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David Baqaee, University of California, Los Angeles
Emmanuel Farhi, Harvard University
Michael Mina, Harvard University
James H. Stock, Harvard University

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Policies for a Second Wave

David Baqaee
Department of Economics, UCLA

Emmanuel Farhi
Department of Economics, Harvard University

Michael Mina
Chan School of Public Health, Harvard University

James H. Stock
Department of Economics and Harvard Kennedy School, Harvard University

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Abstract

Although confirmed COVID-19 cases and deaths are declining in the Northeastern states that have been hardest hit by the pandemic, in other parts of the nation confirmed cases are rising and deaths are declining more slowly. As the nation reopens, this raises concerns about a second wave of deaths which, if countered by a second round of economic shutdowns, could have severe and long-lasting economic consequences. We use a five-age epidemiological model, combined with 66-sector economic accounting, to examine policies to avert and to respond to a second wave. We find that a second round of economic shutdowns alone are neither sufficient nor necessary to avert or quell a second wave. In contrast, non-economic non-pharmaceutical interventions, such as reintroducing restrictions on social and recreational gatherings, stressing wearing masks and personal distancing, increasing testing and quarantine, and enhancing protections for the elderly and the most vulnerable, together can mitigate a second wave while leaving room for an economic recovery.

Key words: Epidemiological models, macroeconomics, shutdowns

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In the second and third weeks of March 2020, vast swaths of the US economy shut down in response to the rapidly spreading novel coronavirus and exponentially rising death rates from COVID-19. The shutdown triggered the sharpest and deepest recession in the postwar period, with more than 30 million new claims for unemployment insurance filed in the six weeks starting March 15. The economic shutdown, combined with other non-pharmaceutical interventions (NPIs), slowed then reversed the national weekly death rate and brought estimates of the effective reproductive number of the epidemic to one or less in nearly all states. With the epidemic seemingly under control, state authorities, with federal guidance, began relaxing both economic and non-economic restrictions, with some of the least hard-hit states starting in late April or early May and others starting in late May or June. As of the date of this conference, however, the weekly number of confirmed cases is rising nationally, especially outside the Northeast, raising the specter of a second wave of deaths. If countered by a second round of economic shutdowns, short-term unemployment could become long-term, firms could close, and prospects for a quick recovery could be significantly impaired.

This paper examines policy options for avoiding or mitigating a second wave of deaths and economic shutdowns. To do so, we use a combined epidemiological-economic model that permits considerable granularity in NPIs. We distinguish between economic NPIs, which directly constrain economic activity (such as closing certain sectors), and non-economic NPIs, which do not (such as personal distancing).

Our main finding is that a second wave can be avoided or, if it starts, turned around through the use of non-economic NPIs, avoiding the need for a second round of economic shutdowns. Effective non-economic NPIs include limits on sizes of group activities, especially indoors; personal distancing and the wearing of masks; increasing testing and quarantine rates; and enhancing protections for the elderly. There is strong evidence that much of the decline in economic activity was the result of self-protective behavior by individuals, not government shutdown orders, so simply reversing those orders will not by itself revive the economy. By using non-economic NPIs, not only can shutdown orders can be avoided but, at least as importantly, a declining trend in deaths also can reassure consumers and workers that it is safe to return to near-normal economic activity.

Our baseline scenarios have schools reopening in the fall, creating another route for transmission of the virus (although the limited current evidence suggests lower transmission rates involving children than adults). Keeping schools closed, however, constrains the labor supply of workers with no other childcare options and imposes substantial and disparate developmental costs on schoolchildren. Our modeling suggests that a second wave can be reversed through the adoption of non-economic NPIs without needing to close either schools or the economy.

Deploying non-economic NPIs entails a combination of government guidance and financial support, compliance by firms and retail establishments, and public acceptance and adoption. For example, increasing quarantine rates requires wider availability of tests and enhanced support to encourage individuals to self-isolate. Similarly, additional protections for the elderly, such as regular testing of staff and residents in nursing homes – who to date account for an estimated 42% of COVID-19 deaths (Kaiser Family Foundation (2020)) – requires financial and operational support. Wearing masks and maintaining personal distancing requires leadership and education at all levels of government and, at the level of the individual, a desire not to be the reason someone else gets sick. Each of these NPIs is imperfect (which is how we model them) but together they can reduce the probability of transmission sufficiently to make room for people to return to working, shopping, and eating out, even if a second wave reemerges.

EPIDEMIOLOGICAL-ECONOMIC ANALYSIS Our analysis uses a model that combines epidemiological and economic components at a level of granularity that allows us to consider NPIs that vary by age (such as school closings) and by economic sector (such as phased economic reopenings). The epidemiological component is an age-based SEIQRD model with 5 age bins with mortality rates that vary by age. After calibration using multiple different data sources, the model has five free parameters (including the basic case reproduction rate R_0) which we estimate from national daily death rate data. The population infection-fatality rate (IFR) is unknown (because total infections are unmeasured); our central case uses a population-average IFR 0f 0.6%, but we consider alternatives from 0.4% to 1.1%.

The model has 66 economic sectors. We use work by Dingel and Nieman (2020) and Mongey, Pilossoph and Weinberg (2020) to estimate the ability for working from home, and of personal proximity at work, by sector, plus BLS and BEA data on the age distribution of workers by sector. This allows us to compute a GDP-to-Risk index by sector, which measures the marginal contribution of an additional worker in a given sector to GDP, relative to the marginal contribution to the basic reproduction number. We use this index to quantify the benefits of nuanced sectoral reopening policies.

The model is closed using a decision-maker who follows CDC guidelines and tracks data on deaths and unemployment to decide on the level of economic activity. Decision-making in this health and economic crisis involves federal, state, and local officials and individuals who decide whether to engage in self-protective behavior. Our representative decision-maker, who for convenience we call a governor, stands in for this complex decentralized web.

RELATED LITERATURE There is a rapidly growing literature that merges epidemiological and economic modeling to undertake policy analysis for the pandemic.[1] Although most of the models in the literature are highly stylized, they provide useful qualitative guidance.

Broadly speaking, this literature provides six main lessons. First, for a virus with a high fatality rate like SARS-CoV-2, the optimal policy is to take aggressive action early to drive prevalence nearly to zero (Alvarez et. al. (2020), Jones et al. (2020), but also see Farboodi et al. (2020)); doing so not only decreases the costs from deaths, but also provides an environment in which endogenously self-protecting individuals choose to return to economic activity. Second, testing and quarantine have high value and reduce the need for a severe economic lockdown (Alvarez et. al. (2020), Berger et al. (2020), Eichenbaum, Rebelo, and Trabant (2020b)). Third, because deaths are highest among the elderly, focusing resources on protecting older workers or the most vulnerable can provide large benefits (Acemoglu et al. (2020), Rampini (2020)). Fourth, non-economic NPIs such as masks and social distancing can reduce both economic costs and deaths (Bodenstein et al. (2020), Farboodi et al. (2020)). Fifth, nuanced economic NPIs, for example with sectoral or age variation, can facilitate a quicker reopening (Azzimonti et al. (2020), Favero et al (2020), Glover et al. (2020)). Sixth, a common theme through these papers is that individual self-protective behavior both anticipates and reduces the effect of regulatory interventions like lockdowns, although because of the contagion and other externalities, individual response alone is typically less than socially optimal.

