	97.34	75.48
Hrs @ home (old) - peak	108.43	89.26	108.43	103.39
Hrs @ home (yng) - 6m	57.27	54.77	67.38	69.13
Hrs @ home (old) - 6m	97.45	89.26	97.45	99.51
Value - healthy (yng)	5029.40	5027.40	2196.50	2193.00
Value - healthy (old)	2377.90	2358.40	2377.90	2374.20
Value - healthy (all)	4604.60	4599.80	2225.60	2222.00

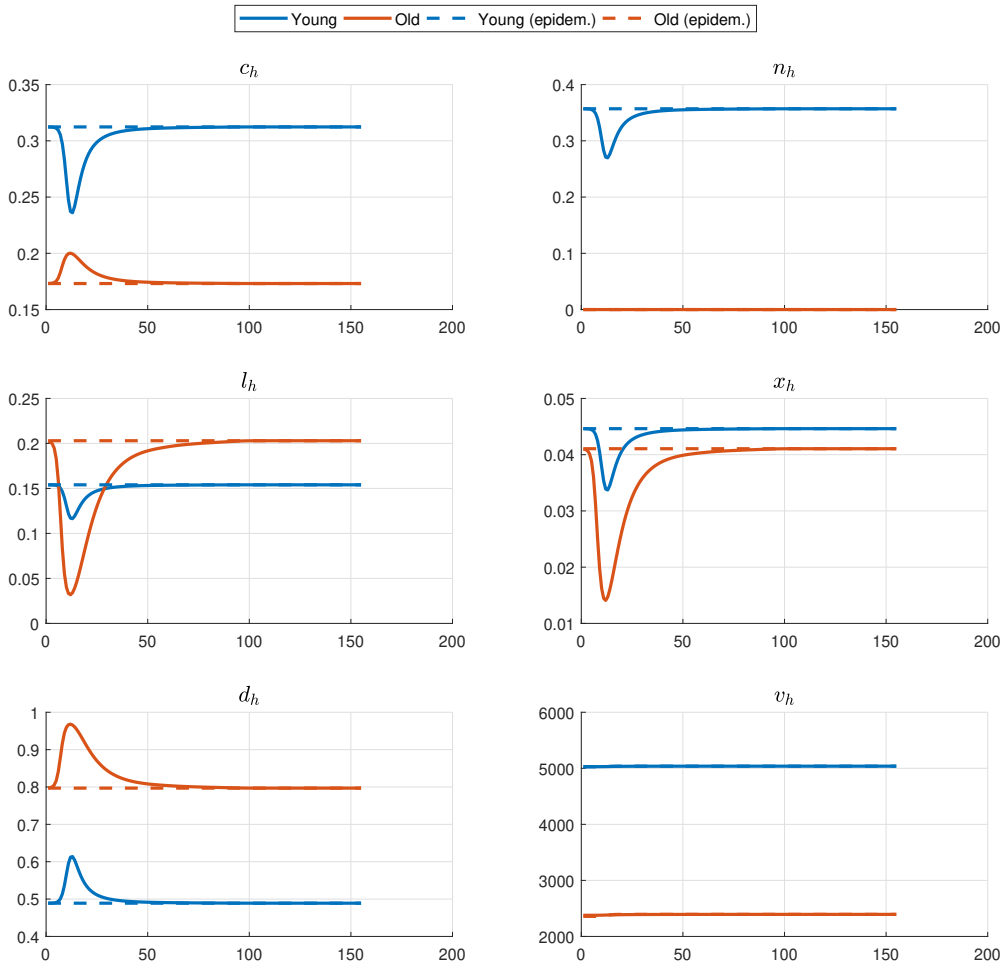
countries like Italy and Norway, it reached 50%.[18] Note that, though our model generates a number in the lower range, in reality, the initial rise in the data was probably partly due to a ramp-up in testing as well.

Third, in the benchmark only 34% of all deaths are accounted for by those over 65. Some of the available empirical estimates put this number much higher, as high as 80%.[19] Note that the 34% comes from the entire duration of the epidemic; in our calibration, after almost three years. Table 5 reports the fraction of overall deaths accounted for by old agents for the first weeks of the epidemic in the model. Note that in the first two weeks, more than three quarters of deaths are of old individuals. After eight weeks, still more than 60% of deaths come from this group. Only as time goes by and the disease develops, more young people die and it increases their relative death rate. We will explore more dramatic age differences in mortality in Section 7.1.

Table 6 reports our baseline results. Again, this concerns the economy with

[18] Again, see the University of Oxford's ourworldindata.org website.
[19] https://www.cdc.gov/nchs/nvss/vsrr/covid19/index.htm

Figure 1: Choices of healthy agents (Benchmark equilibrium)



Covid-19 but no policy intervention (Column Benchmark). Note that it takes about 15 weeks for an unchecked epidemic to reach its peak in terms of seriously ill patients.[20] The death count is substantial: 2.03 deaths per 1,000 people. This number masks considerable age heterogeneity: the death rate is 4.41 per 1,000 old individual and 1.58 for the young. Note that most of these deaths happen within the first year of the epidemic, related to the quickness with which it reaches its peak. In the long run, about 58% of the population becomes immune to the disease; i.e. were infected at some point and recovered.

We compare the benchmark results to an epidemiological version of the model,

[20] In Section 7.2, we evaluate the impact imposed on medical resources by having such a high fraction of the population in need of care at the same time.

which assumes there is no change in behavior compared to a world without the disease (Column Epidem. in Table 6). We find that people adjust their behavior quite a bit, i.e. the individual risk of dying leads people to increase their time at home substantially (see lower left panel in Figure 1). This happens especially for the old, who do not need to work but are also more likely to die if they get infected. The young cut both time at work and leisure outside (again, see Figure 1). This reduces the overall number of infected people in the long run by about 20%. The total death rate declines by half, but markedly more so among the old (see the middle lower panel in Figure 2). The timing of the disease does not change much (weeks to peak are identical in a purely epidemiological model), but the peak is much lower (see lower right panel in Figure 2). The economic costs of this self-preservation is sizeable: GDP for the first year of the epidemic is reduced by 3% (see Figure 3 for the time path of GDP). At the peak of the disease GDP would be 24% higher in an economy without behavioral adjustments. In other words, compared to the no-disease economy, voluntary reductions in activity reduce GDP substantially at the peak of the disease.[21]

As seen above, the time paths for the disease experienced by the young and the old are markedly different. Moreover, the young have more incentives to leave their house because of work. They can then contribute more to the spread of the disease; and the burden will fall more heavily on the old. In order to get a sense of this externality, we run two counterfactuals. Suppose the preferences of the young feature the same death and symptoms probabilities as those of the old (keeping the actual transition rates at their true levels). That is, the young, who still need to work for their income, believe they are subject to the same risks as the old. One counterfactual (second to last column in Table 6) runs such scenario in a partial equilibrium sense: we observe the difference in behavior of the young assuming they cannot affect the aggregate infection rates. The other counterfactual performs the same thought experiment in general equilibrium (last column in Table 6). In partial equilibrium, the young become substantially more careful and considerably increase their hours at home. This lowers the infections among

[21] Although a decline of 3% appears small compared to an estimate provided by Hall, Jones, and Klenow (2020). Using a similar mortality rate and a simple utilitarian welfare function, they estimate people's willingness to pay to avoid COVID-19 deaths to be 18% of annual consumption. This is an order of magnitude similar to what we find in some of our shelter-at-home experiments discussed in the next section.

Figure 2: Distribution of agents (Benchmark equilibrium)

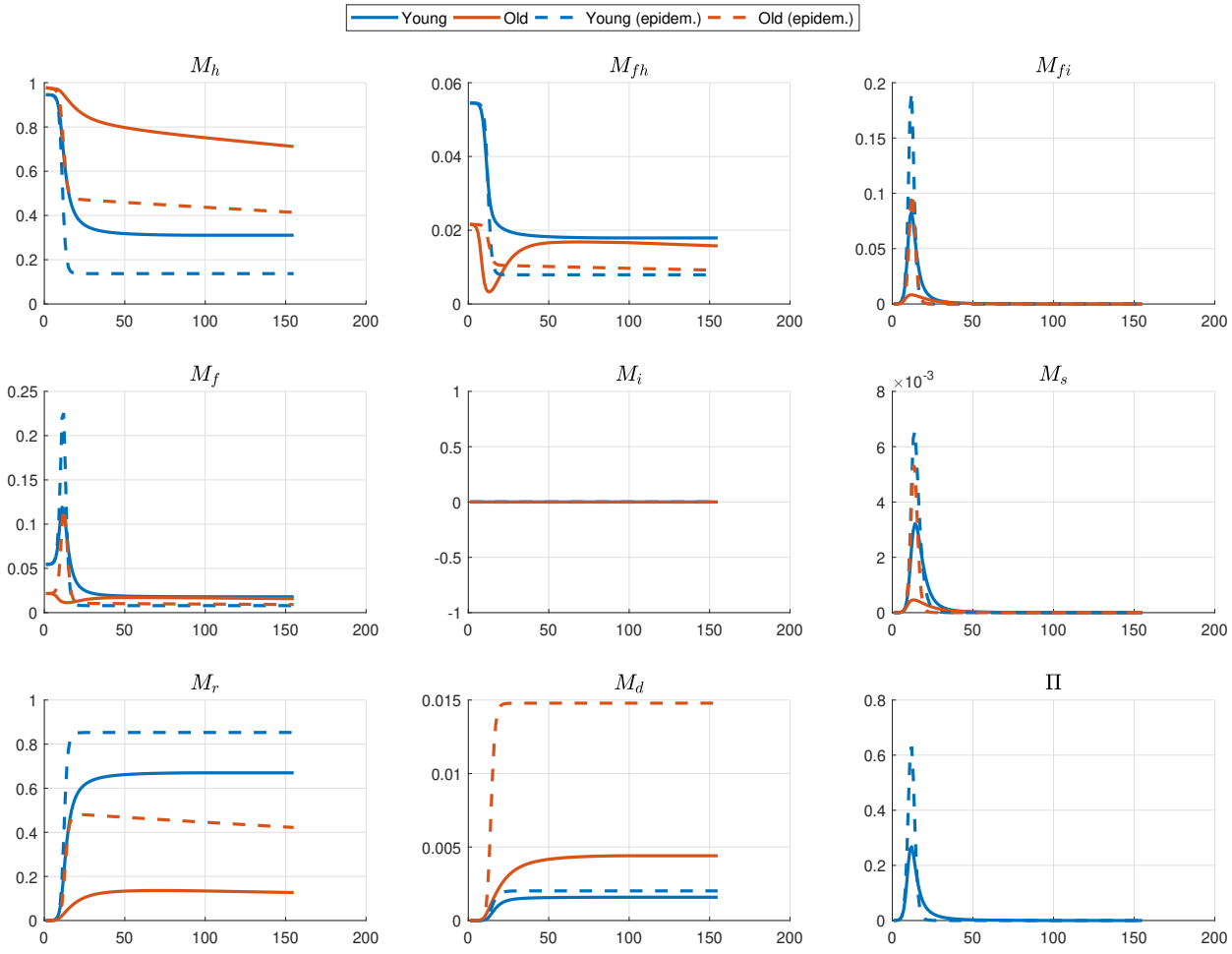
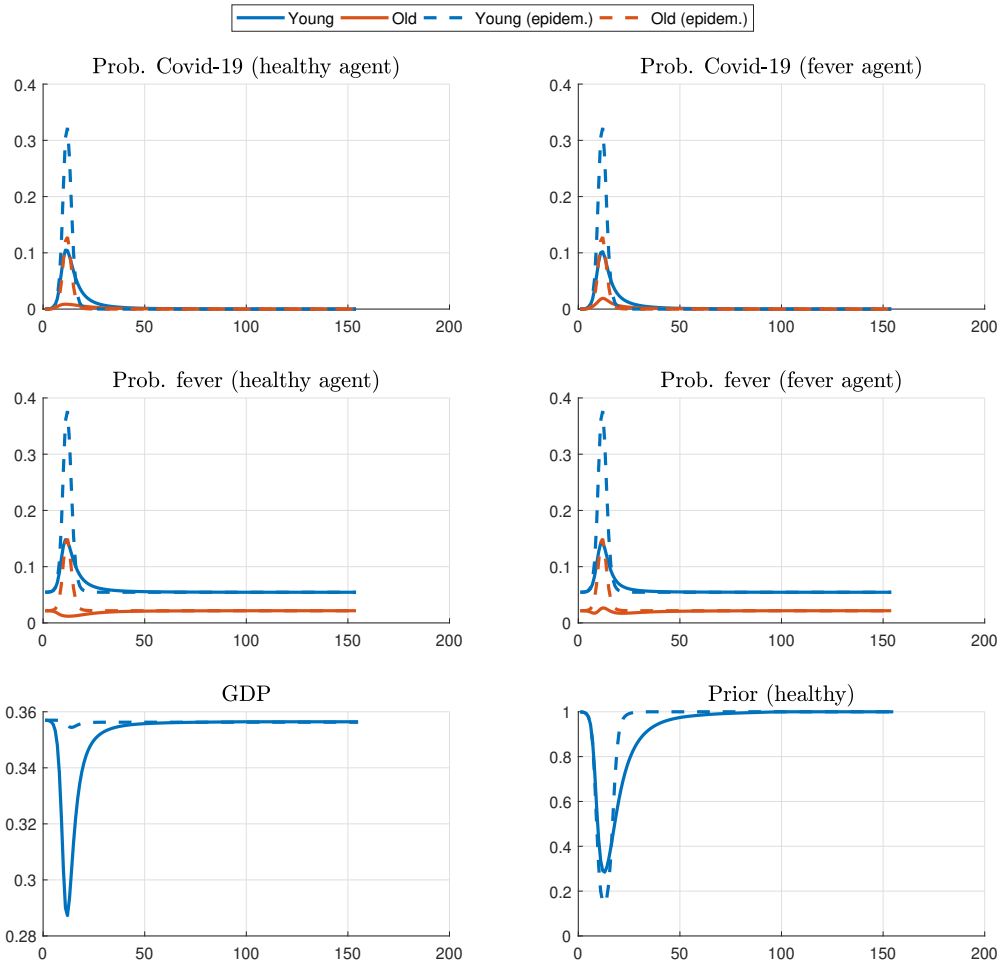


Figure 3: Other variables (Benchmark equilibrium)



this group and they consequently die in much lower numbers. One might expect this effect to reduce the infection burden on the old. However, when we put these modified preferences into general equilibrium (again keeping the transition rates at their true levels), we find that the old are dying more both within the first year and in the long run. In fact, the long-run death rate even goes up. The reason is that, with a swifter epidemic (such as in the benchmark), the old can shield themselves by staying at home during the peak before the disease dies out because of herd immunity, which is mostly driven by the young. If the young are more cautious, but the herd immunity level is not substantially changed, then the old find it harder to wait out the disease and end up catching it more. This shows that keeping the young longer at home in this model might not help the old, or even overall.

