An economic model of the Covid-19 pandemic with young and old agents: Behavior, testing and policies*

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Abstract

This paper investigates the importance of the age composition in the Covid-19 pandemic. We augment a standard SIR epidemiological model with individual choices on work and non-work social distancing. Infected individuals are initially uncertain unless they are tested. We find that older individuals socially distance themselves substantially in equilibrium. Confining the old even more reduces their welfare. Confining the young extends the duration of the epidemic, with negative consequences on the old if the epidemic cannot be controlled after confinement. Testing and quarantines save lives, even if conducted just on the young, as does separation of activities by age. Combining policies can increase the welfare of both the young and the old.

Keywords: Covid-19, testing, social distancing, age, age-specific policies
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1 Introduction

A striking feature of the Covid-19 pandemic is the difference in death rates by age: those above 65 have a much higher chance of dying than those aged 20-65. This raises a number of important points: How much social distancing do these different individuals do? What are the externalities between these age groups? How does that interact with policy; and should one target lockdown or testing to particular subgroups? While we explore these questions in the context of the current Covid-19 pandemic, a similar age gradient can be observed in other outbreaks such as SARS and the main insights should carry over more generally to fast-moving epidemics in which certain groups face higher risk.

Our tool is a calibrated economic model of the pandemic that features *age heterogeneity* and *individual choice* regarding risky labor and leisure activities, embedded in an SIR epidemiological model with vaccine arrival at 1.5 years. Initial symptoms leave individuals and the government with *incomplete information* whether they have Covid, rendering testing valuable. We study the equilibrium interaction between age groups and 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.

The model predicts that older individuals shield themselves substantially in equilibrium, especially at the peak of the pandemic. The young also reduce work and outside leisure, but much less so due to a lower risk of dying and the need to earn a living. Relative to a purely epidemiological model where individuals do not adjust their behavior, this more than halves the overall death toll and cuts it by more than 2/3 for the elderly, at a GDP reduction of 6%.

Perhaps surprisingly, there is a positive externality from the young to the old: if the young become more cautious, the death rate of the old increases, though overall deaths decline. This arises in a hypothetical experiment where the young believe that they die at the same rate as the old. The reason is that the only recourse from the disease in the benchmark is a vaccine, and without further intervention the pandemic peaks prior to its arrival. More caution by the young extends the duration of the pandemic, making it more costly for the old to shield themselves. This externality has powerful consequences for policy.

Confinement of the population has to be well designed. Short and mild lockdowns have little or even negative effects, as the disease rebounds before a vaccine arrives. The old also find it more costly to shield themselves as the disease lasts for longer. This leads to more deaths and depresses GDP. This happens when all are mildly confined for short periods, and is exacerbated when confining just the young. Harsher and longer lockdowns can save some lives by delaying the peak and moving it closer to the vaccine arrival. But the number of lives saved is still modest compared to the enormous economic cost of these policies. They tend to reduce welfare for all, including the old who gain most in terms of lives saved. If confinement lasts until the arrival of a vaccine, the old actually benefit both in terms of saved lives and welfare, while for the young it saves lives but at a cost to utility due to lost income. No shelter-in-place policy alone raises average welfare, but some come close which gives hope that combined with non-modelled benefits (such as provision of masks, learning about better treatments) the best confinement policies will be welfare enhancing.

A particular confinement policy that has attracted attention in other work actually saves lives at no cost to GDP: confining only the elderly. These individuals do not work but have a high risk of dying. While they are already very careful voluntarily, further mandatory confinement of just the old saves additional lives among this group, leaving the young virtually unaffected. While seemingly attractive, we find that such interventions reduce the welfare of the elderly. The reason is intuitive: what is optimal behavior for one elderly person remains optimal for all elderly together unless their joint behavior affects aggregates such as the overall risk of infection. But if the group is small, the latter effect is also small, and one cannot improve upon their own choices. The elderly are a small group precisely because they are so careful: they are 16% of population, but only 7% of steady-state interaction because they do not need to work, and only 1.9% of social interactions at the peak of the pandemic because of their additional precautions.

Most confinement scenarios - including confinement of the elderly - would be preferred by individuals to a purely epidemiological scenario where the behavior is fixed as in normal times. But relative to voluntary optimal behavior, confinements are very costly and only beneficial when designed very carefully. So what are other options? Separating some activities such as shopping times by age group does save lives, but increases deaths among the young and reduces their labor supply because they are operating in a riskier environment.

Testing on the other hand is very beneficial if carried out in large scale. If one could test all individuals who are unsure of their Covid status with tests that provide immediate results, this would reduce deaths by 35% even without further interventions and with slight improvements to GDP. The reason is that individuals that are told they have Covid have some partial altruism and reduce their social interactions in our model. This frees up others to take more risk and increases their labor supply and their demand for goods that complement outside leisure (e.g., restaurant meals). This requires a testing capacity of 5.6% of the population in a week, though. If one additionally quarantines the infected, the same reductions in deaths can be achieved by testing only half the population, requiring a test capacity of 2.6%. If one could test everyone and apply quarantines, this would stop the outbreak on its tracks, yielding hardly any deaths and GDP improvements of 6%, at a testing capacity of 5%. These are welfare-improving measures, though the costs of testing capacity lies outside of the model and is not accounted for here. Yet, we calculate the increase in GDP per test performed and find it is sizeable, between 300 and 1500 dollars, which should easily cover the cost of the test. Further note that the number of tests are an upper bound that could be reduced through contact tracing. The benefits of testing are only minimally reduced if one just tests the young, as the old are few and careful and hardly affect the dynamics of the disease.[1]

We also explore the impact of combined policies, particularly focusing on milder versions of them that are probably more likely to be implemented. Such combinations have strong effects on curtailing the number of deaths, even compared to each policy in isolation. We find that combining partial but widespread testing with a medium strength lockdown until vaccine arrival essentially eradicates the disease. This policy benefits the old substantially but reduces the welfare of the young who bear the majority of the costs compared to only testing.

[1]Obviously one might want to test the severely ill old to identify them correctly for treatment as having Covid. We do not model this medical necessity.

On the other hand, combining the same amount of testing with an even milder lockdown that also lasts until a vaccine arrives cuts deaths by 60% (or about 800,000 deaths averted in the US). This combined policy in fact improves the welfare of *both* the young and the old beyond testing alone.

The next section reviews the pre- and post-Covid literature. It makes clear that there is little pre-Covid work on how to calibrate epidemiological models with behavior. We draw on some experiences from Greenwood et al. (2019, 2017, 2013) for the HIV/AIDS epidemic. There are clearly many differences and novel modelling choices in the current setting, however, so results need to be viewed with caution. Regarding the Covid literature, most works focus on homogeneous agents. Those papers that have age heterogeneity do not model individual behavior, which is central to our benchmark and to the effects of our policies. Few papers have testing, and only combine this with optimal behavior. We differ by taking insights from epidemiology that agents have some altruism, which changes some results, as well as having age heterogeneity. Section 3 outlines the model, followed by the benchmark calibration (Section 4), baseline results (Section 5), and policy experiments (Section 6). The online appendix discusses alternative scenarios without vaccine, with limited hospital beds, without altruism, and other features. These affect the quantitative numbers, but leave most of the qualitative insights unchanged. Section 7 concludes.

2 Literature Review

This paper contributes to the literature that combines epidemiological models in the style of Kermack and McKendrick (1927) with equilibrium behavioral choice. In economics, efforts to incorporate behavioral responses to disease progression through equilibrium models have mostly been theoretical. Such works have long pointed out a negative externality of too little prevention efforts by self-interested agents; see, e.g., Kremer (1996) for SI models, Quercioli and Smith (2006) for SIR models, and more recently Toxvaerd (2019). These studies consider homogeneous populations, though Kremer (1996) also considers heterogeneous preferences for risky activities and shows that increased activity of the low-activity group can eradicate the disease. In our setting differences in activity are partially a consequence of different death rates and we obtain very different results: increases in activity of the more careful (i.e., at-risk) group increases deaths in a no-vaccine setting.[2]

There are few quantitative economic models of disease transmission that predate the Covid crisis. 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 matter for the valuation of medical innovations. Keppo et al. (2020) expand Quercioli and Smith (2006) to a calibrated homogeneous-agent model and argue that a substantial behavioral elasticity is necessary to match the Swine Flu and the Covid-19 pandemic.

In the great influx of recent economics papers studying different aspects of Covid-19, most consider homogeneous populations. Some analyze optimal containment policies that trade off economic well-being of living individuals versus lost lives (Alvarez, Argente, and Lippi (2020), Eichenbaum, Rebelo, and Trabandt (2020a), Farboodi, Jarosch, and Shimer (2020), Garobaldi, Moen, and Pissarides (2020), McAdams (2020)). Other papers introduce uncertainty about one's infection status and the role for testing (Berger, Herkenhoff, and Mongey (2020), von Thadden (2020), Piguillem and Shi (2020)). Only Eichenbaum, Rebelo, and Trabandt (2020b) combine testing with individual choices about social distancing as in our paper. Unlike our setting, however, infected individuals display no altruism and become more reckless if tested, which renders

[2]There are many differences between these papers: Kremer (1996) considers a steady-state SI model without vaccine with standard incidence common in HIV papers, while ours is a dynamic SIR model with mass action incidence common to Covid-19 papers and the comparable no-vaccine-arrival case is a robustness check. Other work that considers heterogeneity includes Galeotti and Rogers (2012) who study two identical populations but with non-random mixing patterns, and work on transmission in networks where individuals occupy different positions (e.g., Acemoglu, Malekian, and Ozdaglar (2016)).

testing counter-productive unless combined with quarantines.

Our paper differs from these in its focus on a key heterogeneity: different ages and, hence, different risk groups. The are a few other studies that incorporate age differences: Favero, Ichino, and Rustichini (2020) and Gollier (2020a) argue that re-opening should focus on the young while shielding the old, Gollier (2020b) argues that herd immunity has less deaths when built on the young, Glover et al. (2020) analyze how a blanket lockdown affects young and old agents differently and how this leads to disagreement on optimal policy, Alon et al. (2020b) argue that shielding the old while the young work is even more important in developing countries. Acemoglu et al. (2020) characterize the optimal frontier between GDP and lives lost in a model with three age groups and argue that the tension between lives saved vs GDP lost can be best addressed with targeted group-specific policies.[3] Except for the latter, these papers do not consider uncertainty about the infection status nor testing. They assume that individual behavior can be affected directly through policy, but is otherwise fixed, and usually trade off lost production vs lives saved. This implies large benefits to confinement of the elderly who are at risk but do not produce. Our work focuses on voluntary behavioral change which has been empirically found to be a large driver behind social distancing (e.g., Maloney and Taskin (2020)) and how this interacts with age-specific policies. In our model the elderly confine themselves voluntarily and further mandatory confinement lowers their welfare.

On a more empirical side Kuhn and Bayer (2020) suggest differences in the amount of interaction between old and young as a possible explanation for the cross-country differences in death rates. We take up this idea about selective mixing as part of our policy analysis.

[3] Brotherhood et al. (2020) extend our framework to study heterogeneity on income and housing arrangements in developing countries (including slums). Fernández-Villaverde and Jones (2020) study many countries and cities to analyze possible reopening scenarios. While there are no explicit economic choices, behavioral adjustments are captured through an exogenous contact function which changes over time as the disease spreads.

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 $a \in \{y, o\}$.[4] 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, a status denoted by $j = s$. This happens with probability $\alpha(a)$. If the agent develops serious symptoms, he can die with probability $\delta_t(a)$, on top of the natural death probability $\overline{\delta}(a)$ in the absence of the pandemic.[5] The Covid death rate is time-dependent because the death rate for individuals who obtain a bed in an intensive care unit ($\tilde{\delta}_1(a)$) 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 pandemic. 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 $j = r$.[6] Thus, $j \in \{h, f, i, s, r\}$. Agents discount the future at a common factor $\tilde{\beta}$, but since

[4] With minor notation changes the theoretical model can accommodate any number of age groups, but for transparency we focus on just two. This is in line with Acemoglu et al. (2020) who highlight large benefits from separately targeting the elderly and the working age population but little further improvements in sub-dividing those who work.

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

[6] While in reality permanent immunity is unlikely, immunity in the short run appears quite possible. As long as immunity lasts until a vaccine is available, all our results go through.