[1] See Acemoglu, Chernozhukov, Werning & Whinston (2020), Alvarez, Argente, and Lippi (2020), Aum, Lee, and Shin (2020), Atkeson (2020a, b), Baqaee and Farhi (2020a, b), Azzimonti et al. (2020), Berger, Herkenhoff & Mongey (2020), Bodenstein, Crosetti & Guerrieri (2020), Budish (2020), Eichenbaum, Rebelo & Trabant (2020a, b), Farboodi, Jarosch, and Shimer (2020), Favero, Ichino, and Rustichini (2020), Glover, Heathcoate, Krueger & Rios-Rull (2020), Guerrieri, Lorenzoni, Straub & Werning (2020), Jones, Philippon, and Venkateswaran (2020), Krueger, Uhlig, and Xie (2020), Lin and Meissner (2020), Ludvigson, Ma, and Ng (2020), Morris et. al. (2020), Moser and Yared (2020), Mulligan (2020), Rampini (2020), Rio-Chanona, Mealy, Pichler, Lafond & Farmer (2020), and Stock (2020).

Our modeling underscores many of these conclusions. Additionally, we are able to examine the interactions among various NPIs in a setting that is carefully calibrated to current US conditions, so that the effects of the various approaches can be compared directly.

An additional pertinent literature estimates the extent to which the economic contraction starting in March was an endogenous response to the virus or the direct causal consequence of government strictures. This question is a topic of papers in this volume by Bartik et. al. (2020) and by Gupta et al. (2020), so we refer the reader to their discussion of this literature.

I. The Model

We use an age-based SIR model with exposed and quarantined compartments and with age-specific contact rates. An age-based approach matters for four reasons. First, death rates vary sharply by age. Second, workplace shutdowns affect working-age members of the population. Third, different industries have different age structures of workers, so reopening policies that differentially affect different industries could have consequences for death rates as a result of the death-age gradient. Fourth, some policies affect different ages differently, such as closing and reopening schools and only allowing workers of a certain age back into working from work.

I.A. Age-based SEIQRD model

The model simplifies Towers and Feng (2012) and follows Hay et al. (2020), adding a quarantined compartment. We consider 5 age groups: ages 0-19, 20-44, 45-64, 65-74, and 75+. The epidemiological state variables are *S* (susceptible), *E* (exposed), *I* (infected), *Q* (quarantined), and *D* (dead). The state variables are all 5-dimensional vectors, with each element an age group, so for example I_2 is the number of infected who are ages 20-44. The unit of time is daily. We assume that the recovered are immune until a vaccine and/or effective treatment becomes available.[2]

Let S_a (etc.) denote the a^{th} element of *S* (a^{th} age group). The SEIQRD model is:

$$dS_a = -\beta S_a \sum_b \kappa_{ab} C_{ab} \left(\frac{I_b}{N_b} \right) \tag{1}$$

[2] The assumption of subsequent immunity among the recovered is a matter of ongoing scientific investigation. A working hypothesis based on the related coronaviruses causing MERS and SARS is that immunity could decay but last for 1-3 years. Because our simulations run through the end of 2020, our assumption is that the recovered are immune through that period.

$$dE_a = -dS_a - \sigma E_a \tag{2}$$

$$dI_a = \sigma E_a - \gamma I_a - \delta_a I_a - \chi I_a \tag{3}$$

$$dQ_a = \chi I_a - \gamma Q_a - \delta_a Q_a \tag{4}$$

$$dR_a = \gamma I_a + \gamma Q_a \tag{5}$$

$$dD_a = \delta_a I_a + \delta_a Q_a \tag{6}$$

The total number of individuals of age a is $N_a = S_a + E_a + I_a + Q_a + R_a$.

The parameters of the model are the adult transmission rate β, the recovery rate γ, the latency rate σ, the age-dependent death rate δ_a, the quarantine rate χ, the 5×5 contact matrix C (with element C_{ab}), and age-dependent transmission factors κ_{ab}. The adult transmission rate β reflects the probability of an adult becoming infected from a close contact with an infected adult. The factors κ_{ab} allow for transmission rates involving children to differ from the adult-adult rate; κ_{ab} is normalized to be 1 for adult-adult contacts. Transmission can be mitigated by protective measures such as masks. As discussed below, we model those protective measures separately and accordingly define β to be the transmission rate without mitigation, so that β is determined by the biology of the disease and preexisting social customs (e.g., hand-shaking). The latency rate σ and the recovery rate γ are biological characteristic of the disease. The death rate δ_a varies by age. The death rate can vary over time as treatment improves or hospital beds become scarce, however during spring 2020 hospital surge capacity was sufficient to handle patient caseload and we do not model time variation in δ. The parameter χ is the removal rate into quarantine, the value of which depends on quarantine policy. Calibration and estimation of the model is discussed in Section 4.

The contact matrix C is the mean number of contacts among different age groups in the population. Thus, according to equations (1) and (2), a susceptible adult of age a who comes into contact with an adult of age b has an instantaneous infection probability of β times the probability that the age-b adult is infected. Transmission for contacts involving children are reduced by the factor κ_{ab}. The total instantaneous probability of infection is the sum over the expected transmission by contacts of different ages if those contacts are infected, times the probability that the contacted individual is infected.

In the model, an infected individual is placed into quarantine with some probability, at which point they no longer can infect others. In practice, identifying the infected individual requires testing and tracing. In addition, in the United States, quarantine is imperfect and amounts to strong advice to self-isolate. Our simple model abstracts from these complexities.

Other than the quarantine rate χ, the parameters in the model represent preexisting conditions at the start of the epidemic. Policy and/or self-protective behavior can be thought of as either changing the values of these parameters or, alternatively, introducing additional parameters in the model. For example, the probability of transmission from a contact is reduced substantially if both individuals are wearing masks. In addition, lockdown orders, or self-limiting behavior, can reduce the number and ages of contacts, that is, alter the elements of the contact matrix. Our modeling of such NPIs, both self-protective and mandated, is discussed in Section 3.

In a model without quarantine and with a death rate that depends on age, the initial reproductive rate R_0 is,

$$R_0 = \beta \max\mathrm{Re}\left[\mathrm{eval}\left(\tilde{C} \bullet \Gamma\right)\right], \tag{7}$$

where $\max\mathrm{Re}\left[\mathrm{eval}(.)\right]$ denotes the maximum of the real part of the eigenvalues of the matrix argument, $\tilde{C}$ is the normalized contact matrix with elements $\tilde{C}_{ab} = \left(C_{ab}N_a / N_b\right)$, $\Gamma_{ab} = \kappa_{ab} / (\gamma + \delta_b)$, and $\bullet$ is the element-wise product.[3] Equation (7) generalizes the familiar expression for R_0 in a scalar SIR model ($R_0 = \beta/(\gamma + \delta)$) to age-based contacts with age-dependent transmission and death rates.[4]

I.B. Sector- and activity-based contact matrices

The contact matrix C represents the expected number of contacts in a day between individuals in different age bins. We distinguish between contacts made in three activities: at home, at work (on the work site), and other. Other includes both contacts made as a consumer engaging in economic activity, such as shopping, air travel, and dining at a restaurant, and in non-economic activities such as free recreation and social events. In a given day, an individual can be one, two, or all three of these three states.

The expected number of contacts made in a day is the sum of the contacts made at home conditional being at home, plus those made at work conditional on being at work, plus those

[3] Equation (7) is derived using the next-generation matrix method, see Towers and Feng (2012) and van den Driessche (2017)

[4] The parameters β in the scalar and age-based settings differ, where β in the scalar model is the transmission rate β in the age-based model times the expected number of contacts.

made while engaged in other activities conditional on doing other activities, times the respective probabilities of being in those three states. Because we are interested in differentiating between work in different sectors, which among other things differ by the degree of personal proximity and numbers of contacts at the workplace, we further distinguish between different workplace contacts. Thus, the expected number of contacts at work is the weighted average of the expected number of contacts, conditional on working in sector i, times the probability of working in sector i. We therefore have,

$$C_{ab} = p_a^{home} C_{ab}^{home} + p_a^{other} C_{ab}^{other} + \sum_{sectors\ i} p_{a,i}^{work} C_{ab,i}^{work} , \tag{8}$$

where C_{ab}^{home} is the (a, b) element of the contact matrix conditional on being at home, p_a^{home} is the probability of an age-a individual being at home, similarly for other, $C_{ab,i}^{work}$ is the (a, b) element of the contact matrix conditional on being at work in sector i, and $p_{a,i}^{work}$ is the probability of an age-a individual working in sector i, that is, the employment share of sector i as a fraction of the population.