The channel described in the previous paragraph continues to exist even if hospital beds are scarce. In this case, however, not only do the young affect the transmission of the virus to the old, but they also start blocking recovery options that the old would have needed. This additional channel alters some of the conclusions, as we will discuss in Section 7.2 below.

6 Policy Experiments

In this section we will use our baseline calibration to perform a series of policy experiments, namely: testing, test and quarantine, and shelter-in-place policies. In Section 7, we perform robustness analyses to some assumptions made in the baseline.

6.1 Testing

Start with policies that test individuals. In our baseline calibration, upon infection with the coronavirus, individuals remain one week in the ”fever” state, unsure whether they have Covid-19 or a common cold. By testing them, this uncertainty disappears at an earlier stage. Since the agents are partially altruistic, they are more cautious about leaving their homes.

Table 7: Policy Experiments: Testing

	Benchmark	Testing all	Testing young	Testing old	Q90-a-50t	Q90-a-100t	Q90-y-100t
Wks to peak srsly ill (yng)	15.00	19.00	19.00	15.00	27.00	34.00	32.00
Wks to peak srsly ill (old)	14.00	18.00	18.00	14.00	25.00	31.00	29.00
Srsly ill p/ 1,000 @ peak (yng)	3.22	2.85	2.83	3.22	1.03	0.05	0.04
Srsly ill p/ 1,000 @ peak (old)	0.46	0.43	0.43	0.46	0.27	0.02	0.02
Dead p/ 1,000 1year (yng)	1.56	1.43	1.42	1.56	0.87	0.08	0.07
Dead p/ 1,000 1year (old)	4.18	3.57	3.59	4.15	3.13	0.38	0.35
Dead p/ 1,000 1year (all)	1.98	1.77	1.77	1.97	1.23	0.13	0.12
Dead p/ 1,000 LR (yng)	1.58	1.43	1.43	1.58	0.94	0.11	0.10
Dead p/ 1,000 LR (old)	4.41	3.59	3.63	4.34	3.51	0.50	0.46
Dead p/ 1,000 LR (all)	2.03	1.77	1.78	2.02	1.35	0.17	0.15
Immune in LR (yng), %	66.98	60.44	60.39	66.81	39.63	4.46	4.08
Immune in LR (old), %	12.69	10.33	10.43	12.48	10.21	1.46	1.33
Immune in LR (all), %	58.29	52.41	52.39	58.10	34.91	3.98	3.64
Number of tests - peak, %	0.00	9.18	8.93	0.19	2.87	4.89	4.57
Number of tests - LR, %	0.00	2.06	1.81	0.25	1.51	4.66	4.39
GDP at peak - rel to BM	1.00	1.00	1.00	1.00	1.13	1.24	1.24
GDP 1year - rel to BM	1.00	1.00	1.00	1.00	1.01	1.03	1.03
Cost p/ life saved, million $	0.00	0.00	-0.02	1.54	-0.48	-1.10	-1.11
Hrs @ home (yng) - peak	68.56	68.17	68.24	68.66	59.76	55.02	55.00
Hrs @ home (old) - peak	108.43	108.09	108.09	108.45	101.61	90.19	90.09
Hrs @ home (yng) - 6m	57.27	58.30	58.18	57.31	59.65	55.02	54.99
Hrs @ home (old) - 6m	97.45	99.23	99.04	97.51	101.26	90.18	90.08
Value - healthy (yng)	5029.40	5030.20	5030.20	5029.40	5032.90	5037.60	5037.70
Value - healthy (old)	2377.90	2380.20	2380.20	2378.00	2383.40	2392.50	2392.60
Value - healthy (all)	4604.60	4605.70	4605.70	4604.70	4608.20	4613.80	4613.90

Table 7 provides the results of testing all individuals (column Testing all), only the young (Testing young) or only the old (Testing old). Start with the universal policy.

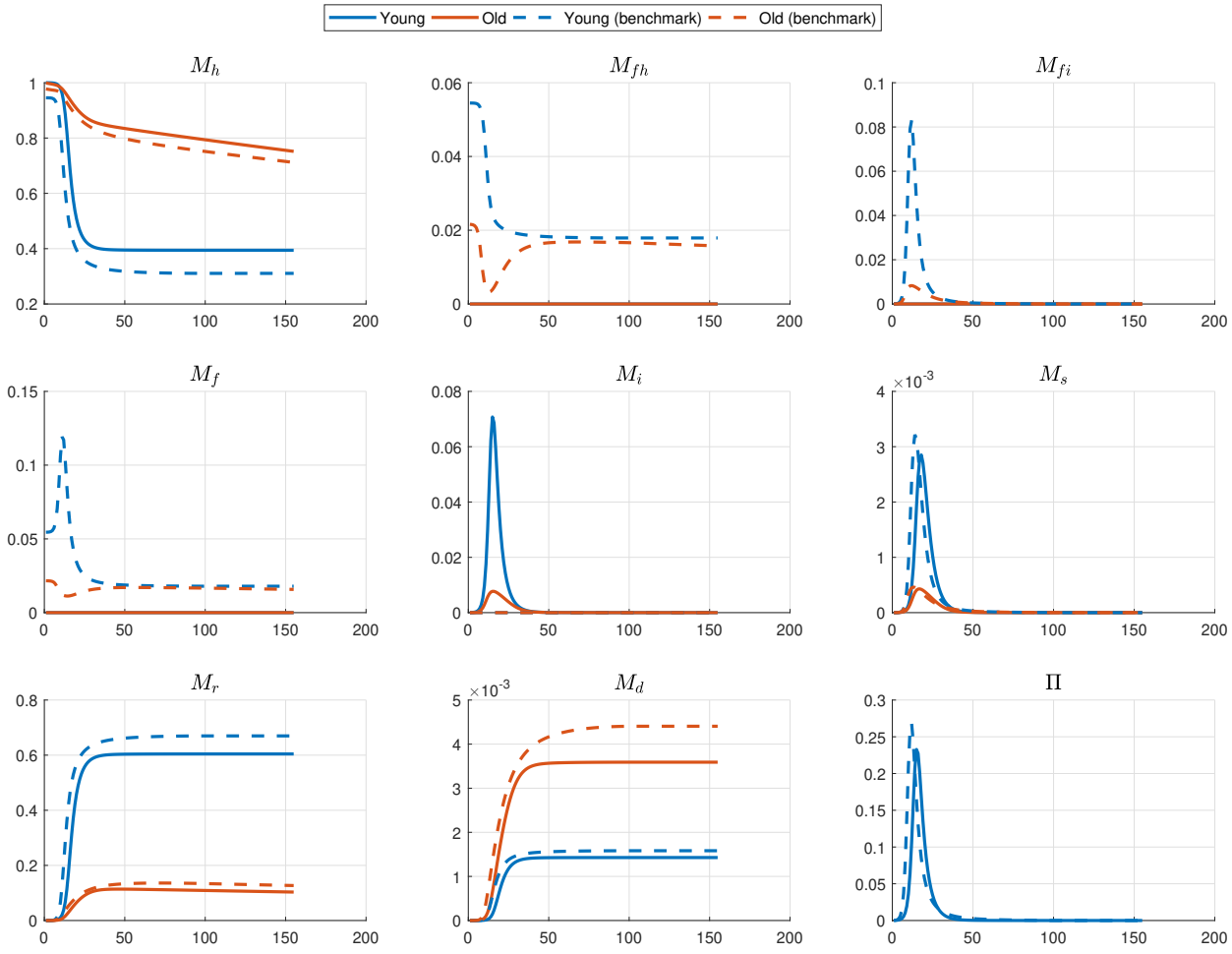
Figure 4 shows that, with universal testing, the mass of agents that are unsure whether they have the disease (M_f) goes to zero. Instead, agents now know they are infected (M_i) and thus act with the according partial altruism. At the peak of the disease, both young and old individuals spend more time at home (see Table 7). This leads the disease to develop at a slower pace; i.e. flattening the curve. The peak now takes about four weeks longer to arrive and is less pronounced (see the bottom-right panel in Figure 4). This translates into fewer deaths for both age groups, but particularly for the old. Fewer people catch the disease overall as can be seen from the lower immunity rates in the long run. Note that this universal testing policy is a massive undertaking: in the week in which the disease hits its peak, about 9% of the population is tested. In the US, this implies about 30 million tests in a single week.

Table 7 also reports age-specific testing policies. First, testing exclusively the old causes only minor changes to the development of the disease. Since this group comprises a minority of the population and they protect themselves more, their partial altruism is not strong enough to generate considerable changes in the economy. Testing the young has the opposite effect. As this group consists of 84% of the population and they protect themselves less, the results are quite similar to those obtained with a universal policy.

While we find that testing works quite well, and testing with quarantine even better (as we will see below), we want to caution the reader that in reality testing will be more difficult than in our model for several reasons. First, in the model we test those (or a fraction of those) with fever. In reality, how would the government, or some testing agency, know who has symptoms? Even if anyone with such symptoms voluntarily got tested, note that there is a large fraction of confirmed asymptomatic Covid-19 cases, which we abstract from in the model.[22] One possibility is to focus on contact tracing, as is being implemented in some

[22]See Sutton et al. (2020) for a study with pregnant women in New York City.

Figure 4: Distribution of agents (Testing all)



countries.[23] New technology is being developed to aid this.[24] This also brings issues related to individual privacy.[25]

A second hurdle is that our model assumes instantaneous test results. In reality this is not the case. While some rapid test that deliver results within an hour exists, those are not largely available and producing them at scale will be costly and logistically problematic. Instead, most countries rely on laboratory analysis, which requires probes being transported to the lab, which already delays the process.

Moreover, unlike in our model, in reality testing involves costs. Scaling up the current test methods to the quantities needed is not easy. The costs may be worth paying, but they are not negligible. Estimates put this cost at $15 billion US dollars per month.[26]

6.2 Test and Quarantine

The previous section discussed the impact of testing policies that rely on individual's altruism to curb the spread of the disease. On top of testing people, one could officially quarantine those that tested positive (which most countries try to do). The last three columns of Table 7 report results of three such experiments.

Start with the column labeled "Q90-a-100t". In this counterfactual, a person that is found to be infected (a positive test result) is forced to quarantine and increase the time at home by 90% (the "Q90" part). Here, we test individuals of all ages ("a") and 100% of the fever agents are tested ("100t"). The higher fraction of time spent at home is achieved by increasing the marginal utility of time at home.[27]

[23] See ECDC (2020).

[24] See NPR, April 10, 2020 "Apple And Google Build Smartphone Tool To Track COVID-19".

[25] See NPR, April 27, 2020 "Germany Backs Away From Compiling Coronavirus Contacts In A Central Database" for a discussion of privacy issues with the recent German experience with contact tracing.

[26] See The Economist, April 25, 2020 "Test of Reason" for a discussion of the difficulties of scaling up testing.

[27] Recall from the model description that λ_p is a policy instrument with which the government can increase the agent's proclivity to stay at home. See Section 3 for details. Computationally, we calibrate λ_p such that we generate the desired rise in time at home. The utility achieved by the individual under this scenario, however, is computed using his own private λ_d. The same is done

This policy is extremely effective. In the long run, only about 4% of the population catches the disease and are thus immune. The death count decreases by an order of magnitude for both age groups. The peak of the disease occurs at a later date (34 instead of 15 weeks in the benchmark) and is much less pronounced (as can be seen by the number of seriously ill individuals at the peak). With the lower burden of the disease, GDP goes up by 3% in the first year of the epidemic. Given that the number of immune individuals is low in the long run, this may be a drawback of this policy: in the event of a new outbreak, the economy would be far from the herd immunity level.

Consider a test-and-quarantine policy that focuses on the young only (the "Q90-y-100t" column in Table 7). Since the young comprises the lion's share of the population and spend more time outside, testing this group only is essentially as effective as testing the entire population. Alternatively, a policy that would focus on the old only (not shown) would not be as useful.

In our model, we assume immediate test results. This is not true in reality, as the results usually take a few days. Focus then on a test-and-quarantine policy that targets 50% of the population. Alternatively, this could be thought of as testing with results delayed to the middle of the week of infection.[28] The results are in the column "Q90-a-50t" in Table 7.