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, leisure outside the house ℓ and hours at home d ("domestic" leisure). The agent time constraint is thus:

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

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 the parameter b. The utility function is given by:

$$u(c, g, d; j, a, p) = \ln c + \gamma \ln g + b + [\lambda_d + \lambda(j) + \lambda_p(j, a)] \ln d.$$

The term $\lambda(j)$ expresses an additional preference for staying at home when being infected, and is a simple 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.[7] 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.[8] 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 ($\lambda_p(j, a) = \bar{\lambda}_p(a)$), quarantines of those who have tested positive ($\lambda_p(i, a) = \bar{\lambda}_p$, $\lambda_p(j, a) = 0$ for $j \neq i$) and more.

The wage per unit of time worked is denoted by w. Old agents get a fixed

[7] This way of modeling partial altruism is of course a shortcut. We discuss in Section 4 how we discipline this parameter.

[8] 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.

retirement income $\bar{w}$. Total earnings are then defined as follows:

$$w(a,n) = \begin{cases} wn & \text{if } a = y \\ \overline{w} & \text{if } a = o. \end{cases}$$

The budget constraint of the agent is thus given by:

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

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 agent 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.[9] 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 immediately whether he is 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.

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

Finally, assume that a vaccine comes along in period T^*. With the vaccine, nobody gets infected with Covid-19 anymore. That is, $\Pi_t(a) = 0$, for $t > T^*$.[10]

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

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

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 corresponds to the fever state (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:

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

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 serious 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

[10] The results for the case case in which a vaccine never arrives are in Appendix D.2.

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

$$\begin{aligned} V_t(f, a) = \max_{c,x,n,\ell,d} & u(c, g(x, \ell), d; f, a, p_t) + \\ & \frac{\Pi^* \, \tilde{V}_t(c, x, n, \ell, d; h, a)}{\Pi_{t-1}(a) + \Pi^*} + \frac{\Pi_{t-1}(a) \, \tilde{V}_t(c, x, n, \ell, d; i, a)}{\Pi_{t-1}(a) + \Pi^*} \\ & \text{s.t. (1) and (2).} \end{aligned} \tag{5}$$

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. Obviously they can enjoy the utility of normal life again if they recover. These agents provide no labor ($n = 0$) 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:

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

This 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:

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

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 spent outside the house in equilibrium. 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 with Covid-19 (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 young individuals spend at work in equilibrium multiplied by their wage rate:

$$Q_t = \sum_j w n_t(j, y) M_t(j, y). \tag{10}$$

For many of the exercises we aggregate these weekly output measures to get overall GDP measures for longer time periods (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 pandemic. To match the basic reproductive number (R_0), 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 counter-productive 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 of Section 6 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 $\{n_t(j, a), \ell_t(j, a)\}_{t=0}^{\infty}$ 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.

We start with the calibration of health-related parameters. These parameters are summarized in Table 1, while Table 3 shows how the model fits the data targets. Start with the common cold. According to Heikkinen and Järvinen (2003), the average American has between two and four colds every year. Suppose an agent in our model has an average of three colds per year. This implies a weekly infection rate of 0.058.[11] 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 start of the pandemic is expected to generate over the course of his disease. In our model, this is closely related to Π_0.[12] We thus pick this parameter to generate an R_0 of 2.5. This falls within the range of values that Atkeson (2020) uses and close to the range Remuzzi and Remuzzi (2020) report. 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 what the WHO reports.[13] The parameter $\phi(0, a)$ then also controls the fraction of agents that move to an ICU. CDC (2020) reports age-specific hospitalization (including ICU) rates for Covid-19 patients. A fraction 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. We thus set $\phi(0, y) = 0.967$ and $\phi(0, o) = 0.909$.

[11] For details, see Appendix B.1

[12] For details, see Appendix B.2.

[13] See the Report of the WHO-China Joint Mission on Coronavirus Disease 2019 (COVID-19).

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 assume 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 $\Delta(y) = 1$.

Recall that a vaccine arrives after T^* periods. After this, nobody gets infected with Covid-19 anymore. Set $T^* = 78$, such that a vaccine arrives after one year and a half (78 weeks).[14]

Now turn to the preference parameters, see Table 2 for a summary. 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. Following Kopecky (2011), set $\rho = -1.72$, which implies an elasticity of 0.368 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 three data targets: i) a 40-hour work week ($n = 40/112 = 0.357$), ii) 17.3 hours spent on

[14] Of course there is uncertainty about when a vaccine will be available. Following the medical discussion, our impression is that 1.5 is an optimistic but plausible scenario. See NYT, ''How Long Will a Vaccine Really Take", April 30, 2020 and Hanney et al. (2020). Modelling a stochastic vaccine arrival instead, as Farboodi, Jarosch, and Shimer (2020) do, would likely not change our qualitative results.

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
T^*	78	One and a half year (78 weeks) to vaccine arrival

Table 2: Calibration – Economic & Preference Parameters

Parameter	Value	Interpretation
ρ	-1.72	Elasticity of subst. bw leisure time and goods
θ	0.033	Production of leisure goods
γ	0.636	Rel. utility weight - leisure goods
λ_d	1.565	Rel. utility weight - leisure at home
λ_a	2.937	Rel. utility weight - leisure at home (infected)
b	6.5	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

non-working outside activities ($\ell = 17.3/112 = .154$),[15] and iii) a fraction of

[15] 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 comes from the American Time Use Survey (ATUS). Note that, in our model, the old do not work. In our calibration, the old spend 23 hours in leisure outside; i.e. more than the young. This is consistent with the data; the old spend 19.5 hours in leisure outside. If we include the small reported time at work, this

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	3.33	3.33
% of infected in critical care, old	9.10	9.10
% 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	15.7	15.7 (Sweden)
% $\uparrow$ in time @ home - mild symptoms	50	50 (H1N1)
Replacement rate - social security, %	60	46-64

income spent on x equal to 12.5% ($x/wn = .125$).[16] Set the discount factor to $\tilde{\beta} = 0.96^{1/52}$.

The parameter $\lambda(i) = \lambda_a$ denotes the increase in the marginal utility of staying at home for agents that know that they are infected with Covid. Government advice is clearly to stay at home, and this parameter captures to which extent time at home actually increases absent further legal enforcement. Epidemiologists have been interested in this during other epidemics such as swine flue (H1N1). In their surveys the overwhelming majority is willing to comply voluntarily. Rizzo et al. (2013) is the only study that also reports actual adherence, which averaged roughly 50% across Italy, Finland and Romania. We therefore choose λ_a to match an increase in time spent at home by 50%.[17]

In the model, the parameter b represents the value of being alive over and

number rises to 25.2 hours per week in the data.

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

[17]We analyze the case with no altruism (i.e. $\lambda_a = 0$) in Appendix C.1.

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 pandemic. 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 for Sweden, a country that did not implement severe mobility restrictions.[18] We thus choose a value for b in order to generate the rise in time spent at home in the beginning of the pandemic similar to that observed in Sweden, which was about 15.7%.

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 $Z = 1$, such that there are enough ICU beds to treat everyone (but see Appendix D.1 for the analysis of bed constraints).

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 infection 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 targeted and compare to empirical estimates, where available, see Table 4.

Most empirical estimates report the case fatality rate (CFR), i.e. the number of deaths per confirmed Covid-19 case, which clearly differs from (and is lower

[18] For details, see Appendix B.3

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

Moment	Model	Data (ranges)
Infection fatality rate (IFR), %	0.71	0.5-14
Daily growth of infections, outset of Covid-19, %	15	15-50
Deaths, old/all, %	37	≈80

Table 5: Deaths – Old vs. Young

Week	1	2	3	4	5	6	7	8
Deaths, old/all, %	70.24	67.42	65.73	64.24	62.04	58.30	52.98	47.06

than) the infection fatality rate (IFR) if testing is imperfect. Estimates of CFR vary immensely, ranging from 0.5 in Iceland to 14.5 in Italy as of June 27, 2020.[19] We are clearly on the low side here. However, as more antibody tests become available, it may turn out that many more people were already infected than is currently believed, which would bring the case fatality rate down.

Second, the daily growth rate at the outset of the pandemic 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 countries like Italy and Norway, it reached 50%.[20] 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 37% 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%.[21] Note that the 37% comes from the entire duration of the pandemic; in our calibration, after one and a half year when the vaccine comes along. Table 5 reports the fraction of overall deaths accounted for by old agents for the first weeks of the pandemic in the model. Note that in the first two weeks, more than two thirds of deaths are of old individuals. After eight weeks,

[19]See the University of Oxford's ourworldindata.org. A recent study from Ischgl finds an IFR as low as 0.24 based on testing 79% of the population for antibodies. See *The Telegraph*, "High coronavirus immunity found in 'super-spreader' Austrian ski resort," June 25, 2020.

[20]Again, see the University of Oxford's ourworldindata.org website.

[21]See https://www.cdc.gov/nchs/nvss/vsrr/covid19/index.htm

Table 6: Benchmark Results

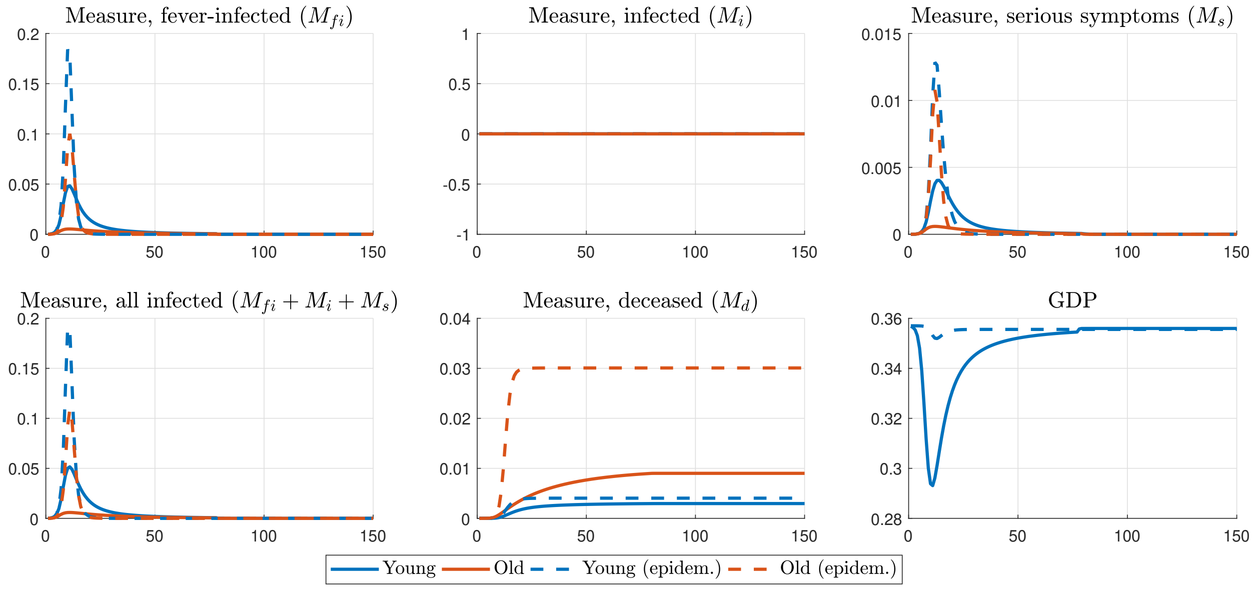
	Benchmark	Epidem.	Age ext. partial	Age ext. general	No disease
Wks to peak srsly ill (yng)	14.00	12.00	13.00	14.00	–
Wks to peak srsly ill (old)	12.00	12.00	12.00	12.00	–
Srsly ill p/ 1,000 @ peak (yng)	4.03	12.84	1.97	1.27	–
Srsly ill p/ 1,000 @ peak (old)	0.59	10.78	0.59	0.42	–
Dead p/ 1,000 1year (yng)	2.81	4.04	1.92	1.71	–
Dead p/ 1,000 1year (old)	7.81	30.07	7.81	7.28	–
Dead p/ 1,000 1year (all)	3.61	8.21	2.87	2.61	–
Dead p/ 1,000 LR (yng)	2.96	4.04	2.13	2.16	–
Dead p/ 1,000 LR (old)	9.00	30.07	9.00	9.68	–
Dead p/ 1,000 LR (all)	3.93	8.21	3.23	3.37	–
Immune in LR (yng), %	62.46	85.24	44.92	45.70	–
Immune in LR (old), %	12.00	39.45	12.00	13.00	–
Immune in LR (all), %	54.38	77.90	39.64	40.46	–
GDP at peak - rel to BM	1.00	1.21	0.48	0.83	1.22
GDP 1year - rel to BM	1.00	1.05	0.81	0.85	1.06
Cost p/ life saved, million $	–	–	12.42	13.30	–
Hrs @ home (yng) - peak	65.49	54.77	92.99	73.48	54.77
Hrs @ home (old) - peak	107.60	88.98	107.60	101.93	88.98
Hrs @ home (yng) - 6m	58.88	54.77	74.01	70.40	54.77
Hrs @ home (old) - 6m	100.73	88.98	100.73	99.80	88.98
Value - healthy (yng)	3740.80	3736.30	1610.30	1615.50	3753.35
Value - healthy (old)	1802.00	1770.60	1802.00	1803.30	1825.47
Value - healthy (all)	3430.20	3421.40	1641.00	1645.60	3444.50

still roughly 50% of deaths come from this group, even though they represent only 16% of the overall population. Only as time goes by and the disease develops, more young people die and it increases their relative death rate.