The (unconditional) probabilities $p_{a,i}^{work}$ are the fraction of the population employed in the indicated sector. Let $L_{a,i}$ be the number of workers of age a employed in sector i. Then,

$$p_{a,i}^{work} = L_{a,i} / N_a . \tag{9}$$

The disaggregation of the contact matrices in (8) allows for distinguishing the nature of contacts. A server in a restaurant will have contact with a customer in his or her capacity as a worker (work contact matrix for restaurants), while customers will have contact with the server in their capacity as consumers engaged in "other" activities. Similarly, a home health aide providing services to an elderly person at that person's home will be in contact with the elderly person as part of work, while the elderly recipient will be making that contact at home.

Estimation of the conditional contact matrices and non-work probabilities is discussed in Section 2.

I.C. Employment, unemployment, and output

Employment by age, by sector, and total (L) are respectively sums over sectors, ages, and overall. Let the subscript "•" denotes summation over the subscript. Then,

$$L_{a,\bullet} = \sum_{sectors\ i} L_{a,i} , \ L_{\bullet,i} = \sum_{ages\ a} L_{a,i} , \text{ and } L = \sum_a L_{a,\bullet} = \sum_i L_{\bullet,i} , \tag{10}$$

The departure of output from its full-employment level is estimated using Hulten's (1978) theorem, which says that that the elasticity of real GDP to the total hours worked in a given sector is given by the total labor income in this sector, Ψ_i, as a share of nominal GDP:

$$d \ln Y = \sum_{sectors\ i} \Psi_i d \ln L_{\bullet,i} \; . \tag{11}$$

We discuss this approximation further in Section VI.C.

In the counterfactual simulations, labor supply is constrained in two ways. First, if schools are closed, a fraction of workers will not have other childcare options so will be unable to return to work. Second, the virus reduces labor supply because some workers are temporarily quarantined and some have died.

II. Data Sources

We briefly summarize the data used to calibrate the model and historical NPIs, with details provided in the online Appendix.

II.A. Economic data

Employment by age and industry were computed using the 2017 American Community Survey.

An important NPI is reducing workplace density by workers working at home. Using data from the Bick-Blandin (2020) Real-time Population Survey, Bick, Blandin and Mertens (2020) estimate that 35.2% of the workforce worked entirely from home in May 2020, up from 8.2% in February. the fraction of workers working from home from their Real-time Population Survey to estimate the fraction of workers working from home in February and the end of May. A daily time series of the national fraction working from home was constructed by interpolating and extrapolating these points using the national Google workplace visit mobility index.[5] This aggregate time series was apportioned to the sector level using the Dingel-Neiman (2020) estimates of the (pre-pandemic) fraction of workers in an occupation who can work from home, cross-walked to the 66 input-output sectors.

Mongey, Pilossoph and Weinberg (2020) construct an index of high personal proximity (*HPP*) by occupation, which measures an occupation as high personal proximity if the

[5] https://www.google.com/covid19/mobility/

occupation is above the median value of proximity as measured by within-arms length interactions by occupation. This occupational index was cross-walked to the 66 sectors.

Daily sectoral shocks to labor shares by industry are estimated from hours reductions reported in the February-May Establishment Survey (Tables B1, broken down to the sectoral level proportionally to the sectoral employment changes reported in Table B2). These provide the estimates of the sectoral shocks to hours for the Establishment Survey reference weeks. Between the reference weeks, the sectoral shocks were linearly interpolated, and extrapolated after the May reference week, using the Google workplace visit mobility index.

Data on workers' childcare obligations are from Dingel, Patterson, and Vavra (2020).

II.B. Contact matrices and epidemiological data

The contact matrices are estimated using POLYMOD contact survey data (Mossong et. al. (2017)). Conditional contact matrices for home, work, and other were computed by sampling contact matrices from the POLYMOD survey data and then reweighting them to match US demographics on these three activities.

We used the age distribution of workers by industry and the Mongey-Pilossoph-Weinberg (2020) personal proximity index, cross-walked to the sector level (HPP_i), to construct industry-specific conditional contact matrices, $C_{ab,i}^{work}$ as the product of HPP_i times the overall conditional mean contact matrix, with all sectoral matrices scaled so that the weighted mean equals the overall mean work contact matrix.[6]

The probabilities p^{other} in (8) are estimated from the POLYMOD contact data (normalized for US demographics). The probability p^{home} is nearly 1 in the POLYMOD diaries (i.e., nearly everyone spends part of their day at home) and is set to 1 for all simulations.

Daily death data, which are used to estimate selected model parameters, are from the Johns Hopkins COVID-19 Github repository.[7]

II.C. Calibration of Historical NPIs

We use an index of non-work Google mobility data and school closing data to estimate the historical pattern of reduction in non-work, non-home (other) activities and thus "other" contacts.

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[6] As an alternative, we sampled from the POLYMOD contact diary data to compute the conditional distribution (element-wise) for at-work contacts and sampled from the 15%, median, and 85% percentiles to construct low, median, and high conditional contact matrices, then assigned an industry to one of these three groups based on its *HPP* value. This approach yielded similar contact matrices by sector to the first approach and behaved similarly in simulations.

[7] https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data

We refer to these generally as historical NPIs, some of which are a consequence of government decisions (e.g., closing schools) and some of which represent voluntary self-protection. We construct a mobility index (GMI) using three Google mobility measures at the daily level (national averages): retail and recreation, transit stations, and grocery & pharmacies. These three measures are averaged, normalized so that 1 represents the mean of the final two weeks of February 2020, and smoothed (centered 7-day moving average). Dates of school closings are taken from Kaiser Family Foundation (2020), aggregated to the national level using population weighting. Section 4 explains the use of these data to create time-varying contact matrices.

II.D. Epidemiological Parameters

We reviewed 20 papers with medical estimates of incubation periods and duration of the disease once symptomatic. These papers provided 23 estimates of the incubation (the latency period) period and 16 estimates of the period from becoming symptomatic to being recovered (the recovery period). For the latency period, we used the mean value from the three peer-reviewed studies with estimates, which yields a latency period of 4.87 days and a value of $\sigma = e^{-4.87}-1$. For the recovery period, the studies have very long estimates, from 17.5 to 28.3 days, which appear to represent sample selection in the studies which tend to consider the most severe (and presumably longest-lasting) cases. Estimates for the recovery period used in the epidemiological literature are shorter, and we use Kissler et al.'s (2020) estimate of an infectious period of 5 days (so $\gamma = e^{-5}-1$). As a sensitivity check, we also consider an infectious period of 9 days; as shown in the Appendix our simulation results are not sensitive to this change so the discussion in the text is restricted to the 5-day recovery period.

Salje et al (2020) and Verity et al (2020) provide estimates of the infection-fatality ratio (IFR) by age. Ferguson et al (2020) adjust the Verity et al (2020) IFRs to account for non-uniform attack rates across ages. The more recent Salje et al (2020) study uses data from France and the *Diamond Princess* cruise ship, and has lower IFRs at the youngest ages, and slightly higher IFRs at the older ages, than Ferguson. We adopt the more recent Salje et al (2020) IFR profile.[8] The overall (population-wide) IFR is not known because of the dearth of random population testing. We therefore adopt a range of estimates of the population IFR from 0.4% to 1.1%; the age-specific IFR is then obtained using the Salje et al (2020) IFR age profile. The population-wide

[8] Specifically, our vector of age-IFRs in percentages is $c(0.001, 0.052, 0.53, 1.48, 8.26)$, where c is set to yield the indicated population IFR (0.6% in our base case).