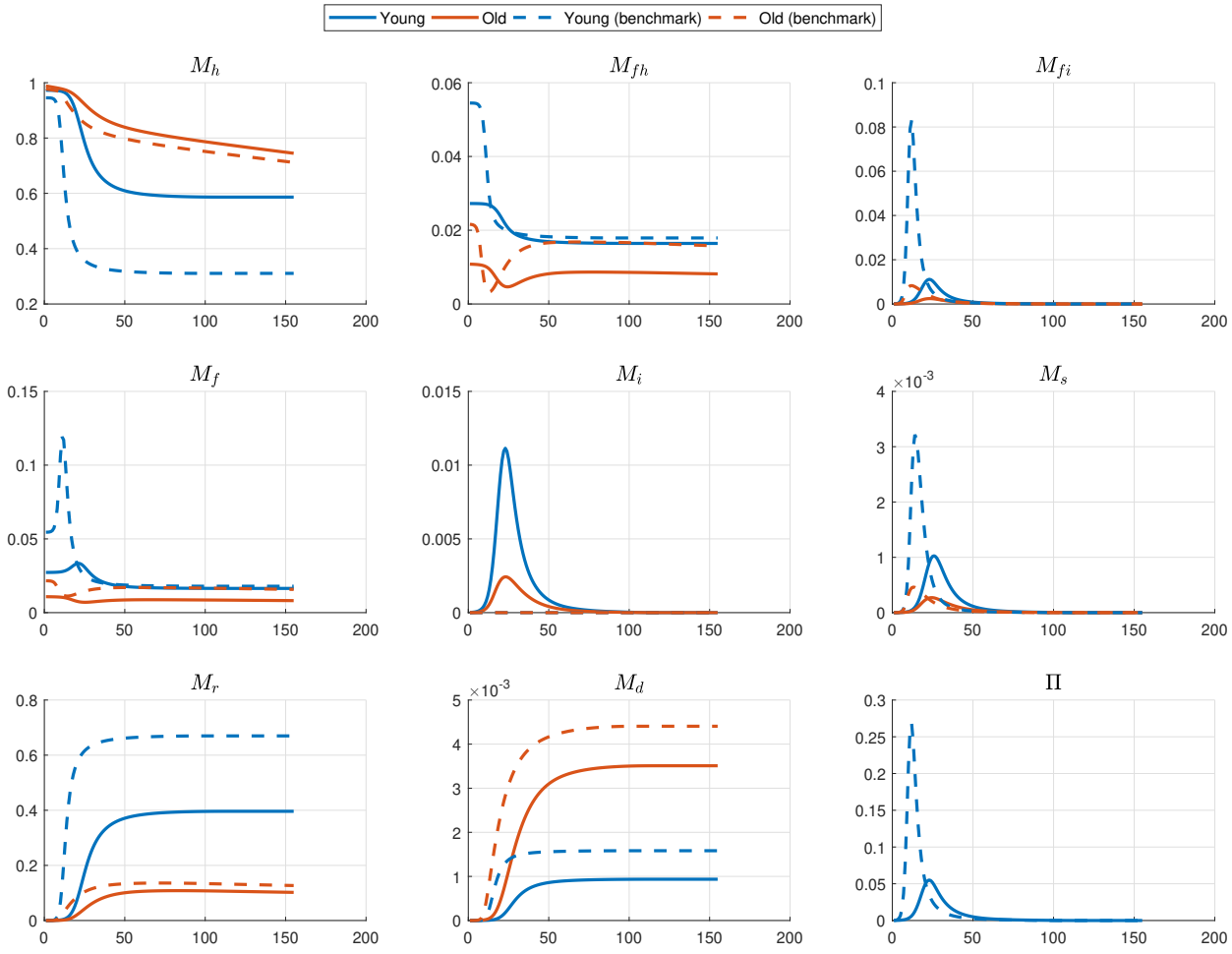
With only a fraction of the population being tested, some agents will move from the unsure "fever" state (M_f) to the infected state (M_i), but not all. See Figure 5. Compared to the benchmark, the peak occurs at a later date and is lower; i.e. the curve is flattened (see the bottom-right panel in Figure 5). There will thus be a much lower fraction of seriously ill individuals (M_s) at the peak. Relative to the baseline, the number of deaths declines by a little over 30% to 1.35 per 1,000 people. This decline is steeper among younger individuals (a drop of about 40% for this group). The total number of cases declines from almost 60% in the benchmark to around 35% here. GDP goes up in the first year by about 1% relative to the baseline.

Even though more than a third of the population catches Covid-19 with a 50%

for the shelter-in-place policies discussed in Section 6.3.

[28]The 100% policies discussed previously can be thought of as the outcome of rapid testing, currently under development.

Figure 5: Distribution of agents (Test and Quarantine, 50%)



test-and-quarantine policy (Q90-a-50t), agents change their behavior and engage in more risk. At the peak of the disease, the young spend about nine hours per week longer outside the home compared to the benchmark. Older individuals, who are more affected by the disease, also spend less time at home: seven hours fewer hours per week relative to the baseline. This risk compensation acts to dampen the effect of the policy.[29]

Policies that involve quarantines require infected agents to stay longer at home, even if this is against their best interest. However, this can be a welfare-improving policy. The last three rows of Table 7 report the lifetime utility for a healthy person at the outset of the disease, for the young, the old and the weighted average (as seen by a utilitarian planner). The thought experiment is whether a healthy individual would like to go through the epidemic with or without the policy being implemented. The welfare for both young and old agents is higher with the quarantine policies in place though they know they might be required to quarantine themselves if they catch the disease.

6.3 Shelter-in-Place Policies

What about government-mandated shelter-in-place policies; i.e. lockdowns? We investigate such policies applied to the young, the old, or all, for various lengths of time or strictness. Table 8 has the results for several constellations of the policy. First, a clarification regarding the notation. The column labeled "SH25-a-4" represents a situation in which agents need to shelter at home for an extra 25% of their time (the "SH25" part), this applies to all ages ("a") and this lasts for four weeks ("4"). Another example is "SH90-o-26", in which only the old have to shelter at home for an extra 90% of their time during 26 weeks. And so on.

Start with the mildest case (SH25-a-4) in Table 8. The universal month-long lockdown only requires a relatively small increase in time at home: 25%. The effects on the statistics related to the disease are small. The disease slows a bit with the peak being achieved three weeks later. The death rate declines slightly for the old but is constant for the young. The economic costs, on the other hand, are

[29] See Greenwood et al. (2019) for a discussion of the quantitative impact of risk-compensation effects on policies that aim to curb the HIV/AIDS epidemic.

Table 8: Policy Experiments: Shelter in Place

	Benchmark	SH25-a-4	SH25-y-26	SH25-y-35	SH50-a-26	SH75-a-12	SH75-a-35	SH90-a-26	SH90-o-26
Wks to peak srsly ill (yng)	15.00	18.00	33.00	27.00	49.00	36.00	68.00	56.00	16.00
Wks to peak srsly ill (old)	14.00	16.00	32.00	25.00	48.00	35.00	67.00	55.00	15.00
Srsly ill p/ 1,000 @ peak (yng)	3.22	3.19	1.95	1.20	3.20	3.21	3.21	3.19	3.17
Srsly ill p/ 1,000 @ peak (old)	0.46	0.46	0.38	0.35	0.44	0.45	0.44	0.44	0.22
Dead p/ 1,000 1year (yng)	1.56	1.56	1.49	1.32	0.90	1.47	0.00	0.03	1.55
Dead p/ 1,000 1year (old)	4.18	4.14	4.91	5.09	1.85	3.46	0.00	0.20	2.08
Dead p/ 1,000 1year (all)	1.98	1.97	2.04	1.92	1.05	1.79	0.00	0.06	1.64
Dead p/ 1,000 LR (yng)	1.58	1.58	1.57	1.57	1.57	1.58	1.58	1.58	1.58
Dead p/ 1,000 LR (old)	4.41	4.38	5.52	6.53	4.19	4.28	4.13	4.18	2.37
Dead p/ 1,000 LR (all)	2.03	2.03	2.20	2.36	1.99	2.01	1.98	1.99	1.71
Immune in LR (yng), %	66.98	66.93	66.51	66.27	66.65	66.79	66.70	66.73	66.91
Immune in LR (old), %	12.69	12.65	16.09	19.10	12.48	12.56	12.51	12.53	6.88
Immune in LR (all), %	58.29	58.23	58.43	58.72	57.97	58.11	58.02	58.05	57.29
GDP at peak - rel to BM	1.00	1.00	1.09	1.16	1.00	1.00	1.00	1.00	1.00
GDP 1year - rel to BM	1.00	0.98	0.88	0.84	0.76	0.83	0.54	0.58	1.00
Cost p/ life saved, million $	0.00	116.45	-120.59	166.33	16.12	56.34	14.66	13.51	-0.03
Hrs @ home (yng) - peak	68.56	68.24	64.25	60.78	68.04	67.71	68.65	68.37	68.13
Hrs @ home (old) - peak	108.43	108.44	106.68	103.77	108.43	108.40	108.42	108.44	110.31
Hrs @ home (yng) - 6m	57.27	58.15	71.11	71.11	82.15	54.90	95.84	104.06	57.16
Hrs @ home (old) - 6m	97.45	99.26	103.07	102.85	101.05	90.63	106.12	109.08	109.27
Value - healthy (yng)	5029.40	5029.00	5026.90	5026.10	5018.60	5015.30	4988.60	4972.40	5029.40
Value - healthy (old)	2377.90	2377.80	2375.50	2373.70	2375.60	2374.10	2366.70	2360.70	2366.90
Value - healthy (all)	4604.60	4602.60	4591.70	4587.20	4574.30	4578.60	4529.40	4520.30	4601.10

non-trivial: yearly GDP goes down by 2% relative to the baseline. This implies that the economic cost for each life saved in the first year of the epidemic is about $116 million dollars. This number is around ten times the statistical value of life used in other contexts.[30]

These milder policies, if focused on the young only (who are causing most of the externality), can even be counter-productive in the sense of increasing the death rate (see columns SH25-y-26 and SH25-y-35 in Table 8).[31] Take the policy that shelters the young only for 26 weeks, for instance. The six-month-long lockdown slows the spread of the disease and the peak now is only achieved after 33 weeks. The overall death rate, however, is even higher now. In the long run, it rises by about 8%. In the first year alone, the total number of deaths increases slightly.

[30]For comparison, the US Environmental Protection Agency (EPA) uses a value of statistical life around $9.5 million in 2019 dollars.

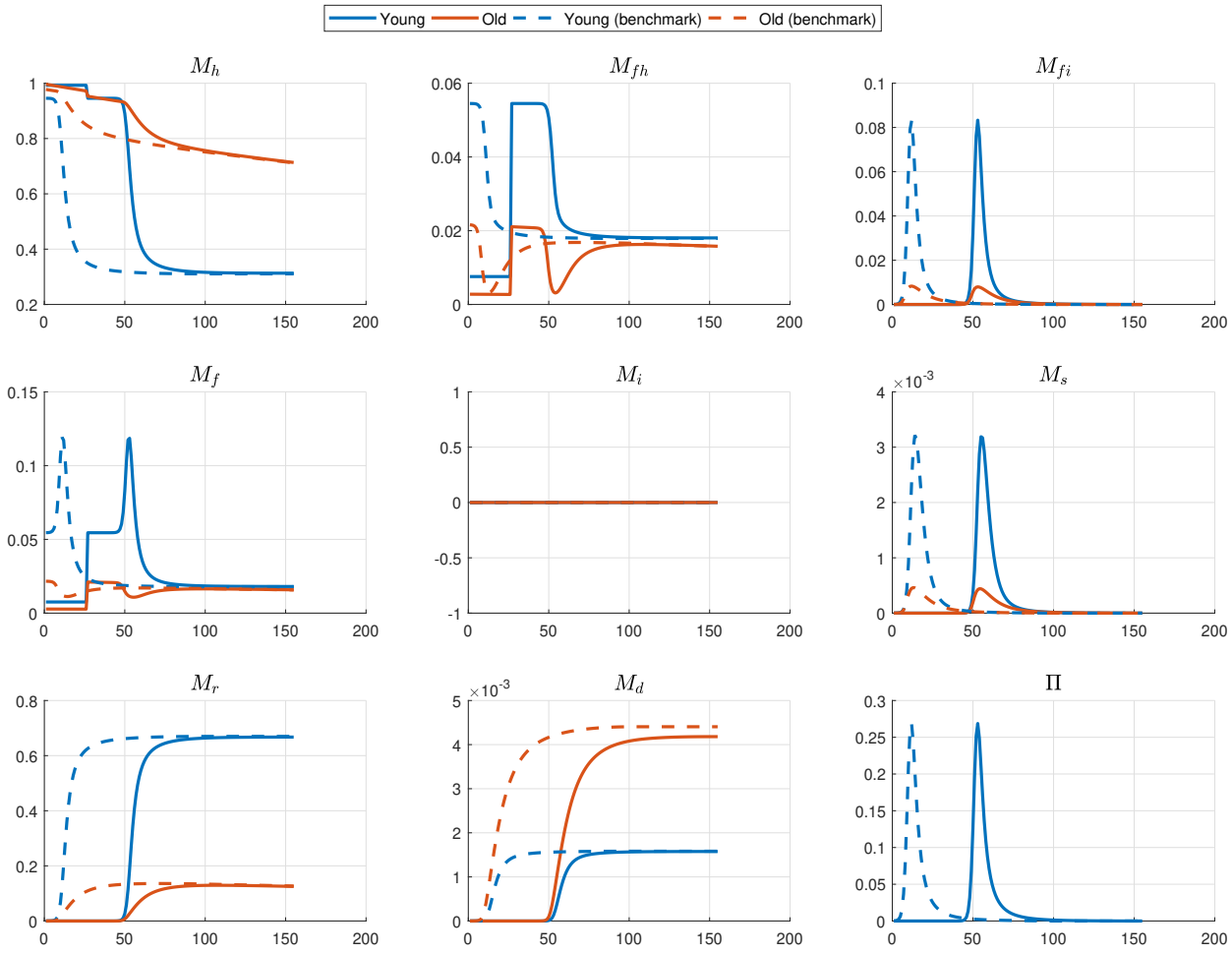
[31]Such counter-productive back-firing happens even in cases where everyone is sheltered; for example for SH25-a-26 in the long run (results omitted). The reason is that the old already shelter themselves substantially even in the absence of the policy. Therefore, such a widespread policy effectively applies mainly to the young.