Table 6 reports our baseline results. Again, this concerns the economy with Covid-19 but no policy intervention (Column Benchmark). Note that it takes about 14 weeks for an unchecked pandemic to reach its peak in terms of seriously ill patients. Recall that a vaccine arrives after 78 weeks. As can be seen in Figure 1, by this time, the pandemic has essentially taken its course. The death count is substantial: 3.93 deaths per 1,000 people. This number masks considerable age heterogeneity: the death rate is 9.00 per 1,000 old individual and 2.96 for the young.[22] Note that most of these deaths happen within the first year of the pandemic, related to the quickness with which it reaches its peak. In

[22]Note that our (realistic) assumption that the old may also die from natural causes does play a role here. Without this assumption, the old would be even more careful leading to a death rate of only 5.9 per 1,000 instead.

Figure 1: Aggregate variables (Benchmark equilibrium)



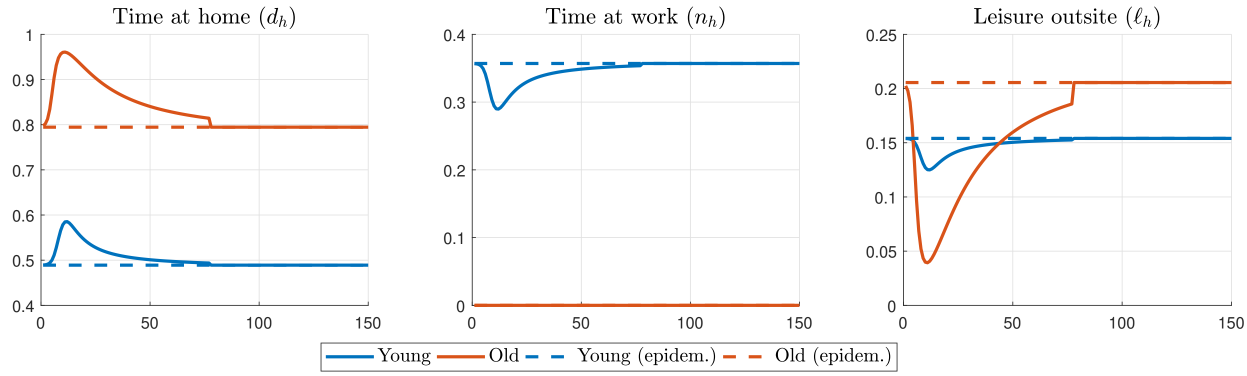
the long run, about 54% of the population becomes immune to the disease; i.e. were infected at some point and recovered.

We compare the benchmark results to an epidemiological version of the model (Column Epidem. in Table 6), which assumes there is no change in behavior compared to a world without the disease (last column in Table 6).[23] 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 left panel in Figure 2). This happens especially for the old, who do not need to work but are also more likely to die if they get infected.[24] The young cut both time at work and leisure outside (again, see Figure 2). This reduces the overall number of infected people in the long run by a little over 20 percentage points. The total death rate declines by slightly more than half, but markedly more so among the old (see the middle lower panel in Figure 1). The timing of the disease does

[23]Recall that infected agents are partially altruistic. We explore the behavioral responses in a world without altruism in Appendix C.1. Altruism here means that a young agent who knows he is infected would spend 82 hours at home per week. At the peak of the disease, the unsure fever agents spend 77 hours.

[24]Belot et al. (2020) find that the individuals aged 65 or older report engaging in less social interactions in several countries, including the US.

Figure 2: Choices of healthy agents (Benchmark equilibrium)



not change much, but the peak is much lower (see Figure 1). The economic costs of this self-preservation is sizeable: GDP for the first year of the pandemic is reduced by 6% relative to a no-disease world (see Table 6 and Figure 1 for the time path of GDP). The no-pandemic scenario has a GDP 22% higher than the baseline at the peak of the disease. In other words, voluntary reductions in activity reduce GDP substantially at the peak of the disease.[25]

As described in the previous paragraph, 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

[25] A decline in GDP of 6% may appear 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 a similar order of magnitude to what we find in some of our shelter-at-home experiments discussed in the next section.

more careful and considerably increase their hours at home. This lowers the infections among 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. The reason is that, with a swifter pandemic (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.

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 (see Appendix D.1).

6 Policy Experiments

In this section we will use our baseline calibration to perform a series of policy experiments, namely: shelter-in-place policies, testing, test and quarantine, selective mixing, and combined policies. Appendix D provides results for alternative scenarios. Interestingly these affect the quantitative numbers, but leave most of the broad qualitative insights unchanged.

6.1 Shelter-in-Place Policies

Start with 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.[26] Table 7 has the results for several constellations of the

[26]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. Computa-

Table 7: Policy Experiments: Shelter in Place

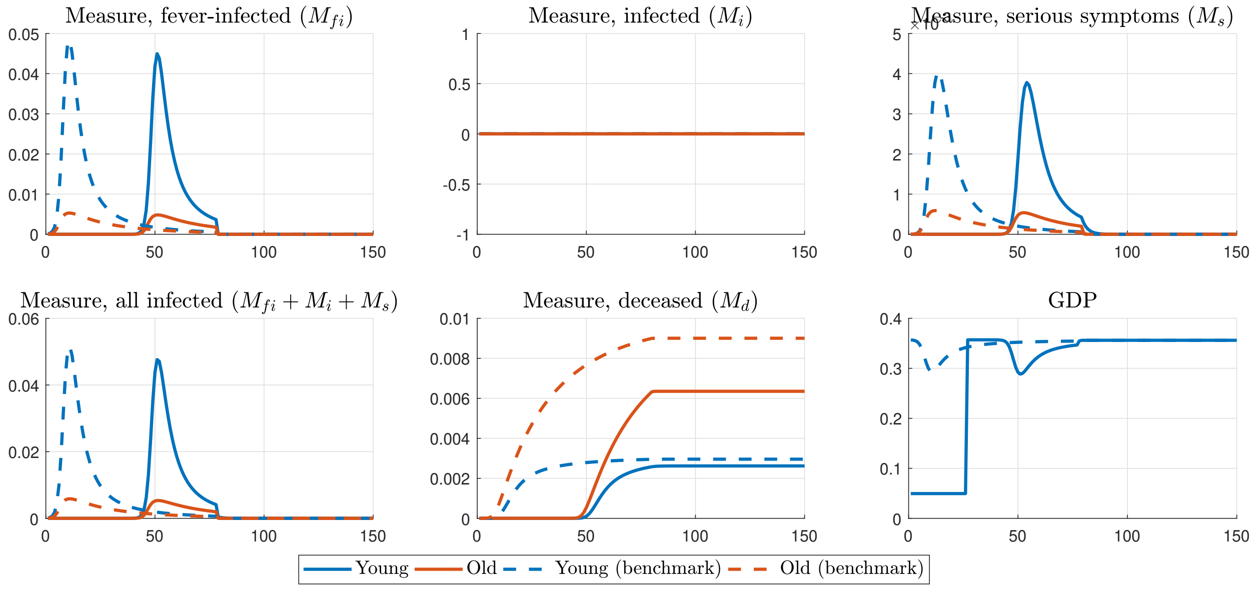
	Benchmark	SH25-a-4	SH25-a-26	SH25-y-26	SH75-a-12	SH75-a-35	SH90-a-26	SH90-o-26
Wks to peak srsly ill (yng)	14.00	16.00	34.00	34.00	33.00	66.00	54.00	14.00
Wks to peak srsly ill (old)	12.00	14.00	33.00	33.00	32.00	64.00	53.00	30.00
Srsly ill p/ 1,000 @ peak (yng)	4.03	4.04	2.34	2.27	3.96	3.50	3.78	4.02
Srsly ill p/ 1,000 @ peak (old)	0.59	0.59	0.48	0.47	0.57	0.51	0.54	0.30
Dead p/ 1,000 1year (yng)	2.81	2.79	2.48	2.49	2.46	0.00	0.32	2.80
Dead p/ 1,000 1year (old)	7.81	7.64	7.52	8.12	5.71	0.00	1.07	4.39
Dead p/ 1,000 1year (all)	3.61	3.56	3.29	3.39	2.98	0.00	0.44	3.06
Dead p/ 1,000 LR (yng)	2.96	2.95	2.87	2.87	2.87	2.23	2.62	2.96
Dead p/ 1,000 LR (old)	9.00	8.93	9.76	10.34	8.10	4.64	6.35	5.73
Dead p/ 1,000 LR (all)	3.93	3.91	3.97	4.07	3.71	2.62	3.22	3.40
Immune in LR (yng), %	62.46	62.31	60.60	60.60	60.57	47.15	55.33	62.47
Immune in LR (old), %	12.00	11.93	13.14	13.89	10.98	6.43	8.74	7.70
Immune in LR (all), %	54.38	54.24	53.00	53.12	52.63	40.62	47.86	53.70
GDP at peak - rel to BM	1.00	1.00	1.08	1.08	1.00	0.97	0.98	1.00
GDP 1year - rel to BM	1.00	0.98	0.88	0.88	0.83	0.55	0.58	1.00
Cost p/ life saved, million $	–	40.40	–	–	29.63	13.53	23.28	0.00
Hrs @ home (yng) - peak	65.49	65.36	62.57	62.43	65.18	67.19	66.08	65.33
Hrs @ home (old) - peak	107.60	107.60	105.68	105.57	107.55	107.41	107.53	110.12
Hrs @ home (yng) - 6m	58.88	59.57	70.59	70.58	57.56	95.85	104.06	58.76
Hrs @ home (old) - 6m	100.73	101.80	102.74	101.00	101.76	106.14	109.09	109.42
Value - healthy (yng)	3740.80	3740.40	3738.50	3738.40	3727.00	3702.70	3685.10	3740.80
Value - healthy (old)	1802.00	1802.00	1799.80	1800.00	1799.50	1799.00	1789.40	1792.60
Value - healthy (all)	3430.20	3429.90	3427.90	3427.90	3418.20	3397.70	3381.40	3428.70

policy. First, a clarification on the labels: 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 7. 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 two weeks later. The death rate declines slightly for the old but is almost constant for the young. The economic costs, on the other hand, are non-trivial: yearly GDP goes down by 2% relative to the base-

tionally, we calibrate λ_p such that we generate the desired rise in time at home for the young in a steady state with no disease. We then feed in this calibrated λ_p to both the young and the old throughout the duration of the policy. The utility achieved by the individual under this scenario, however, is computed using his own private λ_d. The same is done for the quarantine policies discussed in Section 6.3.