IFR is (at best) weakly identified in our model. For our main results we use a population-wide IFR of 0.6%, and report sensitivity analysis in the Appendix.

Boast, Munro, and Goldstein (2020) and Vogel and Couzin-Frankel (2020) provide largely nonquantitative surveys of the sparse literature concerning transmissibility of the virus in contacts involving children. To calibrate the parameters κ_{ab} involving children, we reviewed nine studies on this topic posted between February 21 and May 1. These studies point to a lower transmission rate for contacts involving children, although the estimates vary widely. Of the 7 studies that estimate a transmission rate from children to adults, our mean estimate, weighted by study relevance, is $\kappa_{1b} = 0.44$, $b > 1$. Of the four studies that estimate transmission rates from adults to children, our weighted mean estimate is $\kappa_{a1} = 0.27$, $a > 1$. We are unaware of estimates of child-child transmission rates so lacking data, we set κ_{11} to the average, $\kappa_{11} = (\kappa_{1b} + \kappa_{a1})/2$. These estimates are highly uncertain and some of the simulation results are sensitive to their values, and that sensitivity is discussed further in the text and in more detail in the appendix.

III. GDP-to-Risk Index

One reopening question is whether sectors should be reopened differentially based on either their contribution to the economy or their contribution to risk of contagion. The expressions for R_0 in (7) and for output in (11) lead directly to an index of contributions of GDP per increment to R_0. Specifically, consider a marginal addition of one more worker of age a returning to the worksite in sector i. Then the ratio of the marginal contribution to output, relative to the marginal contribution to R_0, is,

$$\frac{d\ln Y/dL_{a,i}}{dR_0/dL_{a,i}} \propto \frac{\Psi_i/L_i}{\beta d\mathrm{maxRe}\left[\mathrm{eval}\left(\tilde{C}\bullet\Gamma\right)\right]/dL_{a,i}} \equiv \theta_i, \tag{12}$$

where the numerator in (12) does not depend on a because the output expression (11) does not differentiate worker productivity by age.

The derivative in the denominator in (12) depends on the contact matrix, however as is shown in the Appendix, because of the way that $L_{a,i}$ enters C, this dependence on the full contact matrix is numerically small. Thus, while in principle θ_i varies as employment and the other components of the contact matrix vary, in practice this variation in θ_i is small so that the path of θ_i is well approximated by its pre-pandemic full-employment value. For the simulations that examine sequential industry reopening, we therefore used (12) with the derivatives of $\max\text{Re}\left[\text{eval}\left(\tilde{C}\right)\right]$ numerically evaluated at the baseline values of the contact matrix.

Some algebra for a single-age SIR model provides an interpretation of this index in terms of deaths. It is shown in the appendix that the effective case reproduction rate, $R^{eff} = R_0(S/N)$, can be written as,

$$R^{eff} = 1 + \frac{1}{\gamma + \bar{\delta}} \frac{d \ln \dot{D}}{dt} = 1 + \frac{1}{\gamma + \bar{\delta}} \frac{\ddot{D}}{\dot{D}}, \tag{13}$$

where $\dot{D} = dD/dt$ and $\ddot{D} = d^2 D/dt^2$. At the start of the epidemic, when $S/N = 1$, combining expressions (12), and (13) shows that

$$\theta_i = \left(\gamma + \bar{\delta}\right) \frac{d \ln Y / dL_i}{d\left(\ddot{D}/\dot{D}\right) / dL_{a,i}}, \tag{14}$$

where $\bar{\delta}$ is the population-wide death rate (the subscript a is dropped because (13) holds for a single-age SIR). Thus, in a single-age version of the model, θ_i is proportional to the ratio of the marginal growth of GDP to the marginal growth of the daily death rate from adding a worker to sector i. For an incremental worker, both these marginal contributions are small.

It is tempting to translate θ into a GDP increment per death for a marginal reopening of a sector, however the alternative formulation (14) shows that such a calculation depends on the state of the pandemic because the denominator is the contribution to the growth rate of daily deaths. If daily deaths are increasing, adding a worker to a sector is costly because it increases the growth rate of deaths, which are already growing exponentially. The more negative the growth rate of deaths, the smaller is the contribution of the additional worker to the total number of deaths. This is a key insight, that the marginal cost of reopening is contained and can be small by a combination of sectoral prioritization and, especially, ensuring that non-economic NPIs are in place to keep $R^{eff} < 1$ during the reopening.

Values of θ are listed in Appendix Table 1 for the 66 NAICS-code private sectors in our model, both as defined in (12) and standardized to have median zero and unit interquartile range. Evaluated using the baseline model parameters (discussed below), the median value of non-standardized θ is 0.92, with 25^{th} and 75^{th} percentiles of 0.36 and 1.50. These non-standardized values depend on epidemiological parameters whereas, to a good approximation, the only epidemiological parameters on which the standardized version depends are the κ_{ab} factors for transmission involving children (the matrix $\Gamma \approx K\big/\left(\gamma+\bar{\delta}\right)$ because $\delta << \gamma$, where the matrix K has elements κ_{ab}). We therefore work with the standardized version of θ_i, which we refer to as the GDP-to-Risk index.

Generally speaking, the highest GDP-to-Risk sectors are white collar industries such as legal services, insurance, and computer design, along with some high-value moderate-risk production sectors such as oil and gas extraction and truck transportation. Moderate GDP-to-Risk industries include paper products; forestry and fishing; and utilities. Low GDP-to-Risk industries are generally ones with many low-paid employees who are exposed to high levels of personal contacts at work, including nursing and residential care facilities; food services and drinking places; social assistants; gambling and recreational industries; transit and ground passenger transportation; and educational services.

IV. Calibration of Historical NPIs and Estimation

The historical paths of contacts and self-protective measures, which we collectively refer to as historical NPIs, combine calibration using historical daily data and estimation of a small number of parameters to capture the time paths of self-protective measures, such as wearing masks, on which there are limited or no data. Altogether, the model has five free parameters to be estimated: the initial infection rate I_0, the transmission rate β, and three parameters describing the path of NPIs from March 10 through the end of the estimation sample. The model-implied time-varying estimate of R_0 closely tracks a nonparametric estimate of R_0.

IV.A. Time-varying Historical Contact Matrices and NPIs

The NPIs that were implemented between the second week of March and mid-May include: closing schools; personal distancing; prohibiting operation of many businesses and making changes in the workplace to reduce transmission in others; orders against large gatherings; in some localities, issuing stay-at-home orders; wearing masks and gloves; and urging self-isolation among those believed to have come in close contact with an infected individual. These NPIs are a mixture of policy interventions and voluntary measures taken by individuals protecting themselves and their families from infection.

These NPIs enter the model in two ways. The first is through the reduction of contacts, for example working from home, or being furloughed or laid off, eliminates a worker's contacts at the workplace. The second is through reducing the probability of transmission, conditional on having contact with an infected individual; personal distancing and wearing masks falls in this second category. This second type of NPI has the effect of reducing β in situations in which the NPI is adopted.

Our approach to producing time-varying contact matrices and β is a mixture of calibration where we have directly relevant data (for example, dates of school closures, mobility measures of non-work trips, and measures of the number of employed workers and the fraction of those workers working from home), and estimation of the effect of NPIs for which we do not have data, such as personal distancing and the use of masks.