Why does this happen? This policy protects the young for a while; and indeed the death rate among them declines a bit. However, this has a detrimental effect on the old. As the disease takes longer to disappear and the old is not sheltered, there is more time for them to catch the virus and eventually die. Their death rates are higher and, in the long run, more old people are immune, indicating that they were more exposed to the disease. Even though this policy ends up killing more people compared to the benchmark, since the young are sheltered, they die less (though little in the long run) but also produce less. If young lives are valued higher, this could offset parts of the overall increase in deaths, though we do not trade off different deaths here. GDP clearly goes down substantially: 12% in the first year.

Stricter policies, however, can be effective, at least in the short run. Take the SH75-a-35 scenario: increasing time at home by 75% for all ages for 35 weeks. This is a quite strict lockdown that lasts for about eight months. This policy delays the peak of the disease substantially to 68 weeks after the outbreak. Notice that this buys more time than the length of time during which the policy is in place. That is, the new peak will be achieved 33 weeks after the policy is lifted (compared to 15 weeks in the baseline with no policy) because of a reduction of infections when the policy is in place. This comes at a substantial economic costs as GDP in the first year collapses to only 54% of its benchmark value. The death count is essentially non-existent in the first year of the epidemic, which leads to a cost of just under $16 million dollars per saved life in that year.

If a vaccine or a cure becomes available within approximately one year, a policy such as the one described in the previous paragraph may work in the sense that it saves lives long enough for the treatment to arrive. However, if it takes longer, the long-run death toll is similar to the one in the benchmark. Moreover, in order to jump this one-year barrier, the lockdown has to stay in place for a very long time (like the 35 weeks in the policy just described). Compare this to a similar policy that lasts for 12 weeks (SH75-a-12), still a considerable amount of time. The peak would be reached in 36 weeks and the death toll in the first year would be only 10% smaller than the baseline. The costs per life saved in the first year in this scenario would be $56 million dollars. This indicates that shelter-at-home policies have to stay in place sufficiently close to a cure/vaccine to be viable.

Figure 6: Distribution of agents (Shelter in place, 90%, 26 weeks)



Exactly how long depends on the strength of the intervention.

Turn to the last two columns in Table 8. They report the results for extremely strict policies: individuals need to spend an extra 90% of their time at home for 26 weeks. Start with the universal policy SH90-a-26.

Though the policy only lasts 26 weeks, the peak is achieved at a much later date: after 56 weeks. This can also be seen in the bottom-right panel of Figure 6. Though the peak occurs at a much later date, the height of the peak is very similar to the benchmark. The long-run death toll is only marginally lower than no-policy baseline. Deaths in the first year, however, drop considerably. The cost of a saved life in the first year is about $13.5 million dollars. This is due to the

Figure 7: Other variables (Shelter in place, 90%, 26 weeks)

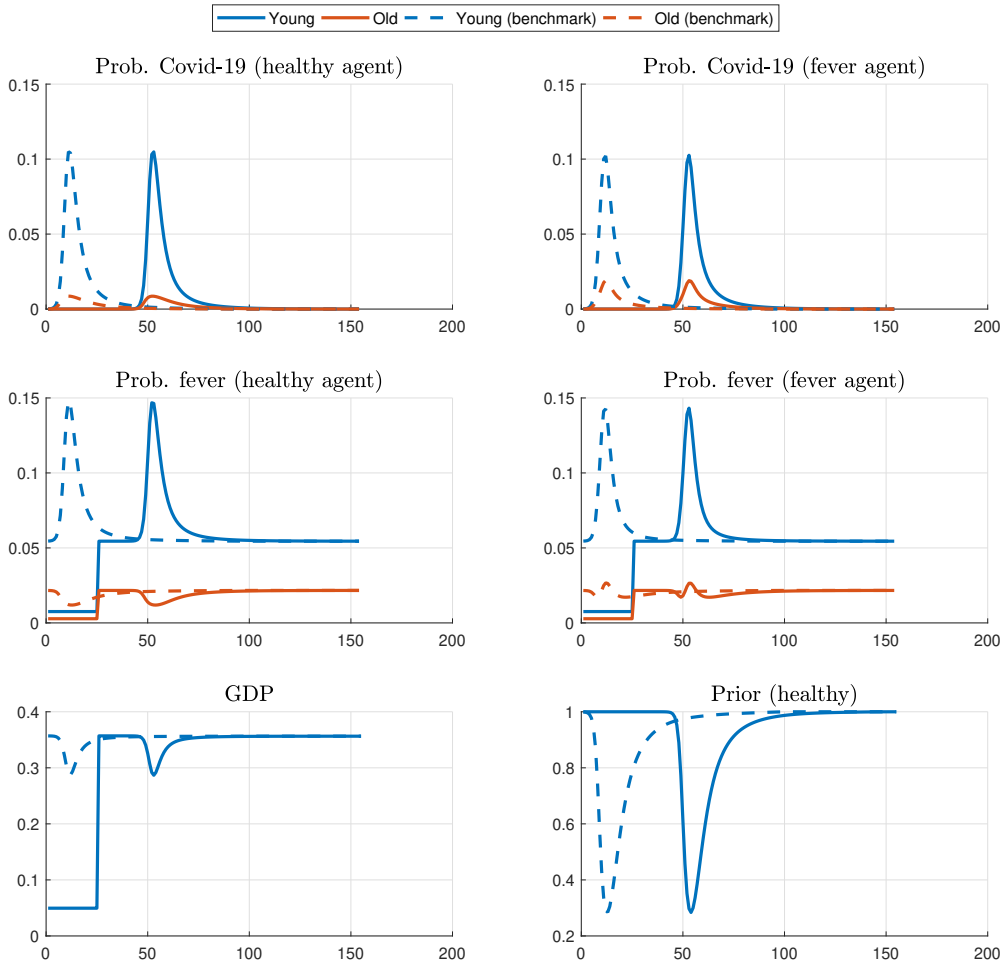
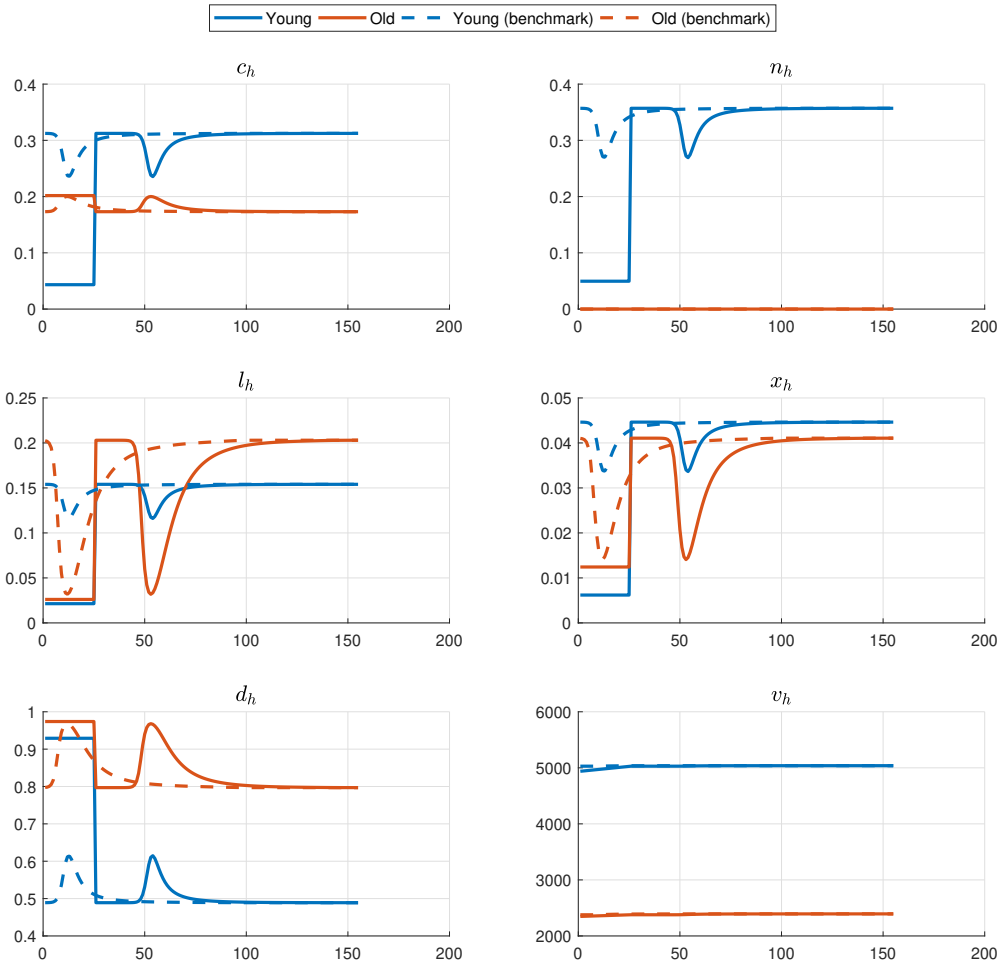


Figure 8: Choices of healthy agents (Shelter in place, 90%, 26 weeks)



very deep recession caused by the shelter-in-place policy (see Figure 7). Note that GDP also drops in the second year following the peak of the epidemic. This is caused by the endogenous decline in labor supply caused by the endogenous response of agents that refrain from working in order to protect themselves at the peak of the disease (see Figure 8).

Now turn to the policy that focuses on the old only (SH90-o-26). The results are in the last column of Table 8. First, note that the peak of the disease is achieved at a similar date relative to the no-policy benchmark. Since the young are not sheltered and they are the majority of the population, most of the development of the disease follows the path of the baseline scenario. Since the peak of the disease is achieved around 16 weeks, the old are still sheltered at that time. So, at the most dangerous stages of the epidemic, they are more protected. This contributes to the lower overall death rates under this policy. This is particularly true among the old, whose death toll declines to almost half of the benchmark value. The young, on the other hand, still die at similar rates. Since the young are not under lockdown, they can work and GDP in the first year is the same as in the no-policy benchmark. Finally, note that, even though the death rate among the old is considerably lower than in the baseline, their welfare falls. This happens since the old are required to stay home for longer than they would have chosen to, and the externality amongst them is not sufficient to justify this level of protection in their view.

7 Alternative Scenarios

This section explores alternative assumptions for the baseline specification. In particular, we explore higher death rates for the old (Section 7.1), scarce medical supplies (Section 7.2), and selective mixing across the different age groups (Section 7.3).

7.1 Higher Death Rates for the Old

In our calibration strategy, the transition rate from infection to ICU of old individuals is three times larger than that of the young. This number is far from the ratio suggested by Ferguson et al. (2020), which is about 30. As a first pass to assess such an alternative scenario, in this section we adjust the probability at which infections for the old people lead to serious symptoms that require ICU treatment from roughly 5% in our initial benchmark to 50%. That means $\phi(0, o) = 0.5$.

Table C1 in the Appendix shows statistics related to the benchmark equilibrium. With higher death rates for the old, the number of fatalities among these agents doubles in the first year, and more than doubles in the long-run, while the number of young deceased agents is roughly the same as before. The increased deaths among the old are substantially lower then the 10-fold increase in their case fatality rate: Healthy old agents now take less risk, spending nine additional hours per week at home six months after the disease outbreak. Because of this, the mass of immune old agents in the long-run falls from 12% to 2%. The epidemiological model predicts a dramatic number of 16% deceased old agents in the long-run.

The effects of testing and quarantine policies are displayed in Table C2. The testing policy has similar impacts if compared to those in the original setting. The same is not true for the quarantine policy with 50%-probability testing. In this case, the number of deceased old agents decreases in the first year, but increases in the long-run.

Table C3 shows the statistics related to shelter-in-place policies. In general, the impacts are similar to those in the previous model, such as the policy effects on the infection peak timing and on GDP. The same policies that back-fire in terms of overall deaths also feature the same characteristic here. However, and maybe surprisingly, even though it now becomes more important to protect the old it turns out that the policy that focuses on sheltering the old is not as efficient as the one in the model where these agents have lower death rates. In the original setting, this policy cuts deaths for the old by almost a half, but now the number of fatalities for this group decreases by only 13%. The reason is that the old voluntarily shelter themselves substantially more in this economy with high death rates.

7.2 Hospital Bed Constraints

The American Hospital Association reports the existence of 84,555 intensive care beds excluding neonatal units, implying a per-capita number of $Z = 0.032607\%$ ICUs.[32] This number is consistent with that reported by Prin and Wunsch (2012). We set $\tilde{\delta}_2(a) = 1$, so that the death for an agent with serious symptoms and no hospital beds is certain to occur.

The first column of Table C4 in the Appendix shows the results for the equilibrium without policies. Since agents without hospital beds die with certainty, the number of deaths increases considerably in comparison with the previous calibration. Indeed, the number of fatalities is more than two times larger. Most of the deaths still occur in the first year. However, now agents protect themselves more, with the young spending seven additional hours at home per week during the peak of the disease.

The economic recession is stronger in this case: during the first year GDP falls by 10.8% compared to the no-disease scenario – a recession almost three times more severe than in the model without hospital bed constraints. The economic impact is bigger because young agents work less and die more. The number of deceased young agents increases by a factor of 2.7 in this alternative scenario.