Figure 3: Aggregate variables (Shelter in place, 90%, 26 weeks)



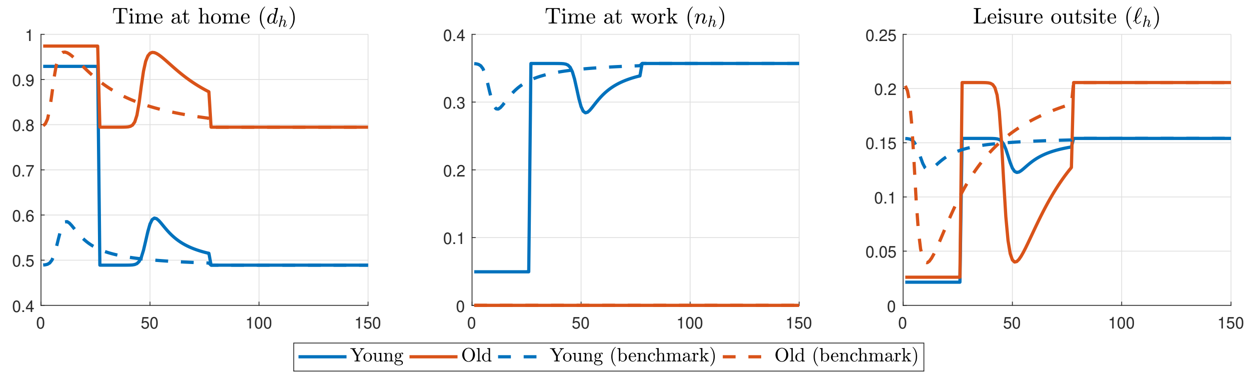
line. This implies that the economic cost for each life saved is about $40 million dollars.[27]

Milder policies can even be counter-productive in the sense of increasing the death rate (see columns SH25-a-26 and SH25-y-26 in Table 7). A six-months lockdown for the young slows the spread of the disease and the peak now is reached only after 34 weeks. The overall death rate, however, is even higher now. In the long run, it rises by about 3.5%. 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 are not sheltered, there is more time for them to catch the virus and eventually die.

Now consider stricter and longer policies, in particular the last two columns in Table 7. They report the results for extremely strict policies: individuals need to spend an extra 90% of their time at home for 26 weeks. When this policy

[27]The cost of a life saved in the model is computed as the total output lost relative to the benchmark divided by the decrease in deaths from the benchmark to a specific policy. For comparison, the US Environmental Protection Agency (EPA) uses a value of statistical life around $9.5 million in 2019 dollars. This measure does not take into account remaining years of life or quality-adjusted life year.

Figure 4: Choices of healthy agents (Shelter in place, 90%, 26 weeks)



is applied to all (SH90-a-26), the peak of the disease is much delayed. It is reached after 54 weeks, even though the policy lasts only 26 weeks. As Figure 3 shows, though the peak occurs at a much later date, the height of the peak is very similar to the benchmark. Deaths in the first year drop considerably. Even the long-run death toll is still 18% lower than in the no-policy baseline, mostly because this policy gets us close to the arrival of the vaccine.[28] In other words, the main effect of lockdown policies is that they buy time at a sizeable economic cost. There is a very deep recession in the first year caused by the shelter-in-place policy (see Figure 3). Note that GDP drops again in the second year in parallel with the peak of the pandemic. This is due to the 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 4).

To avoid the large economic costs of lockdowns it has been widely suggested to focus on shielding the old instead. Consider a policy that forces the old to increase their time at home by 90% for 26 weeks (last column of Table 7). Note that the peak of the disease among the young is achieved at the same week as in the no-policy benchmark. Since this peak is reached around 14 weeks, the old are still sheltered at that time. So, at the most dangerous stages of the pan-

[28]The longer a lockdown is, the more it delays the disease, which in our world with vaccine arrival prevents some deaths. This effect can be clearly seen by comparing SH75-a-12 with SH75-a-35 in Table 7. A harsh 35-week long lockdown cuts death by about a third, while the same policy for only 12 weeks reduces deaths by less than 6%. In a world without vaccine arrival, these policies hardly save any lives at all, as we show in Appendix D.2.

demic, they are protected. This leads to a 36% lower death rate among the old compared to the benchmark. Note, however, that the peak of the disease among the old only happens after the policy is lifted (see Figure 5). This generates two peaks of the disease for the old (the second one, at 30 weeks, being higher). The first peak arises together with the peak among the young. As the old still interact a bit while sheltered, this generates a wave of infections among this group. As the policy is lifted and the old leave their homes more, there are still sick youngsters around and this gives rise to the second wave. Despite these two waves of infection, the old still die less compared to the benchmark. However, even though the death rate among the old is lower than in the baseline, their welfare falls.[29] 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.[30]

Some of the longer policies discussed above lead to less deaths. What if a shelter-in-place policy was implemented until a vaccine arrives (i.e. for 78 weeks in our model)? Table 8 provides the results for two such policies: shelter-in-place policies that last for 78 weeks that are applied to all individuals and require them to spend either an extra 25 or 50% more time at home. Both policies reduce deaths considerably: the milder policy (SH25) decreases deaths by 40%, while the stricter policy (SH50) essentially eliminates deaths altogether. The young are never better off with such policies, but the welfare of the old rises.[31]

All shelter-in-place policies discussed so far were implemented at the very start of the outbreak. What happens if such a policy is implemented only after

[29] Belot et al. (2020) find that individuals 65 or older experience worse negative non-financial effects from lockdowns. Andersson et al. (2020) report that the old in Sweden are willing to pay more to avoid confinement.

[30] In fact, we never found a policy (including several not reported) that shelters only the old and that improves the welfare of this group. They do not influence much the overall path of the disease. They are a small group (only 16% of the population) and they spend less time outside. In a no-disease steady state, their hours outside correspond to only 7.1% of the total. At the peak, since the endogenously protect themselves more, this number falls to 1.9%.

[31] We also implement the stricter policies for each age group separately (last two columns in Table 8). A policy that targets the young only is just as effective as the universal one. In this case, the welfare of the old rises even more as they are not confined. A policy that shelters the old only is not nearly as effective (though deaths still decline by 13.5%). In contrast to the other policies, the welfare of the old declines.

Figure 5: Aggregate variables (Shelter in place for the old, 90%, 26 weeks)

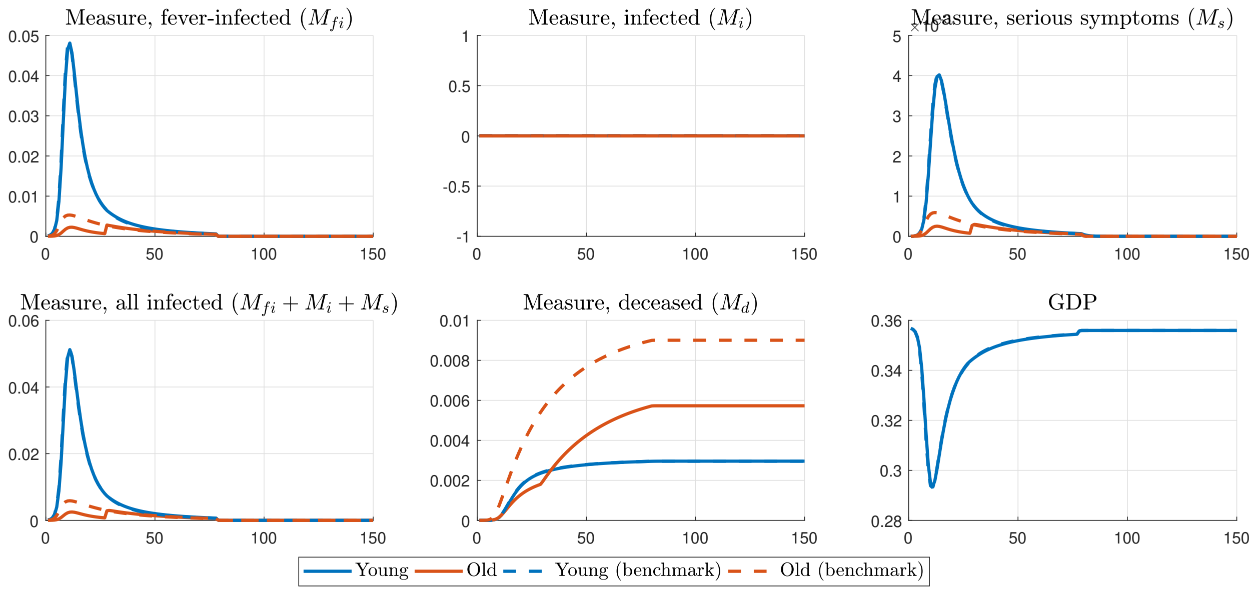


Table 8: Shelter in Place that lasts for 78 weeks

	Benchmark	SH25-a-78	SH50-a-78	SH50-y-78	SH50-o-78
Wks to peak srsly ill (yng)	14.00	23.00	4.00	4.00	14.00
Wks to peak srsly ill (old)	12.00	21.00	2.00	3.00	13.00
Srsly ill p/ 1,000 @ peak (yng)	4.03	1.17	0.01	0.01	3.99
Srsly ill p/ 1,000 @ peak (old)	0.59	0.32	0.00	0.01	0.47
Dead p/ 1,000 1year (yng)	2.81	1.39	0.00	0.00	2.78
Dead p/ 1,000 1year (old)	7.81	4.95	0.01	0.03	5.39
Dead p/ 1,000 1year (all)	3.61	1.96	0.00	0.01	3.20
Dead p/ 1,000 LR (yng)	2.96	1.64	0.00	0.00	2.92
Dead p/ 1,000 LR (old)	9.00	6.11	0.02	0.04	5.97
Dead p/ 1,000 LR (all)	3.93	2.36	0.01	0.01	3.40
Immune in LR (yng), %	62.46	34.64	0.08	0.10	61.54
Immune in LR (old), %	12.00	8.20	0.02	0.05	7.94
Immune in LR (all), %	54.38	30.40	0.07	0.09	52.96
GDP at peak - rel to BM	1.00	0.86	0.63	0.63	1.00
GDP 1year - rel to BM	1.00	0.77	0.55	0.55	1.00
Cost p/ life saved, million $	–	9.23	7.34	7.35	-0.01
Hrs @ home (yng) - peak	65.49	71.66	82.17	82.17	65.53
Hrs @ home (old) - peak	107.60	103.22	101.10	89.21	108.45
Hrs @ home (yng) - 6m	58.88	71.40	82.15	82.15	58.92
Hrs @ home (old) - 6m	100.73	102.62	101.05	88.99	104.69
Value - healthy (yng)	3740.80	3737.90	3720.80	3720.80	3740.90
Value - healthy (old)	1802.00	1807.30	1815.60	1825.40	1796.60
Value - healthy (all)	3430.20	3428.60	3415.60	3417.10	3429.50

the disease is developing. Consider a shelter-in-place policy that applies to everyone and requires individuals to stay an extra 90% of the time at home, but only starts 8 weeks after the outbreak and lasts for 12 weeks. The results are in Figures C1 and C2 in Appendix C.2. As the disease develops in the first 8 weeks, a wave of infections develops. With the shelter-in-place policy, infections decline substantially. When the policy is lifted after 12 weeks, a second wave appears. After both waves, the long-run death toll is almost the same as in the benchmark with no policy: only a 4.4% decline in total deaths.

In sum, shelter-in-place policies only work in decreasing the death toll of the pandemic if they last for a long time, until close to an arrival of a vaccine. In this case, some policies can make the old better off, but the welfare of the young never increases. Neither does average welfare across groups. Any shelter-in-place policy that directly impacts the young (either universal or young-specific lockdowns) come with substantial economic costs as the young must cut their labor supply. And if the policies on the young are in place for too short, they can even increase the total number of deaths in the long run. Lockdowns that target the old only, even if they manage to decrease the number of deaths within this group, do not increase old individuals' welfare. This happens because they are a small group that already protects itself substantially due to the higher risk they face. All such policies, however, buy time as they postpone the peak of the disease. If time is need to set up production of means to avoid infections (e.g. masks), maybe infections stay low after the lockdown even though activities resume to some extent. Also, time may be needed to set up infrastructure for testing. As we will see in the next few sections, testing can be a powerful policy.