We introduce these NPIs by modifying (8) to allow for time-varying contacts and mitigation:

$$C_{ab,t} = \left[0.8 + 0.2\phi_t\right] p_a^{home} C_{ab}^{home} + \phi_t \lambda_{ab,t}^{other} p_a^{other} C_{ab}^{other} + \phi_t \sum_{sectors\ i} s_{it} (1-\lambda_{wfh,t}) p_{a,i}^{work} C_{ab,i}^{work} \quad . \qquad (15)$$

As in (8), the total contacts made by someone of age a meeting someone of age b at time t is the sum of the contacts made at home, in other activities, and at work. The conditional contact matrices C_{ab}^{home}, C_{ab}^{other}, and $C_{ab,i}^{work}$ and the probabilities p_a^{home}, p_a^{other}, and $p_{a,i}^{work}$ in (15) refer to pre-pandemic contacts and population weights in (8). The remaining factors $\lambda_{ab,t}^{other}$, $\lambda_{wfh,t}$, and s_{it} , in (15) represent measured reductions in contacts, and the factor and φ_t captures NPIs that have the effect of reducing transmission conditional on a contact (e.g., masks).

We briefly describe these factors and motivate the structure of (15), starting with the second term, contacts made during other activities. The expected number of contacts made by a meeting b is $\lambda_{ab,t}^{other} p_a^{other} C_{ab}^{other}$. Attending school is an "other" activity, so for age <20 we model school closings by letting $\lambda_{ab,t}^{other}$ be linear in the national average fraction of students with schools open on day t, with $\lambda_{ab,t}^{other} = 1$ if all schools are open and $\lambda_{ab,t}^{other} = 0.3$ if all are closed (accounting for non-school other contacts). For contacts made by adult, we set $\lambda_{ab,t}^{other}$ to the Google mobility index for other activities described in Section 3.

The factor φ_t represents the reduction in the transmission probability, relative to the unmitigated transmission rate $\beta\kappa_{ab}$, resulting from self-protective NPIs, such as personal distancing, hand hygiene, and wearing a mask. Guidance concerning and use of these protective measures evolved over the course of the pandemic. Early in the pandemic, public health guidance stressed hand-washing and disinfecting surfaces. Until April 3, the CDC recommended that healthy people wear masks only when taking care of someone ill with COVID-19. On April

3, the CDC changed that guidance to recommend the use of cloth face coverings. Masks do not appear to have been in widespread use, even in the hardest-hit states, until more recently. For example, New York implemented a mandatory mask order on April 15, Bay Area counties did so on April 22, Illinois on May 1, Massachusetts on May 6, and many states have not required masks although some businesses working in those states have. There is now considerable evidence that personal distancing and the use of masks are effective in reducing transmission of the virus.[9] Although there are data on mandatory personal distancing measures by state (e.g., Kaiser Family Foundation (2020)), we are not aware of data on the actual uptake of those measures. Lacking such data, we estimate the aggregate effect of those measures through the scalar risk reduction factor φ_t, parameterized using a flexible functional form, specifically, the first two terms in a Type II cosine expansion, constrained so that $0 \leq \varphi_t \leq 1$:

$$\phi_t = \Phi\left\{ f_0 + f_1 \cos\left[\pi(t - s_0 + 1/2)/(T - T_0)\right] + f_2 \cos\left[2\pi(t - s_0 + 1/2)/(T - T_0)\right]\right\} \tag{16}$$

where Φ is the cumulative normal distribution. We set the start date of the NPIs, s_0, to be March 10, three days before the declaration of the National Emergency, reflecting the short period between the first reported Covid-19 death in the US on February 28 and the start of the lockdown. The date T denotes the end of the estimation sample. This parameterization introduces three coefficients to be estimated, f_0, f_1, and f_2.

The second term in (15) parameterizes contacts made at home. Most but not all contacts at home involve household members. Using the American Time Use Survey, Dorélien, Ramen, and Swanson (2020) estimate that 85% of contacts made at home or in the yard involve household members, however their total home contacts are fewer than in our contact matrices, especially for children under age 15, for whom they impute contacts because ATUS only surveys adults. We therefore make a modest adjustment of their estimate and assume that 80% of contacts are among household members. Contacts among household members are modeled as unmitigated, with the remaining 20% of at-home contacts that are with non-household members mitigated using the factor φ_t.

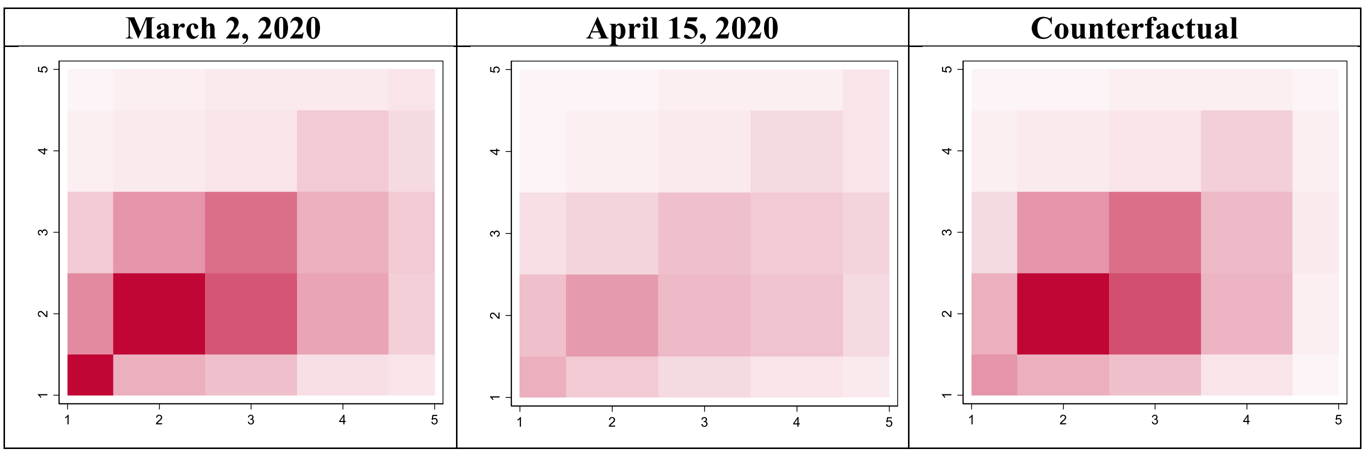
[9] The effect of masks on COVID-19 transmission has been reviewed by Howard et. al. (2020), who suggest that masks reduce the probability of transmission by the factor $(1 - ep_m)^2$, where e is the efficacy of trapping viral particles inside the mask and p_m is the percentage of the population wearing the mask. Chu et. al. (2020) conduct a meta-analysis of 172 studies (including studies on SARS and MERS) on personal distancing, masks, and eye protection; their overall adjusted estimate is that the use of masks by both parties has a risk reduction factor of 0.15 (0.07 to 0.34), however they found no randomized mask trials and do not rate the certainty of the effect as high.

The final term in (15) parameterizes contacts at work. For workers in sector *i*, the baseline contacts are reduced by the fraction s_{it} of workers continuing to work,

$$s_{it} = L_{\bullet,i,t} / L_{\bullet,i,t_0}, \tag{17}$$

where $L_{\bullet,i,t}$ is the all-ages labor force in industry *i* at date *t* and t_0 is the final week in February 2020. Of those still working, a fraction $\lambda_{wfh,t}$ work from home, leaving the fraction $s_{it}(1-\lambda_{wfh,t})$ of sector-*i* workers remaining in the workplace. We set s_{it} and $\lambda_{wfh,t}$ equal to, respectively, the daily sectoral shock to the labor share and the time series on the fraction of workers working from home fraction working from home by sector, both of which are described in Section II.A. These reduced contacts are then multiplied by the non-contact risk reduction factor φ_t in (16).