The age externality (columns 3 and 4) works differently now. If young agents behave more cautiously, as if they had the death probabilities of the old, in general equilibrium there would be less infection per period, and less hospital beds would be occupied, leading to a smaller number of dead agents for both age groups. Note that this is the opposite of what happens in the model without hospital constraints, where in the long run the level of deaths is linked to the age composition of the cases necessary for herd immunity and lower activity by the young shifts this age composition towards the old. This effect is still present, but is now overpowered by effects on recovery rates.

Table C5 shows the results of the testing and quarantine policies. Qualitatively, the insights from the previous sections remain. One difference between the effects of the testing policies in the case with hospital bed constraint is that agents

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

spend more time at home during the peak of the infection, while the opposite happens in the previous model.

The quarantine policies show some quantitative differences with respect to the model without hospital bed constraints. Although the number of weeks to reach the peak of the infection in both cases is similar if there is no policy, the 100%-testing quarantine moves the peak of the disease to week 44 in the case with hospital bed constraints, while in the previous model it takes 34 weeks for the peak to be reached with the policy.

In the case of quarantine with 50%-probability tests, the proportional decrease in the number of deceased agents is almost twice that in the previous model, and the contraction in the number of immune old agents is two times larger. Finally, the quarantine policy saves 7% of the GDP in the first year, while in the model without hospital constraints it saves only 0.58%.

Table C6 shows the effects of shelter-in-place policies. As before, severe policies (in terms of intensity and duration) that affect the young may have powerful effects in the first year, cutting back the number of deceased agents up to approximately zero. However, in the long-run the policy produces similar results if compared to the no-hospital-constraints model, implying that without relatively fast cure or vaccine none of these policies seem to be very effective.

The cost per life saved for shelter-in-place policies is lower if we consider hospital bed constraints. This is because the GDP contraction produced by the policies are similar across the two models, but the positive impact on lives is considerably higher in the model with hospital bed constraints.

As before, a severe shelter-in-place policy focused on the old has strong positive impacts on the number of fatalities among these agents, without producing economic costs in terms of GDP contraction in the first year. However, the welfare of the old is lower due to a higher confinement.

Another difference from the no-hospital-constraints model is that now shelter-in-place policies no longer back-fire. Sheltering spreads the demand for hospital beds across time, yielding benefits that are not captured in the original setting.

Tables C7-C9 in the Appendix show the results for the model with both a higher

death rate for the old ($\phi(0, o) = 0.5$) and hospital bed constraints.

7.3 Selective Mixing

Now consider a government that reserves some common spaces for a particular age group only. This could entail that certain hours in supermarkets are reserved for a particular age group, or that some parks or leisure centres are dedicated to a particular age group. This leads to *selective mixing* where agents are more likely to meet those of their own type. To capture this, assume that only a fraction $1-\zeta$ of activities remain common and take up a corresponding fraction $1-\zeta$ of the outside space. But a fraction ζ of activities can be separated into age-groups, and for this purpose a fraction ϑ_a of the remaining space is dedicated only to individuals of this specific age group. Those spend $T(\vartheta_a) \leq 1$ of their remaining time there, the rest of the time is lost as individuals arrive in situations where the desired space happens to be dedicated to the other group. Conditional on being in common space where one can get infected, the infection rate now becomes

$$\begin{aligned} \hat{\Pi}_t(a) &= (1-\zeta)\Pi_0 \sum_{\tilde{a},j\in\{f_i,i,s\}} \left(n_t(j,\tilde{a}) + \ell_t(j,\tilde{a})\right) M_t(j,\tilde{a}) \\ &\quad +\zeta T(\vartheta_a)\Pi_0 \sum_{j\in\{f_i,i,s\}} \frac{T(\vartheta_a)}{\vartheta_a} \left(n_t(j,a) + \ell_t(j,a)\right) M_t(j,a). \end{aligned} \tag{14}$$

The first line reflects the $1-\zeta$ of a person's time spent in the unrestricted space where everything is unchanged from (11): other individuals spend $1-\zeta$ of their time across $1-\zeta$ of the space which leaves the number per area unchanged. The second line reflects the fraction ζ of a person's time spent on age-restricted activities, of which $T(\vartheta_a)$ is lost, where he only meets others of the same age who spend $T(\vartheta_a)\zeta$ of their time on $\vartheta_a\zeta$ parts of the space. The expression reduces to the random mixing rate (11) if selectivity is $\zeta = 0$. It also reduces to random mixing rate independent of selectivity ζ if young and old would be completely identical and space is divided up such according to group size ($\vartheta_y = \sum_j (M(a,j))/\sum_{a,j} M(a,j)$, say, in steady state) and there is no loss of time due to separation ($T(\vartheta_a) = 1$). If a particular part of time is lost (i.e., $T(\vartheta_a) = \vartheta_a^{1/2}$) then ϑ_a cancels in (14) and the expression reduces to "preferred

matching" in Jacquez et al. (1988) and Kremer (1996), only that infected agents are here weighted by their activity outside the house.

The cost of selective mixing is that at some times some of the common space is no longer available to a person who would like to use it. That is, there is a time loss of $(1 - T(\vartheta_a))\zeta > 0$ per time unit spent outside, which acts as a tax on both labor time n and outside leisure time ℓ, which are reduced by this as this time is lost and neither brings income nor utility. The simplest version is $T(\vartheta_a) = \vartheta_a$, where each unit of space dedicated to the other group is lost.

In order to generate quantitative results for the selective-mixing scenario, we must pick values for ζ and ϑ. Suppose $\zeta = 1/2$ so that half of the activities can be divided among the two age groups. Moreover, set $\vartheta_o = 0.16$ and $\vartheta_y = 0.84$. The latter divides the space up according to the relative sizes of each group in the overall population. As explained above, this leaves a priori no reason for efficiency costs (i.e., if the groups were identical, the infections would not change).

Table 9 reports the results for this counterfactual. First note that the overall death rate falls, both within the first year of the epidemic as well as in the long run. There is heterogeneity, however, across the two groups: the young die more and the old die less compared to the benchmark. With partially separated spaces, the old interact more among themselves, a group that naturally protects itself more. The opposite happens to the young. Life is now riskier for this group and they behave accordingly. Note that, at the peak of the disease, the young spend more time at home compared to the benchmark. The overall effects on the young are quantitatively small and their labor supply hardly changes, keeping the GDP in the first year of the epidemic essentially the same as in the no-policy baseline. As this policy saves lives, the cost per life saved is relatively low.

8 Conclusion and Outlook

This paper provides a first path at studying the link between age heterogeneity, incomplete information/testing of the disease status, and the behavioral adjustments that individuals make to protect themselves during the ongoing Covid-19

Table 9: Selective mixing

	Benchmark	Sel. mix.
Wks to peak srsly ill (yng)	15.00	14.00
Wks to peak srsly ill (old)	14.00	14.00
Srsly ill p/ 1,000 @ peak (yng)	3.22	3.53
Srsly ill p/ 1,000 @ peak (old)	0.46	0.40
Dead p/ 1,000 1year (yng)	1.56	1.62
Dead p/ 1,000 1year (old)	4.18	3.05
Dead p/ 1,000 1year (all)	1.98	1.85
Dead p/ 1,000 LR (yng)	1.58	1.63
Dead p/ 1,000 LR (old)	4.41	3.12
Dead p/ 1,000 LR (all)	2.03	1.87
Immune in LR (yng), %	66.98	68.84
Immune in LR (old), %	12.69	8.95
Immune in LR (all), %	58.29	59.25
GDP at peak - rel to BM	1.00	0.97
GDP 1year - rel to BM	1.00	1.00
Cost p/ life saved, million $	0.00	0.27
Hrs @ home (yng) - peak	68.56	69.97
Hrs @ home (old) - peak	108.43	106.96
Hrs @ home (yng) - 6m	57.27	57.07
Hrs @ home (old) - 6m	97.45	94.20
Value - healthy (yng)	5029.40	5029.10
Value - healthy (old)	2377.90	2383.00
Value - healthy (all)	4604.60	4605.20

crisis. These seem to be first order in the spread of the infections and the deadliness of the disease. We embed these elements in an otherwise standard SIR model of disease transmission, calibrate it, investigate the externalities between age groups in the benchmark equilibrium, and study stylized policy interventions such as shelter-at-home, testing and quarantines for infected people, both in general and targeted to particular age groups.

Especially the old protect themselves during the crisis, which is beneficial because they have a higher chance of dying. Imposing limits on mobility affects especially the young, as the old already shelter themselves substantially. This is a risky policy option as the epidemic continues for longer and exposes the old to extended periods of risk, unless a cure/vaccine is found relatively quickly. Imposing shelter-at-home policies on the old reduces deaths, but also reduces their utility. Strong shelter-at-home policies for everyone have to stay in place sufficiently close to the time a cure/vaccine is in place, as otherwise the disease rebounds too quickly and the policies have negligible impact on deaths. Testing and quarantine are excellent ways of reducing the disease if feasible, even if just

concentrated on the young. Most of these insights carry over to a scenario with constraints on hospital beds, though the constraints are quantitatively important and more caution by the young now relaxes this constraint to the benefit of all.

Clearly there remain caveats to these results, in terms of calibration inputs, outputs and model assumptions. Estimates of the reproductive number and of the fatality rate per infection still vary widely and will become more precise as wider testing is implemented. This will also provide more clarity on the infection probabilities and the transitions from infection to hospitalization including their age gradient. As information about these issues hardens, it will inform adjustments to the parameters of the model. Further, the predictions of the calibrated model regarding preventive behavior over the course of the epidemic arise from plausible specifications of the utility function that have been useful in other settings, but have yet to be validated by ongoing surveys on the behavior of individuals during the epidemic. And in terms of model assumptions, we have to reduce the complexity of reality along a number of dimensions, and future work will have to assess how much this impacts accurate predictions. An obvious point is for example our assumption that testing provides immediate results, which is more reminiscent of new prototypes rather than of tests that are currently widely used in the field which feature a few days of delay. We can interpret partial testing similar to testing with delays, but the accuracy of this interpretation is to be seen.

The model is richer than many existing counterparts, but important margins are still missing. The model is already written to allow several of them: teleworking is present but not used in the calibration. It will make the young more elastic in their prevention efforts relative to the current benchmark. The model allows for many age groups, and we in particular intend to separate the 20-45 from the 45-65 old, as the latter already face substantial risk of dying from Covid but still need to earn a living. We already lay out selective mixing in theory, which separates the old from the young, and intend to explore this as a policy option and as an explanation of differences across countries.

We intend to evaluate welfare in more depth, including an analysis of optimal policy, which is complicated by the rich set of interventions that are possible in our framework. It is also complicated by the lack of easily available information about costs, for example of increasing testing capacity. At the moment, we pro-

vide insights of the likely effects of such capacity extensions, which can guide policy makers with better knowledge of the costs of doing so. As a first step to enrich the current analysis we intend to analyze combined interventions such as testing/quarantining coupled with milder forms of shelter-at-home policies.

Further, our current framework starts interventions early in the disease, but future versions will also consider the case of countries that implement interventions only several weeks into the unrestricted outbreak. Starting interventions once the epidemic has already reached a non-trivial level also allows us to tackle questions of how to end the current lock-down. A simple starting point for this is to start with a larger number of infected and recovered agents at time zero, i.e., at the beginning of the interventions. We expect many of our insights to remain even if we start with a larger number of initially infected, and therefore we expect our main policy insights still to be valid even when considering moving forward from the current state of the epidemic.

In a future version we will consider incorporating the possibility of a vaccine or cure explicitly. We will also consider implementing differential shelter-in-place policies for work and leisure. These policies might also come with differential costs, e.g., between parents (especially single ones) and those without children. Explicitly accounting for children and transmission through them is linked to this, which raises interesting questions about their interaction and their ability to adjust to the epidemic. At the other end of the age spectrum we might consider explicitly the transmission during care for the elderly.[33]

References

Acemoglu, Daron, Victor Chernozhukov, Ivan Werning, and Michael D. Whinston. 2020. "A multi-risk SIR model with optimally targeted lockdown." *NBER working paper 27102*.

[33]In our current setup conceptually care should be part of "outside leisure" even if it is at home because it implies interaction with outside people, and in our setting it shares the leisure elasticity. Many non-essential health and care services have been voluntarily and institutionally be postponed, suggesting some elasticity, but additional work needs to consider the exact magnitudes.

Akazawa, Manabu, Jody L. Sindelar, and A. David Paltiel. 2003. "Economic Costs of Influenza-Related Work Absenteeism." *Value in Health* 6 (2): 107–115.

Alvarez, Fernando, David Argente, and Francesco Lippi. 2020. "A Simple Planning Problem for COVID-19 Lockdown." Working paper.

Arias, Elizabeth, and Jiaquan Xu. 2019. "United States life tables, 2017." *National Vital Statistics Reports* 68, no. 7.

Atkeson, Andrew. 2020, March. "What Will Be the Economic Impact of COVID-19 in the US? Rough Estimates of Disease Scenarios." Working paper 26867, National Bureau of Economic Research.

Backer, Jantien A, Don Klinkenberg, and Jacco Wallinga. 2020. "Incubation period of 2019 novel coronavirus (2019-nCoV) infections among travellers from Wuhan, China, 20–28 January 2020." *Eurosurveillance* 25, no. 5.

Berger, David W, Kyle F Herkenhoff, and Simon Mongey. 2020, March. "An SEIR Infectious Disease Model with Testing and Conditional Quarantine." Working paper 26901, National Bureau of Economic Research.

Biggs, Andrew G., and Glenn R. Springstead. 2008. "Alternate Measures of Replacement Rates for Social Security Benefits and Retirement Income." *Social Security Bulletin* 68, no. 2.