6.2 Testing

Health authorities around the world emphasize the importance of testing. Accordingly, many countries have been vastly ramping up their testing capacities since the start of the pandemic. But what exactly is the benefit of testing? Does it work by itself or only in combination with quarantines? In the limit, if everyone was tested every day and, if found Covid-19 positive, immediately quarantined, the pandemic would stop almost immediately. Yet such a policy is clearly

Table 9: Policy Experiments: Testing

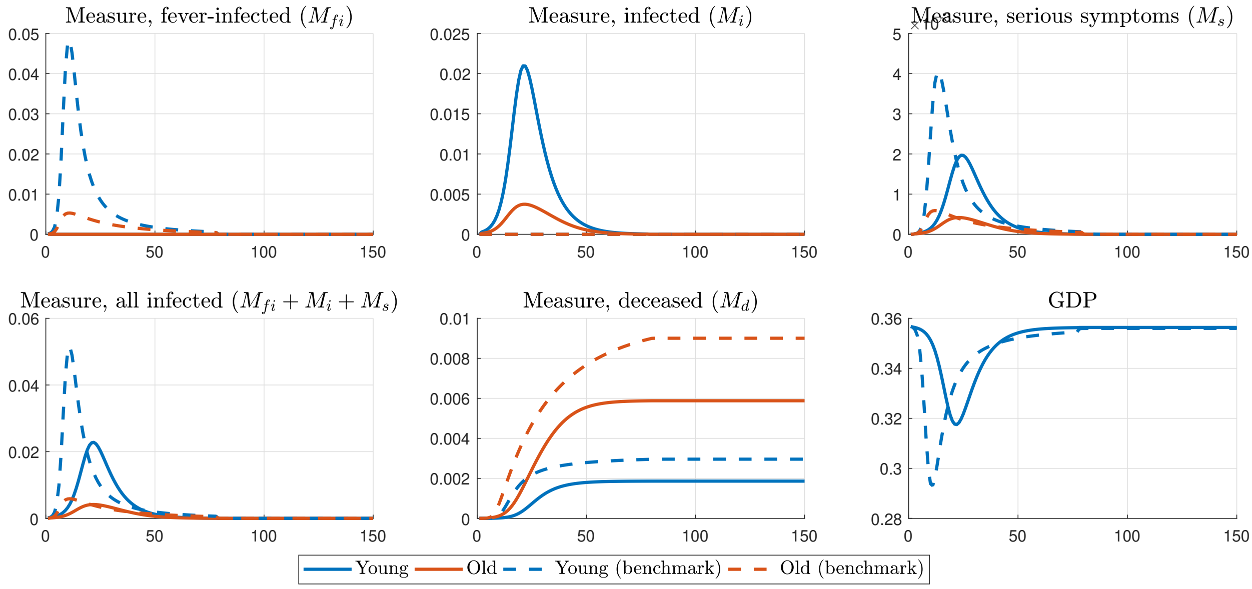
	Benchmark	Testing all	Testing young	Testing old	Q90-a-50t	Q90-a-100t	Q90-y-100t
Wks to peak srsly ill (yng)	14.00	24.00	24.00	14.00	22.00	3.00	4.00
Wks to peak srsly ill (old)	12.00	23.00	22.00	12.00	20.00	3.00	3.00
Srsly ill p/ 1,000 @ peak (yng)	4.03	1.97	1.98	4.03	1.29	0.01	0.01
Srsly ill p/ 1,000 @ peak (old)	0.59	0.42	0.42	0.59	0.34	0.01	0.01
Dead p/ 1,000 1year (yng)	2.81	1.81	1.82	2.80	1.50	0.00	0.00
Dead p/ 1,000 1year (old)	7.81	5.62	5.68	7.76	5.38	0.01	0.02
Dead p/ 1,000 1year (all)	3.61	2.42	2.44	3.59	2.12	0.00	0.01
Dead p/ 1,000 LR (yng)	2.96	1.86	1.88	2.94	1.71	0.00	0.00
Dead p/ 1,000 LR (old)	9.00	5.88	6.00	8.86	6.45	0.01	0.02
Dead p/ 1,000 LR (all)	3.93	2.50	2.54	3.89	2.47	0.00	0.01
Immune in LR (yng), %	62.46	39.30	39.80	62.05	36.20	0.06	0.07
Immune in LR (old), %	12.00	7.84	8.00	11.80	8.63	0.02	0.02
Immune in LR (all), %	54.38	34.26	34.70	54.00	31.79	0.06	0.06
Max. n. of tests in a week, %	0.00	5.58	5.41	0.35	2.66	4.94	4.59
GDP at peak - rel to BM	1.00	1.08	1.08	1.00	1.13	1.22	1.22
GDP 1year - rel to BM	1.00	1.01	1.01	1.00	1.02	1.06	1.06
Cost p/ life saved, million $	–	-0.48	-0.48	-0.05	-0.42	-0.65	-0.65
GDP gain per test, 1year, $	–	373.13	394.44	–	870.61	1410.28	1515.77
Hrs @ home (yng) - peak	65.49	61.58	61.50	65.58	58.92	54.87	54.87
Hrs @ home (old) - peak	107.60	103.95	103.95	107.61	100.81	89.42	89.41
Hrs @ home (yng) - 6m	58.88	60.96	60.67	58.93	58.41	54.77	54.77
Hrs @ home (old) - 6m	100.73	103.03	102.73	100.77	99.61	88.98	88.98
Value - healthy (yng)	3740.80	3745.60	3745.50	3740.80	3746.00	3753.30	3753.30
Value - healthy (old)	1802.00	1811.20	1810.90	1802.30	1811.20	1825.40	1825.40
Value - healthy (all)	3430.20	3435.70	3435.60	3430.30	3436.10	3444.50	3444.50

not very realistic. So what is the benefit of partial testing? What about imperfect quarantines? This section and the next consider various combinations of testing and quarantining policies to assess their effect on deaths and GDP.

We start with policies that only test individuals without further quarantines. 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 earlier. Since the agents are partially altruistic, they are more cautious about leaving their homes.

Table 9 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 6 shows that, with universal testing, the mass of infected agents that are unsure whether they have the disease (M_{fi}) goes to zero. Instead, agents now know they are infected (M_i) and thus act according to their partial altruism. This leads the disease to develop at a slower pace; i.e. flat-

Figure 6: Aggregate variables (Testing all)



tening the curve. The peak now takes about ten weeks longer to arrive and is less pronounced (see Figure 6). This translates into fewer deaths for both age groups. 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 5.6% of the population is tested. In the US, this implies about 18 million tests in a single week. This is accompanied by a rise in GDP compared to the baseline due to a milder pandemic. In the end of the first year, this translates to about 373 dollars in extra GDP per test performed.

Table 9 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), implementing this policy faces some hurdles.[32] First, in the model we test a fraction of those with fever. In reality, one needs to know who to test. One possibility is to focus on contact tracing. A second issue is that our model assumes instantaneous test results, while in reality this is not the case. However, some rapid test that deliver results within an hour exists by now. They are not widely available yet, but testing technology is rapidly evolving.[33] Finally, unlike in our model, in reality testing involves costs. Scaling up the current test methods to the quantities needed is not easy. Even if scaling up testing comes at a substantial cost, these costs are likely worth paying, especially since our analysis has shown that there are substantial gains in GDP per test performed, which should be more than enough to cover the costs.

6.3 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 quarantine those that tested positive (which most countries try to do). The last three columns of Table 9 report results of three such experiments.

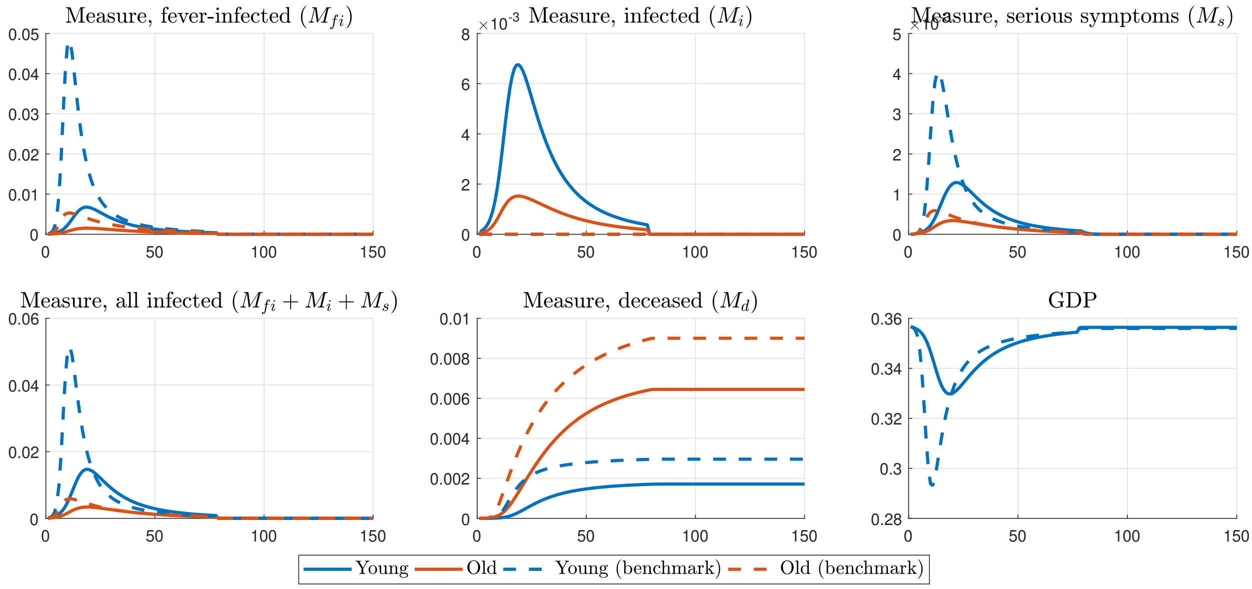
Consider a policy where 100% of those with a fever are tested, and those that test positive are forced to quarantine by increasing the time at home by 90% (see column "Q90-a-100t"). This policy leads the young to spend 92% of their time at home (the old even more).[34] So while it is a relatively strict quarantine, it is not 100%. This captures the fact that enforcement of quarantines is never perfect in reality. It can be thought of as people still escaping from their quarantine 8% of the time (about 8h/week), or that 8% of agents are not complying at all. This policy is extremely effective. In the long run, less than a tenth of one percent of the population catches the disease and are thus immune. The death count is almost zero. With the lower burden of the disease, GDP goes up by 6% in the first year of the pandemic. Given that the number of immune individuals

[32] See The Economist, April 25, 2020 "Test of Reason" for difficulties of scaling up testing.

[33] For example, a new test with results in 16 minutes was announced in Germany on July 7.

[34] Technically, the quarantines are achieved by increasing the marginal utility of time at home, as in the shelter-in-place policies of Section 6.1, but only for those that test positive. That is, we increase $\lambda_p(i, a)$ for all a.

Figure 7: Aggregate variables (Test and Quarantine, 50%)



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 9). Since the young comprise 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. In fact, if one factors in that tests cost some money, then this is the better policy since fewer people are tested, which increases the GDP gain per test to more than $1,500. Alternatively, a testing policy that applied to 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. The results are in the column ”Q90-a-50t” in Table 9. With only half of those with a fever are being tested, some agents will move from the unsure ”fever” state (M_{fi}) to the infected state (M_i), but not all. See Figure 7. Compared to the benchmark, the peak occurs at a later date and is lower; i.e. the curve is flattened (see Figure

7). 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 about 37% to 2.47 per 1,000 people. This decline is steeper among younger individuals (a drop of about 42% for this group). The total number of Covid-19 cases in the long run falls from almost 55% of the population in the benchmark to around 32%. GDP goes up in the first year by about 2% relative to the baseline. This represents around 870 extra dollars in GDP per test carried out.

Even though around a third of the population catches Covid-19 with a 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 six and a half 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 fewer hours per week relative to the baseline. This risk compensation acts to dampen the effect of the policy.[35]

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 9 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 pandemic 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.