Figure 1. Illustrative contact matrices:
Baseline, estimated for April 15, and counterfactual



Notes: the (*a*,*b*) element is the number of contacts made by individual age *a* (*y* axis) of individuals of age *b* (*x* axis) in a day, for age bins 0-19, 20-44, 45-64, 65-74, and 75+. Darkest is 8-9 contacts, lightest is <0.2 contacts. From the left, the matrices are the baseline pre-pandemic contact matrix, the estimated contact matrix as of April 15 (accounting for working at home, layoffs, no school, reduced travel, but not accounting for masks or other transmission-reducing factors), and contacts under a hypothetical in which there is no school, all workers <64 return to work, workers 65+ work from home (or not at all), and visits to the elderly are reduced by 75% relative to baseline.

Figure 1 illustrates three different contact matrices. The first (left) is the baseline pre-pandemic contact matrix estimated for Monday March 2. The second (center) is the calibrated contact matrix for Wednesday April 15, in the midst of the lockdown, constructed using (15) with $\varphi_t = 1$, so that the matrix represents only the reduced contacts from school closings, layoffs, working from home, and reduced other activities, not from additional (unmeasured but estimated) protective precautions. The third matrix is a counterfactual matrix for a scenario considered below, in which workers ages 675+ work from home or not at all, other workers return to work, there is no school, and visits to the elderly (including by home health and nursing home workers) are reduced by 25%. The effect of these counterfactual adjustments is to reduce contact is the top row and final column (the oldest age groups), reduce child-child contacts (youngest age group), and for contacts among middle ages to be similar to baseline levels.

IV.B. Estimation Results

After the calibration described in Section IV.A, the SEIRQD model has five free parameters: the initial infection rate I_0 on February 21, the unrestricted adult transmission rate β, and the three parameters determining φ_t, f_0, f_1, and f_2. These parameters were estimated by nonlinear least squares to the daily 7-day moving average of national COVID-19 deaths from the Johns Hopkins real-time data base, using an estimation sample from March 15 to June 12, 2020.[10] The mid-March start of the estimation period is motivated by the evidence of undercounting of COVID deaths, especially early in the epidemic (see for example the *New York Times'* estimates by Katz, Lu, and Sanger-Katz (2020)). This systematic undercounting of deaths provides an important caveat on the parameter estimates, in particular the initial infection rate could be higher than we estimate.

Table 1. Estimated parameter values

IFR	$\hat{I}_0$	$\hat{\beta}$	$\hat{f}_0$	$\hat{f}_1$	$\hat{f}_2$	RMSE
0.005	2.575	0.0170	1.053	0.821	0.054	1.059
	(0.296)	(0.0032)	(0.045)	(0.043)	(0.001)	
0.006	2.359	0.0081	1.051	0.802	0.054	1.059
	(0.285)	(0.0022)	(0.042)	(0.048)	(0.001)	
0.007	1.861	0.0171	1.073	0.847	0.054	1.072
	(0.238)	(0.0036)	(0.044)	(0.044)	(0.001)	
0.008	1.873	0.0097	1.073	0.798	0.053	1.067
	(0.215)	(0.0014)	(0.042)	(0.047)	(0.001)	

Notes: The parameters I_0 and β and are respectively the initial number of infections on Feb. 21 (in thousands) and the adult transmission rate. The coefficients f_0, f_1, and f_2 parameterize the scaling factor φ_t. Given the IFR in the first column and the other model parameters given in the text, the parameters in the table are estimated using data on the 7-day moving average of deaths (units: thousands) from March 15 through June 12. Nonlinear least squares standard errors are given in parentheses.

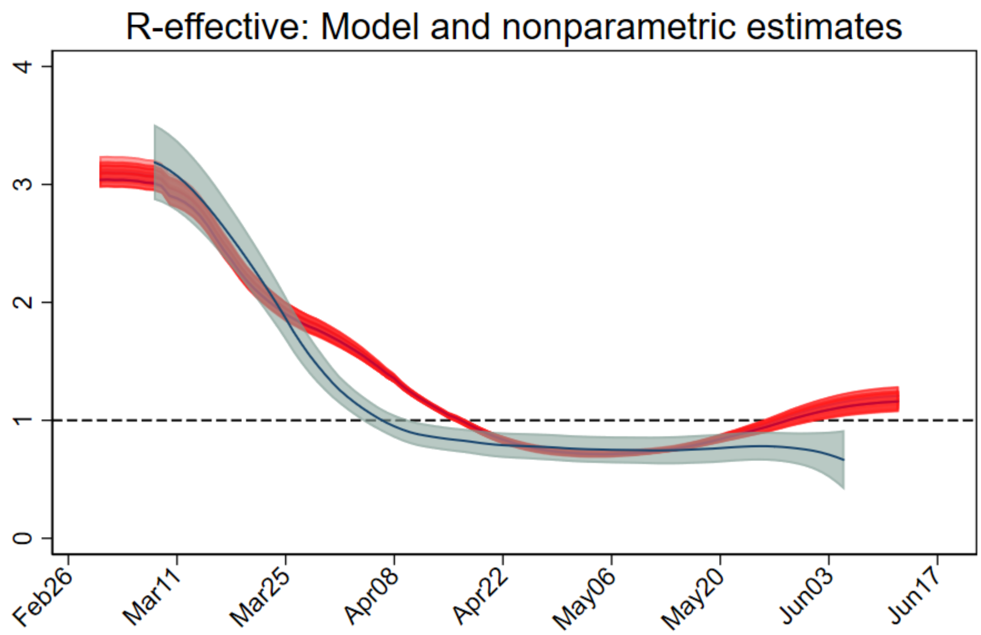
[10] Daily deaths have a weekly "seasonal" pattern reflecting weekend effects in reporting. Using the 7-day trailing change in actual and model-predicted deaths smooths over this substantively unimportant noise.

Table 1 provides estimates of these parameters and their standard errors for selected values of the overall population IFR. Standard errors are reported below the estimates, with the caveat that we are not aware of applicable distribution theory, which is likely to be complicated because of the strongly serially correlated data. The final column reports the RMSE (units are thousands of deaths).

One overall summary of the fit of the estimated model is the time path of the model-implied effective case reproduction rate, $R^{eff} = R_0(S/N)$. This is plotted in Figure 2 over the estimation period (through June 12). The figure also shows a nonparametric estimate computed directly from actual daily deaths using (13).[11] Given the nonstandard serial correlation in the data, neither set of confidence intervals would be expected to have the usual 95% frequentist coverage. Evidently, the model estimates and the nonparametric estimates are quite similar. Both estimate that, early in the pandemic, the initial R_0 was approximately 3.2, which is within the range of other estimates. With the self-protective measures and government-ordered shutdowns, the effective R dropped sharply through March into April, and was estimated to be below 1 from mid-April through mid-May. Subsequently, with the reopening and the increased mobility, the model-based effective R has risen slightly above 1, although the nonparametric estimate remains just below one. The estimated values of R^{eff} are plotted for IFRs ranging from 0.4% to 1.1%; they are nearly the same, indicating that the IFR is not separately identified in the model as discussed by Atkeson (2002b).

[11] The growth rate of daily deaths in (13) is estimated by the average 7-day change in deaths divided by the 7-day average daily death rate, smoothed using a local quadratic smoother.

Figure 2. Model-implied (red) and nonparametric (gray) estimates of R^{eff}



Notes: 95% confidence bands shown. The model-implied estimate is computed from the estimated model, for population IFRs = 0.4% to 1.1%. The nonparametric estimate is computed using (13) with the change in deaths estimated over 7 days and daily deaths averaged over the week, using a local quadratic smoother. Nonparametric estimate is shifted by 14 days to approximate the lag from infections to deaths.