Butler, Rachel, Mauricio Monsalve, Geb W. Thomas, Ted Herman, Alberto M. Segre, Philip M. Polgreen, and Manish Suneja. 2018. "Estimating Time Physicians and Other Health Care Workers Spend with Patients in an Intensive Care Unit Using a Sensor Network." *The American Journal of Medicine* 131 (8): 972.e9–972.e15.

CDC. 2020. "Severe Outcomes Among Patients with Coronavirus Disease 2019 (COVID-19) — United States, February 12–March 16, 2020." *MMWR Morb Mortal Wkly Rep 2020* 69 (12): 343–346.

Chan, Tat, Barton Hamilton, and Nicholas Papageorge. 2016. "Health, Risky Behavior and the Value of Medical Innovation for Infectious Disease." *Review of Economic Studies* 83 (3): 1737–1755.

ECDC. 2020. "Contact tracing: public health management of persons, including healthcare workers, having had contact with COVID-19 cases in the Euro-

pean Union - second update." Technical Report, European Centre for Disease Prevention and Control.

Eichenbaum, Martin S, Sergio Rebelo, and Mathias Trabandt. 2020a, March. "The Macroeconomics of Epidemics." Working paper 26882, National Bureau of Economic Research.

———. 2020b. "The Macroeconomics of Testing and Quarantining." Working paper.

Farboodi, Maryam, Gregor Jarosch, and Robert Shimer. 2020. "Internal and External Effects of Social Distancing in a Pandemic." Working paper.

Faria-e Castro, Miguel. 2020. "Fiscal Policy during a Pandemic." Working paper.

Favero, Carlo, Andrea Ichino, and Aldo Rustichini. 2020, April. "Restarting the economy while saving lives under Covid-19." Technical Report 3580606, SSRN.

Ferguson, Neil M., Daniel Laydon, Gemma Nedjati-Gilani, Natsuko Imai, Kylie Ainslie, Marc Baguelin, Sangeeta Bhatia, Adhiratha Boonyasiri, Zulma Cucunubá, Gina Cuomo-Dannenburg, Amy Dighe, and Ila Dorigatti. 2020, March. "Restarting the economy while saving lives under Covid-19." Technical Report, Imperial College Covid-19 response team.

Fernández-Villaverde, Jesús, and Charles I. Jones. 2020, May. "Estimating and Simulating a SIRD Model of COVID-19 for Many Countries, States, and Cities." Unpublished Manuscript, Stanford University.

Galeotti, Andrea, and Brian R. Rogers. 2012. "Immunization and Group Structure." *American Economic Journal-Microeconomics, 5(2): 1-32.* 5 (2): 1–32.

———. 2015. "Diffusion and protection across a random graph." *Network Science* 3:361–376.

Garobaldi, Pietro, Espen R. Moen, and Christopher A. Pissarides. 2020. "Modelling contacts and transitions in the SIR epidemics model." *Covid Economics* 5 (April): 1–20.

Glover, Andrew, Jonathan Heathcote, Dirk Krueger, and Jose-Victor Rios-Rull. 2020. "Health versus Wealth: On the Distributional Effects of Controlling a Pandemic." Working paper.

Gollier, Christian. 2020. "If the objective is herd immunity, on whom should it be built?" *Working Paper*.

Greenwood, Jeremy, Philipp Kircher, Cezar Santos, and Michèle Tertilt. 2013, March. "An Equilibrium Model of the African HIV/AIDS Epidemic." Working paper 43, National Bureau of Economic Research.

———. 2017. "The Role of Marriage in Fighting HIV: A Quantitative Evaluation for Malawi." *American Economic Review* 117 (5): 158–162 (May).

———. 2019. "An Equilibrium Model of the African HIV/AIDS Epidemic." *Econometrica* 87 (4): 1081–1113 (July).

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Ivan Werning. 2020. "Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?" Working paper.

Hall, Robert E., Charles I. Jones, and Peter J. Klenow. 2020, April. "Trading Off Consumption and COVID-19 Deaths." Unpublished Manuscript, Stanford University.

Heikkinen, Terho, and Asko Järvinen. 2003. "The common cold." *The Lancet* 361 (9351): 51–59.

Jacquez, John A., Carl P. Simon, James Koopman, Lisa Sattenspiel, and Timothy Perry. 1988. "Modeling and analyzing HIV transmission: the effect of contact patterns." *Mathematical Biosciences* 92 (2): 119 – 199.

Kapicka, Marek, and Peter Rupert. 2020. "Labor Markets during Pandemics." Working paper.

Kaplan, Greg, Benjamin Moll, and Gianluca Violante. 2020. "Pandemics According to HANK." Working paper.

Keppo, Juusi, Elena Quercioli, Mariana Kudlyak, Lones Smith, and Andrea Wilson. 2020. "The Behavioral SIR Model, with Applications to the Swine Flu and COVID-19 Pandemics." Technical Report. Work in Progress.

Kremer, Michael. 1996. "Integrating Behavioral Choice into Epidemiological Models of AIDS." *The Quarterly Journal of Economics* 111 (2): 549–573 (05).

Kuhn, Moritz, and Christian Bayer. 2020, March. "Intergenerational ties and

case fatality rates: A cross-country analysis." Technical Report DP14519, CEPR.

Lauer, Stephen A, Kyra H Grantz, Qifang Bi, Forrest K Jones, Qulu Zheng, Hannah R Meredith, Andrew S Azman, Nicholas G Reich, and Justin Lessler. 2020. "The incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: estimation and application." *Annals of internal medicine*.

McAdams, David. 2020. "Nash SIR: An Economic-Epidemiological Model of Strategic Behavior During a Viral Epidemic." *Covid Economics*.

McGrattan, Ellen R, and Richard Rogerson. 2004. "Changes in hours worked, 1950-2000." *Federal Reserve Bank of Minneapolis Quarterly Review* 28 (1): 14–33.

Piguillem, Facundo, and Liyan Shi. 2020. "The Optimal COVID-19 Quarantine and Testing Policies." Working paper.

Prin, Meghan, and Hannah Wunsch. 2012. "International comparisons of intensive care: informing outcomes and improving standards." *Current opinion in critical care* 18 (6): 700–706.

Quercioli, Elena, and Lones Smith. 2006. "Contagious Matching Games." Technical Report. Working paper.

Remuzzi, Andrea, and Giuseppe Remuzzi. 2020. "COVID-19 and Italy: what next?" *The Lancet* 395 (10231): 1225–1228 (2020/04/21).

Sutton, Desmond, Karin Fuchs, Mary D'alton, and Dena Goffman. 2020. "Universal Screening for SARS-CoV-2 in Women Admitted for Delivery." *The New England Journal of Medicine*.

Toxvaerd, Flavio. 2019. "Rational Disinhibition and Externalities in Prevention." *International Economic Review* 60 (4): 1737–1755 (1).

———. 2020. "Equilibrium Social Distancing." Working paper.

Verity, Robert, Lucy C Okell, Ilaria Dorigatti, Peter Winskill, Charles Whittaker, Natsuko Imai, Gina Cuomo-Dannenburg, Hayley Thompson, Patrick GT Walker, Han Fu, et al. 2020. "Estimates of the severity of coronavirus disease 2019: a model-based analysis." *The Lancet Infectious Diseases*.

von Thadden, Elu. 2020. "A simple, non-recursive model of the spread of Covid-19 with applications to policy." *CEPR Covid Economics*, no. 10 (April).

Wu, Zunyou, and Jennifer M. McGoogan. 2020. "Characteristics of and Important Lessons From the Coronavirus Disease 2019 (COVID-19) Outbreak in China: Summary of a Report of 72 314 Cases From the Chinese Center for Disease Control and Prevention." *JAMA*, 02.

Zhang, Sheng, MengYuan Diao, Wenbo Yu, Lei Pei, Zhaofen Lin, and Dechang Chen. 2020. "Estimation of the reproductive number of novel coronavirus (COVID-19) and the probable outbreak size on the Diamond Princess cruise ship: A data-driven analysis." *International Journal of Infectious Diseases* 93:201 – 204.

Appendix

A Laws of Motion

In the main body (8) describes the overall laws of motion, and (9) describes the sub-part that determines the transitions for the healthy agents. The following contains the transitions for all other types. It also includes the accounting of Covid-deaths and new infections.

The number of fever-healthy agents who have a fever and are not tested but are truly healthy is given by

$$\begin{aligned} & M_{t+1}(f_h, a) \\ & = M_t(h,a)\Delta(a)(1-\xi_{p_t}(a))\pi_f(n_t(h,a)+\ell_t(h,a),\Pi_t(a))\frac{\Pi^*}{\Pi_t(a)+\Pi^*} \\ & + M_t(f_h,a)\Delta(a)(1-\xi_{p_t}(a))\pi_f(n_t(f,a)+\ell_t(f,a),\Pi_t(a))\frac{\Pi^*}{\Pi_t(a)+\Pi^*}. \end{aligned} \tag{15}$$

It includes in the first line healthy people from last period who got fever but were not tested, and are truly healthy. The second line again accounts for those in the fever-healthy state, as they can again catch another fever while truly remaining healthy.

A similar logic applies to those in the fever-infected state:

$$\begin{aligned} & M_{t+1}(f_i, a) \\ & = M_t(h,a)\Delta(a)(1-\xi_{p_t}(a))\pi_f(n_t(h,a)+\ell_t(h,a),\Pi_t(a))\frac{\Pi_t(a)}{\Pi_t(a)+\Pi^*} \\ & + M_t(f_h,a)\Delta(a)(1-\xi_{p_t}(a))\pi_f(n_t(f,a)+\ell_t(f,a),\Pi_t(a))\frac{\Pi_t(a)}{\Pi_t(a)+\Pi^*}. \end{aligned} \tag{16}$$

The total number of individuals in the fever state is then

$$M_{t+1}(f,a) = M_{t+1}(f_h,a) + M_{t+1}(f_i,a) \tag{17}$$

To account for infected people one counts those who started last period healthy or fever-healthy and get infected and tested this period, but also those who started last period infected or fever-infected who neither develop severe symptoms nor recover:

$$\begin{aligned} M_{t+1}(i,a) = {} & M_t(h,a)\Delta(a)\xi_{p_t}(a)\pi(n_t(h,a)+\ell_t(h,a),\Pi_t(a)) \\ & + M_t(f_h,a)\Delta(a)\xi_{p_t}(a)\pi(n_t(f,a)+\ell_t(f,a),\Pi_t(a)) \\ & + \left[M_t(f_i,a)+M_t(i,a)\right]\Delta(a)(1-\phi(0,a))(1-\alpha(a)) \end{aligned} \tag{18}$$

People with severe symptoms comprise those who entered last period infected or fever-infected and do not recover but instead develop more severe symptoms, as well as severely symptomatic individuals from the previous period who neither die nor recover:

$$\begin{aligned} M_{t+1}(s,a) = {} & \left[M_t(f_i,a)+M_t(i,a)\right]\Delta(a)(1-\phi(0,a))\alpha(a) \\ & + M_t(s,a)\Delta(a)(1-\delta_t(a))(1-\phi(1,a)) \end{aligned} \tag{19}$$

The total number of individuals with serious symptoms is then

$$M_t(s) = \sum_a M_t(s,a) \tag{20}$$

Recovered and therefore resistant individuals comprise those who were infected or fever-infected and recover, those with severe symptoms who do not die but recover, and resistant individuals from the previous period:

$$\begin{aligned} M_{t+1}(r,a) = {} & \left[M_t(f_i,a)+M_t(i,a)\right]\Delta(a)\phi(0,a) \\ & + M_t(s,a)\Delta(a)\phi(1,a) + \Delta(a)M_t(r,a) \end{aligned} \tag{21}$$

The right hand sides of equations (15) to (21) gives the map T_s for states $s = f_h, f_i, f, i, r$.

For accounting purposes, the measure of deceased agents as a result of Covid-19

is given by new Covid deaths and those who died of it in previous periods:

$$M_{t+1}(deceased, a) = M_t(deceased, a) + (1 - \phi(1, a))\delta_t(a)M_t(s, a)\Delta(a),$$

while the number of newly infected people is given by healthy or fever-healthy agents who get infected

$$\begin{aligned} N_{t+1}(i, a) &= M_t(h, a)\Delta(a)\pi(n_t(h, a) + \ell_t(h, a), \Pi_t(a)) \\ &\quad + M_t(f_h, a)\Delta(a)\pi(n_t(f, a) + \ell_t(f, a), \Pi_t(a)). \end{aligned}$$

B Details on Calibration

B.1 Google's Mobility Data

TBW

B.2 Computing Weekly Rates

Let C be the fraction of the population that catches the common cold every year. Then, the weekly infection rate Π^* is given by:

$$\Pi^* = 1 - (1 - C)^{1/52}.$$

Now, consider an agent that is infected with Covid-19. He may recover with probability $\phi(0)$ or develop serious symptoms with probability α. The following table gives what happens to a measure 1 of agents that are infected right now over the course of the next few weeks.

Week	Frac recovered	Frac still infected	Frac w/ symptoms
1	$\phi(0)$	$(1-\phi(0))(1-\alpha)$	$(1-\phi(0))\alpha$
2	$(1-\phi(0))(1-\alpha)\phi(0)$	$[(1-\phi(0))(1-\alpha)]^2$	$(1-\phi(0))(1-\alpha)(1-\phi(0))\alpha$
3	$[(1-\phi(0))(1-\alpha)]^2\phi(0)$	$[(1-\phi(0))(1-\alpha)]^3$	$[(1-\phi(0))(1-\alpha)]^2(1-\phi(0))\alpha$
4	...	...	...