6.4 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 centers are dedicated to a particular age group. This leads to *selective mixing* where agents are more likely to meet those of their own type. Suppose a fraction ζ of people's

[35]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 10: Selective mixing

	Benchmark	Sel. mix.
Wks to peak srsly ill (yng)	14.00	13.00
Wks to peak srsly ill (old)	12.00	12.00
Srsly ill p/ 1,000 @ peak (yng)	4.03	4.61
Srsly ill p/ 1,000 @ peak (old)	0.59	0.50
Dead p/ 1,000 1year (yng)	2.81	2.95
Dead p/ 1,000 1year (old)	7.81	5.75
Dead p/ 1,000 1year (all)	3.61	3.40
Dead p/ 1,000 LR (yng)	2.96	3.07
Dead p/ 1,000 LR (old)	9.00	6.43
Dead p/ 1,000 LR (all)	3.93	3.61
Immune in LR (yng), %	62.46	64.89
Immune in LR (old), %	12.00	8.55
Immune in LR (all), %	54.38	55.86
GDP at peak - rel to BM	1.00	0.97
GDP 1year - rel to BM	1.00	1.00
Cost p/ life saved, million $	–	0.10
Hrs @ home (yng) - peak	65.49	66.79
Hrs @ home (old) - peak	107.60	105.82
Hrs @ home (yng) - 6m	58.88	58.88
Hrs @ home (old) - 6m	100.73	97.09
Value - healthy (yng)	3740.80	3740.20
Value - healthy (old)	1802.00	1809.80
Value - healthy (all)	3430.20	3431.00

time outside can be separated into the different age groups and a fraction ϑ_a of the common space is allocated for age group a. Conditional on being outside, some infections now occur only within groups. The details are provided in Appendix C.3. In order to generate quantitative results, assume half of the time outside can be separated ($\zeta = 1/2$) between the two groups. Moreover, assume the common space is divided (ϑ_a) according to the relative sizes of each group.

Table 10 reports the results. First note that the overall death rate falls, both within the first year of the pandemic as well as in the long run, where deaths fall by almost 10%. This result masks an important heterogeneity across the two groups though: the death rate for the old is reduced by almost 30%, while the young die about 4% more 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. At the peak of the disease, the young spend more time at home compared to the benchmark. The overall effects on

Table 11: Combination of policies

		Q90-a-25t			Q90-a-50t	
		SH25-a-78			SH25-a-78	SH10-a-78
	Benchmark	$\zeta = 0$	$\zeta = 0.25$	$\zeta = 0.5$	$\zeta = 0$	$\zeta = 0$
Wks to peak srsly ill (yng)	14.00	36.00	33.00	30.00	6.00	33.00
Wks to peak srsly ill (old)	12.00	35.00	31.00	29.00	3.00	31.00
Srsly ill p/ 1,000 @ peak (yng)	4.03	0.43	0.54	0.67	0.01	0.53
Srsly ill p/ 1,000 @ peak (old)	0.59	0.15	0.14	0.13	0.01	0.18
Dead p/ 1,000 1year (yng)	2.81	0.59	0.74	0.89	0.01	0.74
Dead p/ 1,000 1year (old)	7.81	2.45	2.38	2.03	0.05	3.08
Dead p/ 1,000 1year (all)	3.61	0.89	1.00	1.07	0.02	1.12
Dead p/ 1,000 LR (yng)	2.96	0.86	1.01	1.15	0.01	1.01
Dead p/ 1,000 LR (old)	9.00	3.56	3.25	2.64	0.06	4.18
Dead p/ 1,000 LR (all)	3.93	1.30	1.37	1.39	0.02	1.52
Immune in LR (yng), %	62.46	18.23	21.37	24.38	0.28	21.27
Immune in LR (old), %	12.00	4.81	4.39	3.56	0.08	5.64
Immune in LR (all), %	54.38	16.08	18.65	21.04	0.25	18.77
Max. n. of tests in a week, %	0.00	1.01	0.98	0.98	2.44	2.26
GDP at peak - rel to BM	1.00	0.90	0.89	0.88	0.93	1.06
GDP 1year - rel to BM	1.00	0.79	0.78	0.78	0.80	0.93
Cost p/ life saved, million $	–	5.28	5.50	5.61	3.36	2.02
Hrs @ home (yng) - peak	65.49	69.79	70.12	70.46	68.51	62.04
Hrs @ home (old) - peak	107.60	99.29	99.18	98.70	95.63	97.43
Hrs @ home (yng) - 6m	58.88	69.59	70.01	70.44	68.47	61.95
Hrs @ home (old) - 6m	100.73	98.87	99.04	98.69	95.48	97.26
Value - healthy (yng)	3740.80	3741.60	3740.90	3740.20	3745.90	3747.60
Value - healthy (old)	1802.00	1814.60	1815.40	1816.90	1823.10	1815.90
Value - healthy (all)	3430.20	3432.90	3432.40	3432.10	3437.80	3438.10

the young are small and their labor supply hardly changes, keeping the GDP in the first year of the pandemic essentially the same as in the no-policy baseline.

6.5 Combining Policies

The previous sections reported results for different policies in isolation. Some of the policies were quite strict (e.g. sheltering everyone for more than 90% of their time) or a bit unrealistic (e.g. 100% testing of fever agents). We now turn to combining different policies at the same time. We particularly focus on combining milder versions of the policies that are probably more realistic to be implemented. A key question here is whether the effects of different policies simply add up, reinforce one another or crowd each other out.

Start with the first three counterfactuals in Table 11. They all test 25% of the fever agents and quarantine the positive cases (Q90-a-25t) and maintain a shelter-in-place policy that requires all individuals to spend an extra 25% of their time at home and lasts until a vaccine becomes available (SH25-a-78). The first of these contain no selective mixing ($\zeta = 0$). The death toll is substantially lower than the benchmark, by about 2/3. Compared to a similar lockdown implemented in isolation (see Table 8), the death toll is 45% lower. Note also that the amount of tests is lower than other experiments in Sections 6.2 and 6.3: only about 1% of the population would need to be tested at the peak of the disease. If we impose selective mixing on top of the two other policies ($\zeta \in \{0.25, 0.5\}$), an inter-generational "redistribution" of deaths appears: fewer old individuals die at the expense of more deaths among the young.

Consider now ramping up testing to 50% of the fever individuals (the last two columns in Table 11). Maintaining the same lockdown as the previous scenarios (SH25) essentially eradicates the disease. Recall that the test-and-quarantine policy in isolation (Table 9) decreased the number of deaths, but not as dramatically. Interestingly, lives saved are larger than the sum of those saved under each policy separately.[36] In this policy, since the young are partially sheltered, GDP decreases by about 20% compared to the benchmark. Comparing the welfare of both groups with the test-and-quarantine policy in Table 9, we notice that the old are better off while the young are just slightly worse off, even though their labor supply is substantially reduced (as reflected in the GDP numbers). What happens then when we slacken the lockdown a bit? This is reported in the last column of Table 11. In it, we impose a lockdown that requires individuals to spend only an extra 10% of time at home. The death toll is 1.5 per 1,000 people (more than 60% lower compared to the benchmark). It is also more than 40% lower than the test-and-quarantine policy in isolation (again, Table 9). GDP is substantially higher (13 percentage points) than the stricter lockdown described in the previous paragraph. Compared to the test-and-quarantine policy alone, adding the mild lockdown increases the welfare of *both* age groups.

[36]The SH25-a-78 policy alone averts 1.57 deaths per 1,000, while the Q90-a-25t policy averts 1.46, summing up to 3.03. The combined policy averts 3.91, so substantially higher.

7 Conclusions

This paper provides a first path to study the link between age heterogeneity, incomplete information/testing of the disease status, and the behavioral adjustments that individuals make to protect themselves during the Covid-19 pandemic. 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 policy interventions, 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. Imposing shelter-at-home policies on the old reduces deaths, but also reduces their utility. Imposing shelter-at-home policies only on the young can in some cases even lead to more deaths in the long run. Strong shelter-at-home policies for everyone have to stay in place sufficiently close to the time a 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. Separating activities across age groups also decreases the number of deaths, especially among the old. Finally, we explore combination policies and find that adding a mild but long shelter-at-home policy on top of widespread but partial testing leads to welfare gains of all age groups, even beyond testing alone.

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 vary widely. Better estimates of the infectiousness of the disease will provide more clarity on the infection probabilities and the transitions from infection to hospitalization, including their age gradient. Further, the predictions of the calibrated model regarding preventive behavior over the course of the pandemic arise from plausible specifications of the utility function that have been useful in other settings, but have yet to be validated by surveys on the behavior of individuals during the Covid-19 pandemic.

The model is richer than many existing counterparts, but potentially important margins are still missing. The possibility of teleworking may render shelter-in-place policies less costly in terms of lost output.[37] We explore policies that impose selective mixing but individuals may endogenously choose to interact with different groups. The economic impact of the lockdowns differs along other important dimensions such as education, sectors, and gender and that the cost on children in form of closed schools may be particularly large.[38] Adding other forms of heterogeneity beyond age may thus be interesting. These extensions are part of a broader set of topics that warrant attention in future research.

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[37]Brotherhood and Jerbashian (2020) analyze a model in which firms internalize infections among their employees and can resort to employee rotation and telework.

[38]Education and income is highly correlated with the ability to work from home (Adams-Prassl et al. (2020)) and women are hit more by employment losses (Alon et al. (2020a)).

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Online Appendix - Not for Publication

A Laws of Motion

In the main text, equation (8) describes the overall laws of motion, and (9) describes the sub-part that determines the transitions for 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

$$\begin{aligned}
&M_{t+1}(f_h, a) \\
&= M_t(h,a)\Delta(a)(1-\xi_{p_t}(a))\pi_f(n_t(h,a)+\ell_t(h,a),\Pi_t(a))\frac{\Pi^*}{\Pi_t(a)+\Pi^*} \\
&+ M_t(f_h,a)\Delta(a)(1-\xi_{p_t}(a))\pi_f(n_t(f,a)+\ell_t(f,a),\Pi_t(a))\frac{\Pi^*}{\Pi_t(a)+\Pi^*}.
\end{aligned} \tag{14}$$

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:

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

The total number of individuals in the fever state is then

$$M_{t+1}(f,a) = M_{t+1}(f_h,a) + M_{t+1}(f_i,a) \tag{16}$$

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:

$$\begin{aligned} M_{t+1}(i,a) &= M_t(h,a)\Delta(a)\xi_{p_t}(a)\pi(n_t(h,a)+\ell_t(h,a),\Pi_t(a)) \\ &+ M_t(f_h,a)\Delta(a)\xi_{p_t}(a)\pi(n_t(f,a)+\ell_t(f,a),\Pi_t(a)) \\ &+ \left[M_t(f_i,a)+M_t(i,a)\right]\Delta(a)(1-\phi(0,a))(1-\alpha(a)) \end{aligned} \tag{17}$$

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:

$$\begin{aligned} M_{t+1}(s,a) &= \left[M_t(f_i,a)+M_t(i,a)\right]\Delta(a)(1-\phi(0,a))\alpha(a) \\ &+ M_t(s,a)\Delta(a)(1-\delta_t(a))(1-\phi(1,a)) \end{aligned} \tag{18}$$

The total number of individuals with serious symptoms is then

$$M_t(s) = \sum_a M_t(s,a) \tag{19}$$

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:

$$\begin{aligned} M_{t+1}(r,a) &= \left[M_t(f_i,a)+M_t(i,a)\right]\Delta(a)\phi(0,a) \\ &+ M_t(s,a)\Delta(a)\phi(1,a)+\Delta(a)M_t(r,a) \end{aligned} \tag{20}$$

The right hand sides of equations (14) to (20) 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 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

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

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	$(1-\phi(1))(1-\delta)\phi(1)$	$\left[(1-\phi(1))(1-\delta)\right]^2$	$(1-\phi(1))(1-\delta)(1-\phi(1))\delta$
3	$\left[(1-\phi(1))(1-\delta)\right]^2\phi(1)$	$\left[(1-\phi(1))(1-\delta)\right]^3$	$\left[(1-\phi(1))(1-\delta)\right]^2(1-\phi(1))\delta$
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.2 Basic Reproduction Number - R_0

The probability that an infected agent leaves such state is: $\left[\phi(0) + (1-\phi(0))\alpha\right]\Delta + (1-\Delta)$. 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 $\bar{\ell}$ 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:

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

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.

B.3 Google's Mobility Data

Google provides Covid-19 Community Mobility Reports and the corresponding data.[39] By tracking mobile phones, the company provides the change in time people spend in different places: home, work, parks, transit stations, etc. As explained in text, we use this data for Sweden to calibrate the utility of living b.