V. Control Rules and Simulation Design

Decision-making in the coronavirus epidemic has occurred at all levels of society: consumers decide if they feel it is safe to dine out or travel, workers weigh concerns about the safety of returning to work, local officials decide on when to apply for and how to implement reopening, state officials issue closure orders, mandate non-economic NPIs, and permit reopenings, and federal agencies provide guidance. We combine these multiple decision-makers, private and public, into a single representative decision maker who is averse to both deaths and unemployment. For convenience, we refer to this decision-maker as a governor, who have primary authority over decisions to shutdown and to permit reopening, but this term is a stand-in for the more complex collective decision-making process.

V.A. Control Rules

We model reopening decisions as reacting to recent developments with the twin aims of controlling deaths and reopening the economy in mind. In so doing, we treat the governor as following the CDC and White House reopening guidelines (White House, April 16, 2020), which advises reopening the economy if there is a downward trajectory of symptoms and cases for 14 days, along with having adequate medical capacity and healthcare worker testing. Because of changes in test availability, confirmed cases are a poor measure of total infections, so instead we use 14 days of declining deaths as the indicator to follow in the White House/CDC reopening guidelines.

Specifically, we consider a governor who will: restrict activity when deaths are rising or high, relax those restrictions when deaths are falling or low, tend to reopen when the unemployment rate is high, and tend to reopen when the cumulative unemployment gap is high. This final tendency reflects increasing pressures on budgets – personal, business, and public – from an additional month of high unemployment and low incomes on top of previous months.

In the jargon of control theory, the governor follows a proportional-integral-derivative (PID) control rule, in which the feedback depends on current deaths, the 14-day change in deaths (declining death rate), the current unemployment rate, and the integral of the unemployment rate. Accordingly, we suppose that the governor follows the linear PID controller,

$$u_t = \kappa_0 + \kappa_{up} U_{t-1} + \kappa_{ui} \int_{t_0}^{t-1} U_s ds + \kappa_{dp} D_{t-1} + \kappa_{dd} \dot{D}_{t-1}, \tag{18}$$

where U_t is the unemployment rate (= $1 - L_t / L_{t_0}$, where t_0 is the end of February 2020) and $\dot{D}$ is the death rate. The CDC recommends tracking not the instantaneous derivative of infections (or D) but the change over 14 days, and deaths are noisy suggesting some smoothing of D. Similarly, U is unobserved and at best can be estimated with a lag, even using new and continuing claims for unemployment insurance and nonstandard real-time data. For the various terms on the right-hand side of (18) we therefore use, in order: the 14-day average of the unemployment rate, the cumulative daily unemployment rate since March 7, deaths over the previous two days (these are observed without noise in our model), and the 14-day change in the two-day death rate.

The governor must decide whether to allow workplaces to reopen so workers and customers can return, as well as to relax non-work NPIs. In addition, reopening can be staggered across industries, in particular we consider the possibility of reopening industries differentially by sector based on their GDP-to-Risk index. A narrow interpretation of the GDP-to-Risk index would reopen industries sequentially in order of the value of the index. This is unrealistic so instead we consider a phased reopening in which all industries reopen, some faster than others.

We therefore consider a sequence of sectoral reopenings as determined by the PID controller, shifted by the GDP-to-Risk index:

$$s_{it} = s_{it_R} + \Phi\left(u_t + \kappa_\theta \theta_i\right)\left(1 - s_{it_R}\right), \tag{19}$$

where s_{it} is the workforce in sector i at date t as a fraction of its February value (see (17)), t_R is the initial date of the reopening, and Φ is the cumulative Gaussian distribution, which is used to ensure that the controller takes on a value between 0 and 1 (so sectoral relative employment satisfies $s_{it_R} \le s_{it} \le 1$). The industry shifter $\kappa_\theta \theta_i$ preferences industry i based on its GDP-to-Risk index.

Reopening the economy requires not just working but shopping, which is an "other" activity. In the historical period, the factor $\lambda_{ab,t}^{other}$ for a>2 was set to equal the Google mobility index for other activities. We model this factor as increasing to 1 proportionately to GDP as the economy reopens, so that full employment corresponds to $\lambda_{ab,t}^{other} = 1$ for $a > 2$.

V.B. Non-economic NPIs

Non-economic NPIs – reopening school, personal distancing, wearing masks, etc. – are either under the control of the governor (reopening schools) or are decisions made by individuals that are influenced by the governor. Instead of specifying policy paths for these other NPIs, we examine different scenarios in which the governor behaves according to (18) and (19) concerning sectoral reopening. For example, one set of choices entails opening up schools, but with protections (which the governor and school districts can mandate); in the context of (15) opening schools corresponds to setting $\lambda_{ab,t}^{other} = 1$ for ages <20, and protective measures at schools corresponds to restricting $\varphi_t < 1$ as it applies to contacts made at school. For adults, we allow for relaxation of protective measures (masks, personal distancing) according to three reopening phases. For ages 75+, we consider scenarios in which they are subject to additional restrictions on visits and greater use of protection than in the general population. These stand in for regular testing of nursing home employees, requiring visiting families to visit outside and to wear masks, and so forth.

VI. Simulation Results

All the simulations have the same structure: the governor controls economic reopening according to the control rule (18), given a specified path of non-economic NPIs. This structure allows us to quantify the interaction between economic and non-economic NPIs. The simulations consider two economic control rules (two governors). Our slow governors is driven more by health than economic considerations, so executes a slow economic reopening. Our fast governor places relatively more weight on economic considerations, so conducts a fast economic reopening.

The paths of the non-economic NPIs are specified in each scenario. Some of these, like school reopening and maximum group size at organized non-economic group activities, are directly under the governor's control, while others, like masks and personal distancing, are individual decisions that can be influenced by state, federal, and local recommendations and education.

Effective quarantine rates are also specified in each simulation. The effective quarantine rate is the fraction of infected individuals who, at some point during their infection, enter quarantine. The rate that is achieved in practice reflects a combination of government policy concerning subsidizing or mandating virus testing, ensuring test availability, and individual compliance with self-isolation guidelines. Currently, the CDC Website currently advises individuals who test positive or who are symptomatic to self-isolate "as much as possible".[12] We assume a current quarantine rate of 5% which, because of the multiplicative structure of contact and transmission in SIR models, corresponds to 10% of the infected restricting their contacts by half. We consider alternatives of higher quarantine rates later in the summer, if testing and contact tracing becomes more widely available.

Our simulations have the control rule beginning on June 1. This approximately represents the middle of reopening, depending on the jurisdiction. Georgia was the first state to reopen most consumer-facing businesses on April 24, while reopening for some of the hardest-hit regions (for example, Massachusetts, Michigan, and New York City) occurred mainly in June. The reopenings are also partial, for example as of May 16, all but one state (Montana) had school closures required or recommended for the remainder of the 2019-2020 school year.

[12] https://www.cdc.gov/coronavirus/2019-ncov/if-you-are-sick/steps-when-sick.html?CDC_AA_refVal=https%3A%2F%2Fwww.cdc.gov%2Fcoronavirus%2F2019-ncov%2Fif-you-are-sick%2Fcaring-for-yourself-at-home.html (accessed June 19, 2020).

All simulations reported here are for a population-wide IFR of 0.6%; sensitivity analysis is provided in the online Appendix. Uncertainty spreads in the simulation plots are two standard error bands based on the estimation uncertainty for I_0 and β in Table 1. All simulations end on January 1, 2021. Parameter values for all scenarios are available in the online Appendix.