Thus, the fraction of people that will develop symptoms F_s is given by

$$\begin{aligned}F_s &= (1-\phi(0))\alpha + (1-\phi(0))(1-\alpha)(1-\phi(0))\alpha + [(1-\phi(0))(1-\alpha)]^2(1-\phi(0))\alpha + ... \\ &= (1-\phi(0))\alpha\left[1 + (1-\phi(0))(1-\alpha) + [(1-\phi(0))(1-\alpha)]^2 + ...\right] \\ &= (1-\phi(0))\alpha\frac{1}{1-(1-\phi(0))(1-\alpha)}.\end{aligned}$$

Solving out for α gives

$$\alpha = \frac{B\phi(0)}{1-B(1-\phi(0))},$$

where $B = F_s/(1-\phi(0))$. With $\phi(0)$ given by the average time for recovery, one can use the formula above to get α.

We can do something similar for agents with symptoms to figure out at what rate they die. Here is the table:

Week	Frac recovered	Frac still w symptoms	Frac dead
1	$\phi(1)$	$(1-\phi(1))(1-\delta)$	$(1-\phi(1))\delta$
2	$(1-\phi(1))(1-\delta)\phi(1)$	$[(1-\phi(1))(1-\delta)]^2$	$(1-\phi(1))(1-\delta)(1-\phi(1))\delta$
3	$[(1-\phi(1))(1-\delta)]^2\phi(1)$	$[(1-\phi(1))(1-\delta)]^3$	$[(1-\phi(1))(1-\delta)]^2(1-\phi(1))\delta$
4	...	...	...

Using the same steps above and denoting the fraction that die by F_d, we get:

$$\delta = \frac{A\phi(1)}{1-A(1-\phi(1))},$$

where $A = F_d/(1-\phi(1))$.

B.3 Basic Reproduction Number - R_0

The probability that an infected agent leaves such state is: $[\phi(0) + (1 - \phi(0))\alpha]\,\Delta +$ $(1-\Delta)$. The squared brackets term is the probability of recovery and the probability that the agent switches to the serious symptoms case, conditional on surviving natural causes (probability Δ). The last term is death due to natural causes. Hence, the expected amount of time one stays in state i is:

$$T_i = \frac{1}{[\phi(0) + (1 - \phi(0))\alpha]\,\Delta + (1 - \Delta)}.$$

The probability that an agent with serious symptoms leaves such state is: $[\phi(1) +$ $(1 - \phi(1))\delta]\Delta + (1 - \Delta)$. The squared brackets term is the probability of recovery and the death-because-of-Covid probability, conditional on surviving natural causes (probability Δ). The last term is death due to natural causes. Hence, the expected amount of time one stays in state s is:

$$T_s = \frac{1}{[\phi(1) + (1 - \phi(1))\delta]\,\Delta + (1 - \Delta)}.$$

Now, the probability that one moves from the i state to the s state is given by:

$$P_s = \frac{(1 - \phi(0))\alpha\Delta}{1 - (1 - \phi(0))(1 - \alpha)\Delta}.$$

Note that the expressions above should be functions of one's age a, but we have supressed this for notational convenience.

Let $\tilde{n}(a)$ denote the amount of time an infected person of age a spends outside. Let $\overline{\ell}$ be the interaction time for people with serious symptoms. Finally, let $\bar{n}$ be the average (across ages) amount of time people spend outside. At the outset of the disease, a measure 1 of the population is healthy.

Then, $R_0(a)$ (i.e. for an infected person of age a) is given by:

$$R_0(a) = \left[\tilde{n}(a)T_i(a) + \overline{\ell}P_s(a)T_s(a)\right]\bar{n}\Pi_0.$$

This is the average number of people someone infects (for a person of a given age). The economy's R_0 will be the weighted average across ages:

$$R_0 = \sum_a \omega(a) R_0(a),$$

where $\omega(a)$ is the weight of age a in the population.

C Additional Results

C.1 Higher Death Rates for the Old

Table C1: Benchmark results (higher death rates for the old)

	Benchmark	Epidem.	Age ext. partial	Age ext. general
Wks to peak srsly ill (yng)	15.00	15.00	16.00	19.00
Wks to peak srsly ill (old)	14.00	14.00	14.00	14.00
Srsly ill p/ 1,000 @ peak (yng)	3.17	6.57	0.13	0.08
Srsly ill p/ 1,000 @ peak (old)	0.51	59.12	0.51	0.28
Dead p/ 1,000 1year (yng)	1.54	2.03	0.20	0.15
Dead p/ 1,000 1year (old)	8.75	164.89	8.74	6.26
Dead p/ 1,000 1year (all)	2.70	28.12	1.57	1.13
Dead p/ 1,000 LR (yng)	1.57	2.03	0.25	0.42
Dead p/ 1,000 LR (old)	11.19	164.89	11.16	17.90
Dead p/ 1,000 LR (all)	3.11	28.12	2.00	3.22
Immune in LR (yng), %	66.35	85.92	10.69	18.10
Immune in LR (old), %	2.06	29.80	2.06	3.45
Immune in LR (all), %	56.05	76.93	9.30	15.76
GDP at peak - rel to BM	1.00	1.24	0.04	0.77
GDP 1year - rel to BM	1.00	1.03	0.43	0.69
Cost p/ life saved, million $	0.00	0.08	31.47	12.26
Hrs @ home (yng) - peak	68.50	54.77	110.88	76.89
Hrs @ home (old) - peak	111.65	89.26	111.65	101.66
Hrs @ home (yng) - 6m	57.18	54.77	101.87	76.63
Hrs @ home (old) - 6m	108.81	89.26	108.82	101.48
Value - healthy (yng)	5029.50	5027.30	2079.00	2090.40
Value - healthy (old)	2336.10	2002.10	2336.20	2337.20
Value - healthy (all)	4598.00	4542.70	2120.20	2129.90

Table C2: Testing (higher death rates for the old)

	Benchmark	Testing all	Testing young	Testing old	Q90-a-50t	Q90-a-100t	Q90-y-100t
Wks to peak srsly ill (yng)	15.00	19.00	19.00	15.00	27.00	34.00	34.00
Wks to peak srsly ill (old)	14.00	17.00	17.00	14.00	25.00	30.00	30.00
Srsly ill p/ 1,000 @ peak (yng)	3.17	2.81	2.80	3.18	0.99	0.05	0.05
Srsly ill p/ 1,000 @ peak (old)	0.51	0.49	0.49	0.51	0.46	0.16	0.16
Dead p/ 1,000 1year (yng)	1.54	1.41	1.41	1.55	0.85	0.08	0.08
Dead p/ 1,000 1year (old)	8.75	7.36	7.33	8.79	8.13	3.15	3.26
Dead p/ 1,000 1year (all)	2.70	2.36	2.36	2.71	2.01	0.57	0.59
Dead p/ 1,000 LR (yng)	1.57	1.41	1.41	1.57	0.93	0.11	0.11
Dead p/ 1,000 LR (old)	11.19	7.83	7.90	11.14	11.72	4.27	4.46
Dead p/ 1,000 LR (all)	3.11	2.44	2.45	3.10	2.66	0.77	0.81
Immune in LR (yng), %	66.35	59.86	59.76	66.49	39.26	4.59	4.84
Immune in LR (old), %	2.06	1.43	1.45	2.05	2.18	0.79	0.83
Immune in LR (all), %	56.05	50.50	50.42	56.17	33.32	3.98	4.19
Number of tests - peak, %	0.00	8.90	8.86	0.02	2.75	4.79	4.56
Number of tests - LR, %	0.00	2.12	1.84	0.29	1.53	4.66	4.35
GDP at peak - rel to BM	1.00	1.00	1.00	1.00	1.14	1.24	1.24
GDP 1year - rel to BM	1.00	1.00	1.00	1.00	1.01	1.03	1.03
Cost p/ life saved, million $	0.00	-0.02	-0.02	-0.17	-0.58	-0.96	-0.96
Hrs @ home (yng) - peak	68.50	67.94	67.92	68.51	59.57	55.02	55.03
Hrs @ home (old) - peak	111.65	111.59	111.59	111.65	110.38	96.65	96.82
Hrs @ home (yng) - 6m	57.18	58.19	58.17	57.20	59.50	55.02	55.03
Hrs @ home (old) - 6m	108.81	109.59	109.58	108.84	110.29	96.60	96.77
Value - healthy (yng)	5029.50	5030.30	5030.30	5029.50	5032.90	5037.60	5037.60
Value - healthy (old)	2336.10	2348.70	2348.60	2336.00	2342.90	2382.10	2381.50
Value - healthy (all)	4598.00	4600.70	4600.70	4598.00	4601.80	4612.20	4612.00

Table C3: Shelter in Place (higher death rates for the old)

	Benchmark	SH25-a-4	SH25-y-26	SH25-y-35	SH50-a-26	SH75-a-12	SH75-a-35	SH90-a-26	SH90-o-26
Wks to peak srsly ill (yng)	15.00	18.00	33.00	28.00	48.00	36.00	68.00	56.00	16.00
Wks to peak srsly ill (old)	14.00	16.00	31.00	25.00	47.00	34.00	67.00	55.00	15.00
Srsly ill p/ 1,000 @ peak (yng)	3.17	3.16	2.02	1.12	3.18	3.18	3.18	3.16	3.15
Srsly ill p/ 1,000 @ peak (old)	0.51	0.51	0.49	0.49	0.49	0.50	0.48	0.49	0.46
Dead p/ 1,000 1year (yng)	1.54	1.54	1.48	1.31	0.95	1.46	0.00	0.03	1.54
Dead p/ 1,000 1year (old)	8.75	8.50	9.13	9.43	2.82	5.67	0.00	0.71	7.22
Dead p/ 1,000 1year (all)	2.70	2.65	2.71	2.61	1.25	2.14	0.00	0.14	2.45
Dead p/ 1,000 LR (yng)	1.57	1.57	1.56	1.55	1.56	1.57	1.56	1.57	1.57
Dead p/ 1,000 LR (old)	11.19	11.17	13.53	16.09	10.72	11.04	10.46	10.75	9.71
Dead p/ 1,000 LR (all)	3.11	3.11	3.48	3.88	3.03	3.08	2.99	3.04	2.87
Immune in LR (yng), %	66.35	66.33	65.94	65.72	66.19	66.31	66.20	66.27	66.33
Immune in LR (old), %	2.06	2.07	2.52	3.01	2.05	2.08	2.04	2.07	1.80
Immune in LR (all), %	56.05	56.03	55.78	55.67	55.92	56.02	55.92	55.98	56.00
GDP at peak - rel to BM	1.00	1.00	1.09	1.16	1.00	1.00	1.00	1.00	1.00
GDP 1year - rel to BM	1.00	0.98	0.88	0.84	0.76	0.83	0.54	0.58	1.00
Cost p/ life saved, million $	0.00	27.31	-726.61	108.71	10.38	18.89	10.77	10.17	-0.01
Hrs @ home (yng) - peak	68.50	68.20	64.48	61.02	68.68	67.83	68.73	68.41	68.25
Hrs @ home (old) - peak	111.65	111.65	111.44	110.98	111.64	111.64	111.64	111.65	111.68
Hrs @ home (yng) - 6m	57.18	58.07	70.99	70.95	82.15	54.91	95.84	104.06	57.23
Hrs @ home (old) - 6m	108.81	109.64	110.83	110.79	101.05	100.45	106.12	109.08	110.36
Value - healthy (yng)	5029.50	5029.10	5027.00	5026.10	5018.70	5015.40	4988.70	4972.50	5029.50
Value - healthy (old)	2336.10	2336.20	2324.00	2311.40	2336.50	2333.70	2328.90	2321.90	2331.50
Value - healthy (all)	4598.00	4596.00	4583.50	4577.30	4568.10	4572.20	4523.40	4514.10	4596.30

C.2 Hospital Constraints

Table C4: Benchmark results (hospital constraints)

	Benchmark	Epidem.	Age ext. partial	Age ext. general
Wks to peak srsly ill (yng)	13.00	14.00	13.00	13.00
Wks to peak srsly ill (old)	13.00	14.00	13.00	14.00
Srsly ill p/ 1,000 @ peak (yng)	0.72	3.39	0.71	0.66
Srsly ill p/ 1,000 @ peak (old)	0.34	4.63	0.34	0.32
Dead p/ 1,000 1year (yng)	4.20	9.33	3.71	3.09
Dead p/ 1,000 1year (old)	5.78	15.83	5.76	5.12
Dead p/ 1,000 1year (all)	4.45	10.37	4.04	3.42
Dead p/ 1,000 LR (yng)	4.35	9.33	3.87	3.34
Dead p/ 1,000 LR (old)	6.83	15.83	6.82	6.76
Dead p/ 1,000 LR (all)	4.74	10.37	4.34	3.89
Immune in LR (yng), %	64.99	84.15	60.56	58.49
Immune in LR (old), %	19.36	41.67	19.38	19.40
Immune in LR (all), %	57.68	77.35	53.96	52.23
GDP at peak - rel to BM	1.00	1.48	0.97	0.99
GDP 1year - rel to BM	1.00	1.11	0.93	0.96
Cost p/ life saved, million $	0.00	1.19	10.42	2.71
Hrs @ home (yng) - peak	75.43	54.77	76.46	75.64
Hrs @ home (old) - peak	103.92	89.26	103.92	103.30
Hrs @ home (yng) - 6m	66.28	54.77	72.63	69.28
Hrs @ home (old) - 6m	101.12	89.26	101.12	99.61
Value - healthy (yng)	5013.90	4991.00	2189.30	2192.20
Value - healthy (old)	2372.60	2356.00	2372.60	2373.90
Value - healthy (all)	4590.80	4568.90	2218.70	2221.30

Table C5: Testing (hospital constraints)