We match the rise in residential time in the eighth week of the pandemic in the model to the data. The first cases of community spread in Sweden were diagnosed in early March. We thus average the last 14 days in April to represent the "eighth" week. Google reports a rise of 7.78% in residential time during this period. According to our calibration, in a no-disease steady state, individuals spend 57.3 hours per week outside; or $24 \times 7 - 57.3 = 110.7$ hours at home. The increase in residential time in late April then corresponds to 8.6 hours. In our model, agents spend 54.7 of their weekly non-sleeping hours at home. This then translates to a 15.7% rise in non-sleeping time at home.[40] This is the target we use in our calibration.

C Additional Results

This section provides additional details and results for the following scenarios: a world without altruism (Section C.1), shelter-in-place policy with a late start (Section C.2), and details on the model with selective mixing (C.3).

C.1 No Altruism

Table C1 compares the benchmark version of the model with no altruism ($\lambda_a = 0$) versus the epidemiological version with no behavioral adjustments. The qualitative results are very similar to the original baseline results. The main difference is that, without altruism, the death toll is higher. This is due to the fact that, as infected agents do not change their behavior, they end up infecting

[39] See https://www.google.com/covid19/mobility/

[40] Note that Google reports a larger drop (in absolute value) in work time: 22.9%.

Table C1: No altruism

	Benchmark	Epidem.
Wks to peak srsly ill (yng)	12.00	12.00
Wks to peak srsly ill (old)	12.00	12.00
Srsly ill p/ 1,000 @ peak (yng)	9.22	12.84
Srsly ill p/ 1,000 @ peak (old)	1.24	10.78
Dead p/ 1,000 1year (yng)	3.51	4.04
Dead p/ 1,000 1year (old)	8.11	30.07
Dead p/ 1,000 1year (all)	4.24	8.21
Dead p/ 1,000 LR (yng)	3.51	4.04
Dead p/ 1,000 LR (old)	8.11	30.07
Dead p/ 1,000 LR (all)	4.24	8.21
Immune in LR (yng), %	74.02	85.24
Immune in LR (old), %	10.67	39.45
Immune in LR (all), %	63.87	77.90
GDP at peak - rel to BM	1.00	1.18
GDP 1year - rel to BM	1.00	1.02
Cost p/ life saved, million $	–	–
Hrs @ home (yng) - peak	67.71	54.77
Hrs @ home (old) - peak	109.11	88.98
Hrs @ home (yng) - 6m	55.13	54.77
Hrs @ home (old) - 6m	90.87	88.98
Value - healthy (yng)	1644.60	1644.00
Value - healthy (old)	881.10	866.51
Value - healthy (all)	1522.30	1519.50

more people. Note that this world is riskier for healthy people, who behave more cautiously in response. Note that the hours at home for healthy agents are higher compared to the benchmark with altruism.

C.2 Late Shelter-in-Place Policy

This section provides results for a shelter-in-place policies that starts 8 weeks after the outbreak of the disease and lasts for 12 weeks. See Figures C1 and C2.

C.3 Selective Mixing - Details

In order to model selective mixing across age groups, 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

Figure C1: Aggregate variables (late shelter-in-place)

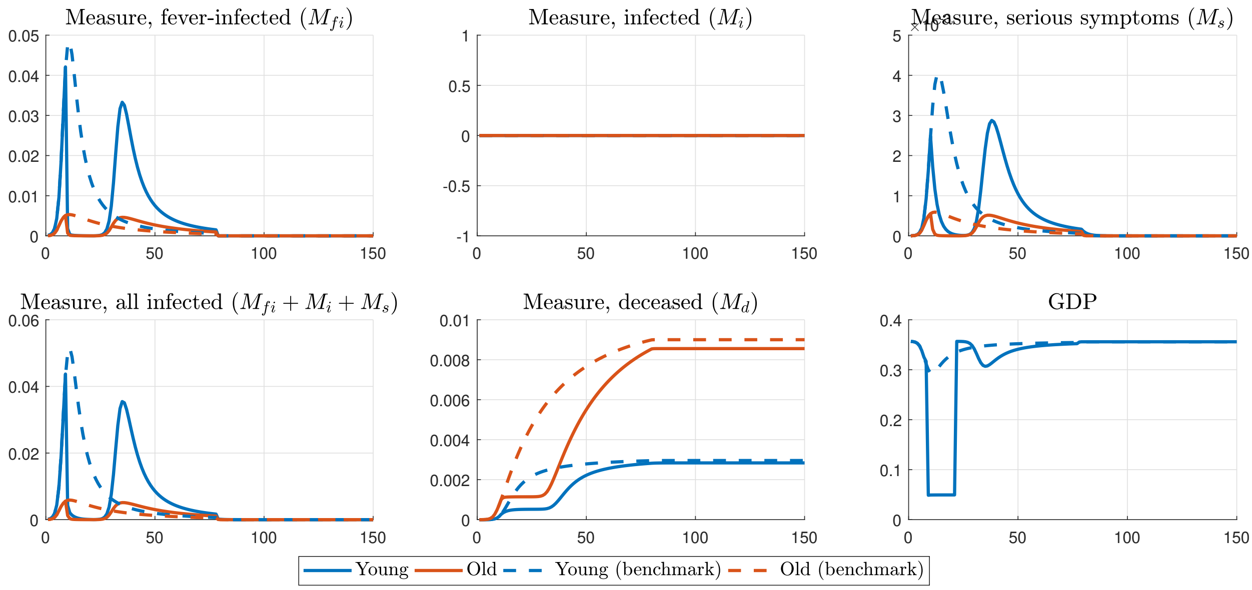
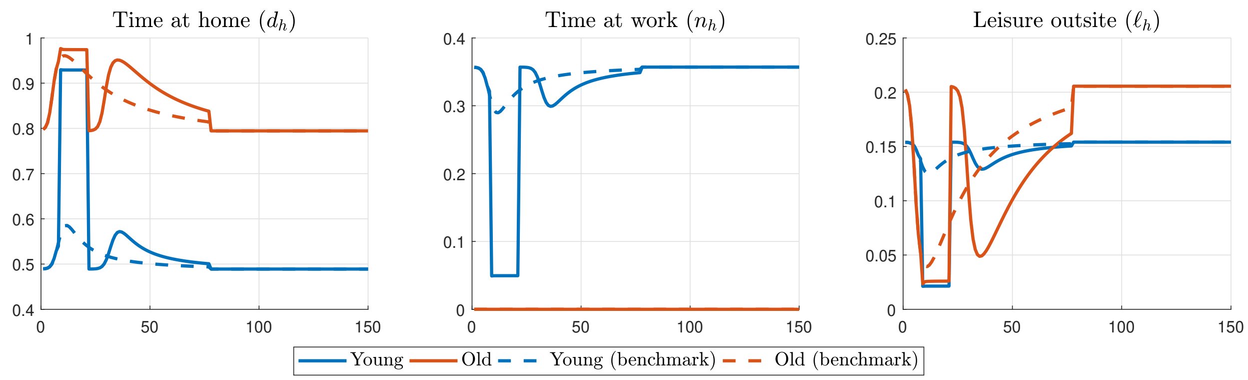


Figure C2: Choices of healthy agents (late shelter-in-place)



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

$$\begin{aligned}\hat{\Pi}_t(a) &= (1-\zeta)\Pi_0 \sum_{\tilde{a},j\in\{f_i,i,s\}} (n_t(j,\tilde{a}) + \ell_t(j,\tilde{a}))\, M_t(j,\tilde{a}) \\ &\quad +\zeta T(\vartheta_a)\Pi_0 \sum_{j\in\{f_i,i,s\}} \frac{T(\vartheta_a)}{\vartheta_a} (n_t(j,a) + \ell_t(j,a))\, M_t(j,a).\end{aligned} \tag{21}$$

The first line reflects the $1-\zeta$ of a person's time spent in the unrestricted space where everything is unchanged from equation (11) in the main text: 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 (21) 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. We suppose $\zeta = 1/2$ so that half of the activities can be divided among the two age groups. Moreover, we 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).

D Alternative Scenarios

This section explores alternative assumptions for the baseline specification. In particular, we explore scarce medical supplies (Section D.1), a world with no vaccine (Section D.2), and different hospitalization and death rates as provided by Ferguson et al. (2020) (Section D.3).

D.1 Hospital Bed Constraints

In this section, we explore the effects of scarce hospital resources. 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.[41] 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.

In the no-policy equilibrium (Table D2), since agents without hospital beds die with certainty, the number of deaths increases considerably compared to the previous calibration (about three times larger). The age externality works differently now. Take the case in which young agents behave more cautiously, as they think they face the death probabilities of the old. In general equilibrium there would be less infections per period, and less hospital beds would be occupied, leading to a smaller number of deaths for both age groups. Note that this is the opposite of what happens in the model without hospital constraints. There, 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.

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

Tables D3 and D4 present the results of the shelter-in-place and testing and quarantine policies, respectively. Qualitatively, the insights from the previous sections remain. One difference is that now shelter-in-place policies no longer backfire. Sheltering spreads the demand for hospital beds across time, yielding benefits that are not captured in the original setting.

Table D2: Benchmark results (hospital constraints)

	Benchmark	Epidem.	Age ext. partial	Age ext. general
Wks to peak srsly ill (yng)	11.00	11.00	11.00	12.00
Wks to peak srsly ill (old)	12.00	12.00	12.00	12.00
Srsly ill p/ 1,000 @ peak (yng)	2.02	6.42	2.02	1.99
Srsly ill p/ 1,000 @ peak (old)	1.34	9.19	1.34	1.33
Dead p/ 1,000 1year (yng)	11.21	18.99	11.07	10.78
Dead p/ 1,000 1year (old)	15.21	31.97	15.20	14.82
Dead p/ 1,000 1year (all)	11.85	21.07	11.73	11.43
Dead p/ 1,000 LR (yng)	11.32	18.99	11.19	10.93
Dead p/ 1,000 LR (old)	16.14	31.97	16.14	15.98
Dead p/ 1,000 LR (all)	12.09	21.07	11.98	11.73
Immune in LR (yng), %	63.51	82.88	62.92	62.26
Immune in LR (old), %	20.41	38.40	20.41	20.24
Immune in LR (all), %	56.61	75.75	56.11	55.53
GDP at peak - rel to BM	1.00	1.20	1.00	1.00
GDP 1year - rel to BM	1.00	1.03	0.99	0.99
Cost p/ life saved, million $	–	–	3.90	1.17
Hrs @ home (yng) - peak	64.57	54.77	64.74	64.69
Hrs @ home (old) - peak	100.56	88.98	100.56	100.47
Hrs @ home (yng) - 6m	56.67	54.77	58.55	58.26
Hrs @ home (old) - 6m	93.58	88.98	93.58	93.28
Value - healthy (yng)	559.80	555.08	240.45	240.58
Value - healthy (old)	405.07	399.50	405.07	405.18
Value - healthy (all)	535.01	530.15	266.82	266.95

Table D3: Shelter in Place (hospital constraints)

	Benchmark	SH25-a-4	SH25-a-26	SH25-y-26	SH75-a-12	SH75-a-35	SH90-a-26	SH90-o-26
Wks to peak srsly ill (yng)	11.00	14.00	32.00	32.00	31.00	64.00	52.00	12.00
Wks to peak srsly ill (old)	12.00	14.00	33.00	33.00	32.00	64.00	52.00	30.00
Srsly ill p/ 1,000 @ peak (yng)	2.02	2.03	1.19	1.15	2.02	1.95	2.01	2.01
Srsly ill p/ 1,000 @ peak (old)	1.34	1.33	0.92	0.87	1.30	1.19	1.25	0.48
Dead p/ 1,000 1year (yng)	11.21	11.18	9.58	9.60	10.82	0.00	2.56	10.85
Dead p/ 1,000 1year (old)	15.21	15.01	13.79	15.17	12.42	0.00	2.44	6.46
Dead p/ 1,000 1year (all)	11.85	11.79	10.26	10.50	11.08	0.00	2.54	10.15
Dead p/ 1,000 LR (yng)	11.32	11.31	9.95	9.97	11.24	10.31	10.98	10.99
Dead p/ 1,000 LR (old)	16.14	16.07	16.41	17.68	15.30	10.69	13.24	7.76
Dead p/ 1,000 LR (all)	12.09	12.08	10.99	11.20	11.89	10.37	11.34	10.47
Immune in LR (yng), %	63.51	63.43	62.55	62.52	62.35	51.21	58.13	63.76
Immune in LR (old), %	20.41	20.37	21.21	22.80	19.68	13.90	17.22	10.19
Immune in LR (all), %	56.61	56.53	55.92	56.16	55.52	45.23	51.58	55.18
GDP at peak - rel to BM	1.00	1.00	1.09	1.09	1.00	0.99	1.00	1.01
GDP 1year - rel to BM	1.00	0.98	0.89	0.89	0.83	0.54	0.58	1.00
Cost p/ life saved, million $	–	38.14	4.17	5.16	30.90	9.85	21.17	-0.03
Hrs @ home (yng) - peak	64.57	64.94	61.29	61.07	64.70	64.96	65.03	64.64
Hrs @ home (old) - peak	100.56	100.63	97.77	97.57	100.63	100.83	100.81	109.43
Hrs @ home (yng) - 6m	56.67	57.39	69.82	69.85	57.01	95.85	104.06	56.58
Hrs @ home (old) - 6m	93.58	94.22	97.92	93.50	94.12	106.14	109.09	109.18
Value - healthy (yng)	559.80	559.43	558.05	558.02	545.73	519.62	502.99	560.00
Value - healthy (old)	405.07	404.99	404.23	404.81	401.04	394.72	388.05	390.47
Value - healthy (all)	535.01	534.69	533.41	533.47	522.55	499.61	484.58	532.84

Table D4: 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)	11.00	22.00	21.00	12.00	19.00	3.00	4.00
Wks to peak srsly ill (old)	12.00	22.00	21.00	12.00	19.00	3.00	3.00
Srsly ill p/ 1,000 @ peak (yng)	2.02	1.12	1.15	2.01	0.84	0.01	0.01
Srsly ill p/ 1,000 @ peak (old)	1.34	0.78	0.80	1.33	0.56	0.01	0.01
Dead p/ 1,000 1year (yng)	11.21	6.43	6.64	11.13	4.56	0.00	0.00
Dead p/ 1,000 1year (old)	15.21	9.36	9.59	15.05	8.37	0.01	0.02
Dead p/ 1,000 1year (all)	11.85	6.90	7.11	11.75	5.17	0.00	0.01
Dead p/ 1,000 LR (yng)	11.32	6.46	6.68	11.23	4.75	0.00	0.00
Dead p/ 1,000 LR (old)	16.14	9.53	9.79	15.89	9.42	0.01	0.02
Dead p/ 1,000 LR (all)	12.09	6.95	7.17	11.98	5.50	0.00	0.01
Immune in LR (yng), %	63.51	40.41	41.49	62.82	38.33	0.06	0.07
Immune in LR (old), %	20.41	12.17	12.49	20.08	12.27	0.02	0.02
Immune in LR (all), %	56.61	35.89	36.84	55.97	34.16	0.06	0.06
Max. n. of tests in a week, %	0.00	6.03	5.74	0.40	2.82	4.95	4.60
GDP at peak - rel to BM	1.00	1.10	1.09	1.00	1.13	1.21	1.21
GDP 1year - rel to BM	1.00	1.02	1.02	1.00	1.02	1.05	1.05
Cost p/ life saved, million $	–	-0.18	-0.18	-0.09	-0.15	-0.19	-0.19
Hrs @ home (yng) - peak	64.57	60.22	60.40	64.52	57.96	54.80	54.80
Hrs @ home (old) - peak	100.56	96.53	96.70	100.54	93.97	89.08	89.08
Hrs @ home (yng) - 6m	56.67	58.87	58.50	56.64	56.89	54.77	54.77
Hrs @ home (old) - 6m	93.58	95.24	94.93	93.54	92.90	88.98	88.98
Value - healthy (yng)	559.80	563.28	563.13	559.86	564.01	567.54	567.54
Value - healthy (old)	405.07	408.53	408.37	405.20	408.74	412.93	412.93
Value - healthy (all)	535.01	538.49	538.34	535.08	539.13	542.77	542.77

D.2 A World with no Vaccine

In our baseline calibration, a vaccine arrives after 78 weeks. After this, nobody gets infected with Covid-19 anymore. In this section, we explore the effects of a scenario in which a vaccine never comes along; i.e. $T^* = \infty$. The benchmark is very similar with slightly more deaths (4% more). The age externality the young impose on the old works in the same way but is stronger now: the overall death toll increases.[42] The main difference comes with longer shelter-in-place policies.

[42] This is not the case with no vaccine and hospital bed constraints (not shown). As the young become more careful, they free up scarce medical resources and this decreases the number of deaths.

Without a vaccine, the long-run death count is very similar to the no-policy benchmark. Now, after the policy is lifted, the pandemic restarts and ends up killing almost the same number of people as there is no vaccine to prevent this.

Table D5: Benchmark results (no vaccine)

	Benchmark	Epidem.	Age ext. partial	Age ext. general
Wks to peak srsly ill (yng)	14.00	12.00	13.00	14.00
Wks to peak srsly ill (old)	12.00	12.00	12.00	12.00
Srsly ill p/ 1,000 @ peak (yng)	4.10	12.84	2.02	1.56
Srsly ill p/ 1,000 @ peak (old)	0.60	10.78	0.60	0.48
Dead p/ 1,000 1year (yng)	2.82	4.04	1.94	1.94
Dead p/ 1,000 1year (old)	7.83	30.07	7.83	8.00
Dead p/ 1,000 1year (all)	3.62	8.21	2.89	2.91
Dead p/ 1,000 LR (yng)	3.03	4.04	2.24	2.88
Dead p/ 1,000 LR (old)	9.71	30.07	9.71	14.12
Dead p/ 1,000 LR (all)	4.10	8.21	3.44	4.68
Immune in LR (yng), %	64.07	85.24	47.37	60.83
Immune in LR (old), %	13.01	39.45	13.01	19.42
Immune in LR (all), %	55.89	77.90	41.87	54.19
GDP at peak - rel to BM	1.00	1.21	0.49	0.85
GDP 1year - rel to BM	1.00	1.05	0.81	0.88
Cost p/ life saved, million $	–	–	12.15	20.53
Hrs @ home (yng) - peak	65.28	54.77	92.71	72.66
Hrs @ home (old) - peak	107.61	88.98	107.61	102.58
Hrs @ home (yng) - 6m	58.70	54.77	73.38	68.87
Hrs @ home (old) - 6m	100.60	88.98	100.60	99.95
Value - healthy (yng)	3740.50	3736.30	1608.60	1603.30
Value - healthy (old)	1800.90	1770.60	1800.90	1795.20
Value - healthy (all)	3429.80	3421.40	1639.40	1634.10

Table D6: Shelter-in-place policies (no vaccine)

	Benchmark	SH25-a-4	SH25-y-26	SH75-a-12	SH75-a-35	SH90-a-26	SH90-o-26
Wks to peak srsly ill (yng)	14.00	16.00	34.00	33.00	66.00	54.00	14.00
Wks to peak srsly ill (old)	12.00	14.00	33.00	32.00	64.00	53.00	30.00
Srsly ill p/ 1,000 @ peak (yng)	4.10	4.11	2.31	4.10	4.10	4.11	4.09
Srsly ill p/ 1,000 @ peak (old)	0.60	0.60	0.48	0.59	0.57	0.57	0.30
Dead p/ 1,000 1year (yng)	2.82	2.80	2.52	2.50	0.00	0.34	2.81
Dead p/ 1,000 1year (old)	7.83	7.67	8.27	5.81	0.00	1.12	4.39
Dead p/ 1,000 1year (all)	3.62	3.58	3.44	3.03	0.00	0.46	3.06
Dead p/ 1,000 LR (yng)	3.03	3.03	3.03	3.03	3.03	3.03	3.04
Dead p/ 1,000 LR (old)	9.71	9.69	11.72	9.51	9.18	9.30	6.50
Dead p/ 1,000 LR (all)	4.10	4.10	4.42	4.07	4.01	4.03	3.59
Immune in LR (yng), %	64.07	64.07	63.93	64.03	63.94	63.98	64.20
Immune in LR (old), %	13.01	13.02	15.87	12.99	12.95	12.97	8.81
Immune in LR (all), %	55.89	55.89	56.23	55.85	55.77	55.81	55.33
GDP at peak - rel to BM	1.00	1.00	1.08	1.00	1.00	1.00	1.00
GDP 1year - rel to BM	1.00	0.98	0.88	0.83	0.55	0.58	1.00
Cost p/ life saved, million $	–	43.00	–	32.05	15.80	26.48	-0.01
Hrs @ home (yng) - peak	65.28	65.12	62.02	64.70	65.22	64.95	65.09
Hrs @ home (old) - peak	107.61	107.61	105.54	107.56	107.61	107.60	110.12
Hrs @ home (yng) - 6m	58.70	59.36	70.46	57.36	95.85	104.06	58.58
Hrs @ home (old) - 6m	100.60	101.68	100.94	101.65	106.14	109.09	109.41
Value - healthy (yng)	3740.50	3740.10	3737.90	3726.40	3699.80	3683.60	3740.50
Value - healthy (old)	1800.90	1800.80	1797.80	1797.20	1790.20	1784.20	1791.30
Value - healthy (all)	3429.80	3429.40	3427.10	3417.40	3393.90	3379.30	3428.20

D.3 Alternative Calibration - Based on Ferguson et al. (2020)

An influential study was conducted by researchers at the Imperial College London: Ferguson et al. (2020). Their results have been used to calibrate recent models in the economics literature.[43] In this section, we recalibrate the disease parameters in our model to reflected those provided by this study. The main differences relative to those from CDC (2020) is that the the young (the old) are less (more) likely to end up in an ICU. On the other hand, the young (the old) are more (less) likely to die, conditional on being in an ICU. In the end, the resulting death probabilities are very similar. The results, therefore, are very close

[43]E.g. Acemoglu et al. (2020).

Table D7: Parameters - baseline calibration and Ferguson et al. (2020)

Parameter	Bench. calibration	Ferguson et al. (2020)
$\phi(0,y)$	0.983	0.991
$\phi(0,o)$	0.954	0.893
$\phi(1,y)$	0.284	0.284
$\phi(1,o)$	0.284	0.284
$\delta(y)$	0.065	0.373
$\delta(o)$	0.738	0.371

to those obtained with our benchmark calibration.

The main differences between Ferguson et al. (2020) and CDC (2020) are between the transition rates from mild to severe symptoms, and from severe symptoms to death. However, the resulting overall death probability for each are very similar across both studies. We take the age-dependent transition rates from Ferguson et al. (2020) and aggregate to our two age groups (20-64 and 65-plus) using the relative population weights for the US. This yields the following weekly probability of recovery from mild symptoms: $\phi(0,y) = 0.991$ and $\phi(0,o) = 0.893$. The age-dependent weekly death rates are: $\delta(y) = 0.373$ and $\delta(o) = 0.371$. Table D7 compares these parameters with the ones from the benchmark calibration. Table D8 provides the results for this calibration.

Table D8: Alternative calibration - based on Ferguson et al. (2020)

	Benchmark	Epidem.
Wks to peak srsly ill (yng)	12.00	12.00
Wks to peak srsly ill (old)	13.00	12.00
Srsly ill p/ 1,000 @ peak (yng)	0.75	2.58
Srsly ill p/ 1,000 @ peak (old)	1.13	16.89
Dead p/ 1,000 1year (yng)	2.52	3.60
Dead p/ 1,000 1year (old)	7.18	25.94
Dead p/ 1,000 1year (all)	3.27	7.18
Dead p/ 1,000 LR (yng)	2.64	3.60
Dead p/ 1,000 LR (old)	8.26	25.94
Dead p/ 1,000 LR (all)	3.54	7.18
Immune in LR (yng), %	62.41	84.87
Immune in LR (old), %	12.70	39.29
Immune in LR (all), %	54.45	77.57
GDP at peak - rel to BM	1.00	1.20
GDP 1year - rel to BM	1.00	1.05
Cost p/ life saved, million $	–	–
Hrs @ home (yng) - peak	64.44	54.77
Hrs @ home (old) - peak	107.24	88.98
Hrs @ home (yng) - 6m	58.20	54.77
Hrs @ home (old) - 6m	99.49	88.98
Value - healthy (yng)	3742.10	3738.20
Value - healthy (old)	1804.40	1777.90
Value - healthy (all)	3431.70	3424.10