	Benchmark	Testing all	Testing young	Testing old	Q90-a-50t	Q90-a-100t	Q90-y-100t
Wks to peak srsly ill (yng)	13.00	16.00	16.00	13.00	22.00	44.00	43.00
Wks to peak srsly ill (old)	13.00	16.00	16.00	13.00	23.00	43.00	43.00
Srsly ill p/ 1,000 @ peak (yng)	0.72	0.71	0.71	0.73	0.46	0.04	0.04
Srsly ill p/ 1,000 @ peak (old)	0.34	0.33	0.33	0.34	0.20	0.02	0.02
Dead p/ 1,000 1year (yng)	4.20	3.76	3.74	4.21	1.48	0.07	0.07
Dead p/ 1,000 1year (old)	5.78	5.03	5.03	5.78	3.12	0.36	0.33
Dead p/ 1,000 1year (all)	4.45	3.96	3.95	4.46	1.74	0.12	0.11
Dead p/ 1,000 LR (yng)	4.35	3.83	3.82	4.36	1.63	0.10	0.09
Dead p/ 1,000 LR (old)	6.83	5.48	5.53	6.78	3.90	0.48	0.44
Dead p/ 1,000 LR (all)	4.74	4.10	4.09	4.74	2.00	0.16	0.15
Immune in LR (yng), %	64.99	56.01	56.18	64.85	38.46	4.32	3.97
Immune in LR (old), %	19.36	15.49	15.64	19.22	11.30	1.41	1.30
Immune in LR (all), %	57.68	49.51	49.68	57.54	34.11	3.86	3.54
Number of tests - peak, %	0.00	5.18	4.93	0.23	2.53	4.84	4.52
Number of tests - LR, %	0.00	2.24	1.99	0.23	1.53	4.67	4.39
GDP at peak - rel to BM	1.00	0.95	0.96	1.00	1.29	1.48	1.48
GDP 1year - rel to BM	1.00	1.00	1.00	1.00	1.07	1.12	1.12
Cost p/ life saved, million $	0.00	-0.40	-0.47	-3.15	-1.54	-1.68	-1.68
Hrs @ home (yng) - peak	75.43	77.59	77.46	75.57	62.78	55.01	54.98
Hrs @ home (old) - peak	103.92	104.50	104.45	103.97	98.56	90.15	90.04
Hrs @ home (yng) - 6m	66.28	68.14	67.88	66.38	61.29	54.99	54.97
Hrs @ home (old) - 6m	101.12	101.65	101.56	101.16	98.07	90.09	90.01
Value - healthy (yng)	5013.90	5016.40	5016.50	5013.80	5029.30	5037.70	5037.70
Value - healthy (old)	2372.60	2376.30	2376.20	2372.70	2382.90	2392.50	2392.60
Value - healthy (all)	4590.80	4593.40	4593.50	4590.70	4605.10	4613.90	4613.90

Table C6: Shelter in Place (hospital constraints)

	Benchmark	SH25-a-4	SH25-y-26	SH25-y-35	SH50-a-26	SH75-a-12	SH75-a-35	SH90-a-26	SH90-o-26
Wks to peak srsly ill (yng)	13.00	15.00	31.00	41.00	46.00	33.00	66.00	54.00	13.00
Wks to peak srsly ill (old)	13.00	15.00	32.00	23.00	47.00	34.00	66.00	54.00	30.00
Srsly ill p/ 1,000 @ peak (yng)	0.72	0.72	0.58	0.51	0.72	0.72	0.72	0.72	0.74
Srsly ill p/ 1,000 @ peak (old)	0.34	0.34	0.28	0.27	0.33	0.33	0.32	0.33	0.25
Dead p/ 1,000 1year (yng)	4.20	4.16	3.50	2.90	1.91	3.51	0.00	0.03	4.13
Dead p/ 1,000 1year (old)	5.78	5.60	5.00	4.74	1.70	3.65	0.00	0.20	3.48
Dead p/ 1,000 1year (all)	4.45	4.39	3.74	3.19	1.88	3.53	0.00	0.06	4.02
Dead p/ 1,000 LR (yng)	4.35	4.34	3.93	3.59	4.34	4.34	4.33	4.33	4.28
Dead p/ 1,000 LR (old)	6.83	6.80	7.14	7.38	6.61	6.68	6.45	6.53	4.66
Dead p/ 1,000 LR (all)	4.74	4.74	4.45	4.19	4.71	4.72	4.67	4.68	4.34
Immune in LR (yng), %	64.99	64.91	64.81	64.74	65.00	64.89	64.81	64.85	65.11
Immune in LR (old), %	19.36	19.33	20.55	21.35	19.39	19.33	19.27	19.30	13.46
Immune in LR (all), %	57.68	57.61	57.72	57.79	57.69	57.59	57.52	57.55	56.84
GDP at peak - rel to BM	1.00	1.00	1.15	1.24	1.00	1.00	1.00	1.00	1.01
GDP 1year - rel to BM	1.00	0.98	0.90	0.87	0.79	0.83	0.58	0.62	1.00
Cost p/ life saved, million $	0.00	21.30	9.27	6.55	5.17	11.42	5.92	5.42	-0.40
Hrs @ home (yng) - peak	75.43	75.38	71.27	68.20	75.27	75.23	75.40	75.38	75.06
Hrs @ home (old) - peak	103.92	103.92	102.58	101.63	103.90	103.89	103.92	103.92	109.65
Hrs @ home (yng) - 6m	66.28	67.69	73.68	73.01	82.15	54.69	95.84	104.06	66.10
Hrs @ home (old) - 6m	101.12	101.52	99.39	99.34	101.05	90.52	106.12	109.08	109.43
Value - healthy (yng)	5013.90	5013.60	5013.90	5015.00	5003.50	5000.10	4973.80	4957.50	5014.40
Value - healthy (old)	2372.60	2372.60	2372.50	2372.30	2370.50	2369.00	2361.80	2355.80	2360.70
Value - healthy (all)	4590.80	4588.70	4580.60	4578.10	4560.80	4565.00	4516.20	4506.90	4587.30

C.3 Higher Death Rates for the Old and Hospital Constraints

Table C7: Benchmark results (higher death rates for the old and hospital constraints)

	Benchmark	Epidem.	Age ext. partial	Age ext. general
Wks to peak srsly ill (yng)	13.00	14.00	17.00	19.00
Wks to peak srsly ill (old)	11.00	14.00	13.00	14.00
Srsly ill p/ 1,000 @ peak (yng)	0.71	3.25	0.14	0.08
Srsly ill p/ 1,000 @ peak (old)	0.46	50.85	0.48	0.28
Dead p/ 1,000 1year (yng)	4.22	9.91	0.24	0.15
Dead p/ 1,000 1year (old)	10.65	177.88	10.39	6.26
Dead p/ 1,000 1year (all)	5.25	36.82	1.87	1.13
Dead p/ 1,000 LR (yng)	4.38	9.91	0.38	0.42
Dead p/ 1,000 LR (old)	16.38	177.88	16.16	17.90
Dead p/ 1,000 LR (all)	6.30	36.82	2.91	3.22
Immune in LR (yng), %	64.11	84.58	16.14	18.10
Immune in LR (old), %	2.97	28.06	3.00	3.45
Immune in LR (all), %	54.32	75.53	14.04	15.76
GDP at peak - rel to BM	1.00	1.48	0.11	0.91
GDP 1year - rel to BM	1.00	1.11	0.29	0.75
Cost p/ life saved, million $	0.00	0.22	13.24	3.82
Hrs @ home (yng) - peak	75.16	54.77	108.65	76.89
Hrs @ home (old) - peak	111.06	89.26	111.06	101.66
Hrs @ home (yng) - 6m	66.25	54.77	106.37	76.63
Hrs @ home (old) - 6m	110.34	89.26	110.34	101.48
Value - healthy (yng)	5013.80	4988.10	2001.70	2090.40
Value - healthy (old)	2307.40	1971.50	2307.20	2337.20
Value - healthy (all)	4580.20	4504.90	2050.70	2129.90

Table C8: Testing (higher death rates for the old and hospital constraints)

	Benchmark	Testing all	Testing young	Testing old	Q90-a-50t	Q90-a-100t	Q90-y-100t
Wks to peak srsly ill (yng)	13.00	16.00	16.00	13.00	22.00	44.00	44.00
Wks to peak srsly ill (old)	11.00	13.00	13.00	11.00	19.00	43.00	43.00
Srsly ill p/ 1,000 @ peak (yng)	0.71	0.69	0.69	0.71	0.43	0.05	0.05
Srsly ill p/ 1,000 @ peak (old)	0.46	0.45	0.45	0.46	0.42	0.15	0.15
Dead p/ 1,000 1year (yng)	4.22	3.74	3.72	4.23	1.49	0.07	0.08
Dead p/ 1,000 1year (old)	10.65	9.86	9.85	10.66	8.38	3.02	3.12
Dead p/ 1,000 1year (all)	5.25	4.72	4.71	5.26	2.59	0.55	0.57
Dead p/ 1,000 LR (yng)	4.38	3.83	3.81	4.40	1.67	0.10	0.11
Dead p/ 1,000 LR (old)	16.38	13.61	13.64	16.38	13.62	4.19	4.38
Dead p/ 1,000 LR (all)	6.30	5.40	5.39	6.32	3.58	0.76	0.79
Immune in LR (yng), %	64.11	55.22	54.98	64.32	37.81	4.44	4.69
Immune in LR (old), %	2.97	2.46	2.47	2.97	2.52	0.78	0.81
Immune in LR (all), %	54.32	46.77	46.57	54.49	32.16	3.85	4.07
Number of tests - peak, %	0.00	4.98	4.94	0.03	2.41	4.75	4.52
Number of tests - LR, %	0.00	2.32	2.04	0.28	1.56	4.67	4.36
GDP at peak - rel to BM	1.00	0.96	0.96	1.00	1.29	1.48	1.48
GDP 1year - rel to BM	1.00	1.00	1.00	1.00	1.07	1.12	1.12
Cost p/ life saved, million $	0.00	-0.49	-0.52	-1.06	-1.59	-1.55	-1.56
Hrs @ home (yng) - peak	75.16	77.20	77.13	75.21	62.53	55.01	55.02
Hrs @ home (old) - peak	111.06	111.11	111.10	111.06	109.38	96.40	96.58
Hrs @ home (yng) - 6m	66.25	67.92	67.86	66.28	61.16	55.00	55.00
Hrs @ home (old) - 6m	110.34	110.42	110.41	110.34	109.12	96.05	96.24
Value - healthy (yng)	5013.80	5016.40	5016.50	5013.70	5029.10	5037.60	5037.60
Value - healthy (old)	2307.40	2323.20	2323.30	2307.10	2336.00	2382.40	2381.80
Value - healthy (all)	4580.20	4585.00	4585.10	4580.10	4597.50	4612.20	4612.10

Table C9: Shelter in Place (higher death rates for the old and hospital constraints)

	Benchmark	SH25-a-4	SH25-y-26	SH25-y-35	SH50-a-26	SH75-a-12	SH75-a-35	SH90-a-26	SH90-o-26
Wks to peak srsly ill (yng)	13.00	15.00	31.00	41.00	46.00	33.00	66.00	54.00	13.00
Wks to peak srsly ill (old)	11.00	13.00	19.00	19.00	43.00	31.00	63.00	52.00	31.00
Srsly ill p/ 1,000 @ peak (yng)	0.71	0.71	0.57	0.49	0.71	0.71	0.71	0.71	0.72
Srsly ill p/ 1,000 @ peak (old)	0.46	0.46	0.45	0.46	0.44	0.46	0.44	0.44	0.42
Dead p/ 1,000 1year (yng)	4.22	4.19	3.51	2.90	2.01	3.51	0.00	0.06	4.18
Dead p/ 1,000 1year (old)	10.65	10.17	9.50	9.45	2.90	5.96	0.00	0.73	8.91
Dead p/ 1,000 1year (all)	5.25	5.15	4.47	3.95	2.16	3.90	0.00	0.17	4.94
Dead p/ 1,000 LR (yng)	4.38	4.38	4.00	3.68	4.39	4.38	4.37	4.38	4.34
Dead p/ 1,000 LR (old)	16.38	16.48	18.01	18.78	16.79	16.72	15.82	16.39	14.70
Dead p/ 1,000 LR (all)	6.30	6.32	6.24	6.10	6.37	6.36	6.20	6.30	6.00
Immune in LR (yng), %	64.11	64.10	64.06	63.93	64.44	64.27	64.14	64.31	64.13
Immune in LR (old), %	2.97	3.00	3.31	3.46	3.17	3.11	3.04	3.11	2.69
Immune in LR (all), %	54.32	54.31	54.33	54.25	54.63	54.47	54.35	54.50	54.28
GDP at peak - rel to BM	1.00	1.00	1.14	1.23	1.00	1.00	1.00	1.00	1.00
GDP 1year - rel to BM	1.00	0.98	0.89	0.87	0.79	0.83	0.58	0.62	1.00
Cost p/ life saved, million $	0.00	11.68	8.48	6.37	4.33	7.76	5.01	4.68	-0.25
Hrs @ home (yng) - peak	75.16	75.09	71.19	68.34	75.13	75.00	75.16	75.11	75.09
Hrs @ home (old) - peak	111.06	111.06	110.78	110.53	111.06	111.06	111.06	111.06	111.27
Hrs @ home (yng) - 6m	66.25	67.59	73.45	72.82	82.15	54.70	95.84	104.06	66.34
Hrs @ home (old) - 6m	110.34	110.46	109.93	109.91	101.05	100.28	106.12	109.08	110.89
Value - healthy (yng)	5013.80	5013.50	5013.70	5014.50	5003.30	4999.90	4973.60	4957.30	5014.00
Value - healthy (old)	2307.40	2307.40	2302.20	2298.90	2306.80	2304.60	2301.70	2293.70	2303.00
Value - healthy (all)	4580.20	4578.20	4569.10	4565.90	4550.40	4554.60	4506.40	4496.80	4578.70