IV.A. Baseline Scenarios

We consider two baseline scenarios, which differ by the extent to which non-economic NPIs are relaxed. The multiple public and private reopening road maps (proliferation of economic reopening roadmaps (e.g., Gottlieb et al (2020), White House/CDC (2020), National Governors' Association (2020), The Conference Board (2020), Romer (2020)) tend to reopen the economy in phases, where transition to the next phase is determined by some "gating criteria." We follow this framework and relax non-economic NPIs in four phases. Each phase is modeled as (1) a proportional step increase in the number of other and non-household home contacts from before the lockdown to pre-pandemic conditions, and (2) a relaxation of personal protective measures (masks, personal distancing) from their mid-May values to a value that is higher but still represents considerable reduction in transmission rates, given a contact, relative to unrestricted conditions. Reopening of nursing homes lags by one phase the social reopening for adults, with reopening commencing in Phase II and a return to full contacts occurring in Phase IV

In the stricter scenario, Phase I reopening occurs on May 18, Phase II reopening occurs on June 8, Phase III reopening occurs on August 15, and Phase IV does not occur within the simulation horizon. The self-protective factor φ rises from its empirical mid-May estimate of 0.2 to 0.36. As a calibration, using the formula in Footnote 9, this factor corresponds to half the population using masks that are 80% effective for all non-household contacts. Workers who are able to work from home continue to do so throughout the simulation period.

In the more relaxed scenario, Phase I occurs on May 18, Phase II occurs on June 8, Phase III occurs on August 1, and Phase IV occurs on October 15. The self-protective factor φ rises from its empirical mid-May estimate of 0.2 to 0.6 (using the formula in Footnote 9, this calibrates to approximately 30% of the population using masks that are 80% effective for all non-household contacts). Workers working at home return to the workplace during Phases I-III.

In both scenarios, school reopens on August 24, and enhanced workplace safety is required throughout the simulation period (no relaxation of workplace safety standards).

Figure 3 and Figure 4 show the time paths of deaths, the unemployment rate, and GDP under the restrictive scenario for, respectively, the slow and fast governor. The weekly death rate is shown in each chart, along with the actual death rate through June 18. Under both governors, the restrictive non-economic NPIs lead to a continuing decline in deaths and reopening of the economy. By the end of the year, under the slow governor there have been 149,000 deaths and the unemployment rate is just under 10%; under the fast governor, there are 165,000 deaths and the unemployment rate and GDP are nearly back to pre-pandemic levels.

Figure 5 shows total deaths and the share of recovered individuals by age. Of the 149,00 deaths by Jan. 1, just over half are among those ages 75+. By Jan. 1, only 8% of the population has been infected, with those ages 20-44 having the highest recovered rates because of low death rates combined with higher rates of contact.

These projections are optimistic, for example as of June 22 the widely-cited IHME model projects more than 200,000 deaths by October 1.[13] In fact, actual deaths two weeks into the simulation (June 14) are above the 95% uncertainty bands under both the fast and slow governor. The restrictive scenario assumes aggressive protections to reduce transmission rates. Moreover, many states have opened ahead of the hypothetical phase dates in this scenario. These observations suggest that this restrictive scenario is overly optimistic.

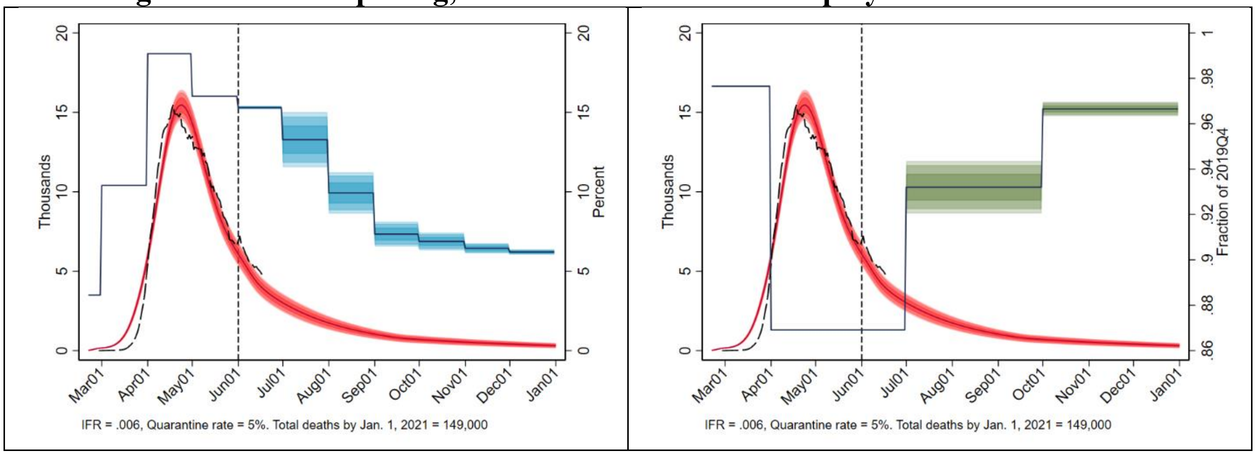
Results for the less restrictive scenario are shown in Figure 7 for the two governors. To save space, these and subsequent figures only show deaths and the unemployment rate. In this less restrictive scenario, both governors start to reopen the economy, but the relaxed self-protective measures lead to a plateau in weekly deaths which turns into a second wave when Phase III starts, exacerbated by the opening of schools in the end of August. The slow governor reacts by closing down businesses and ends the year with 372,000 deaths and an unemployment rate approaching 15%. After aggressively opening the economy, the fast governor reverses course in the fall, with the unemployment rate rising to 10%; the fast governor ends the year with 446,000 deaths, an unemployment rate of approximately 7.5%, and a W-shaped recession.

The assumptions underlying the less restrictive scenarios are well within the range of preliminary evidence (mainly anecdotal) about the relaxation of movement, personal distancing, group gatherings such as religious services, and use of masks that has coincided with the

[13] https://covid19.healthdata.org/united-states-of-america, accessed June 22, 2020.

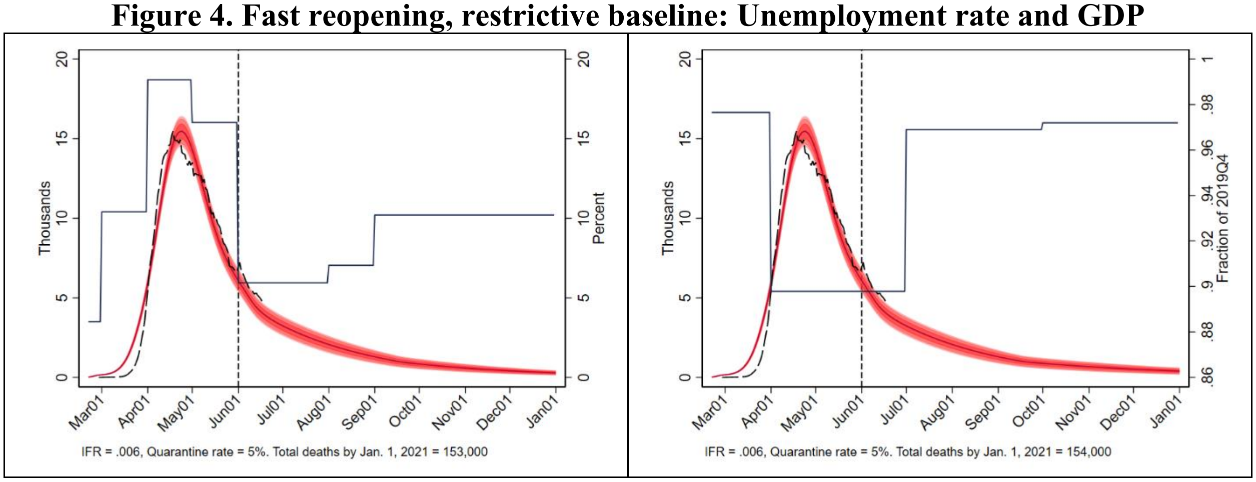
reopening phases. We therefore turn to the question of what options the governor might have to mitigate the second wave.

Figure 3. Slow reopening, restrictive baseline: Unemployment rate and GDP



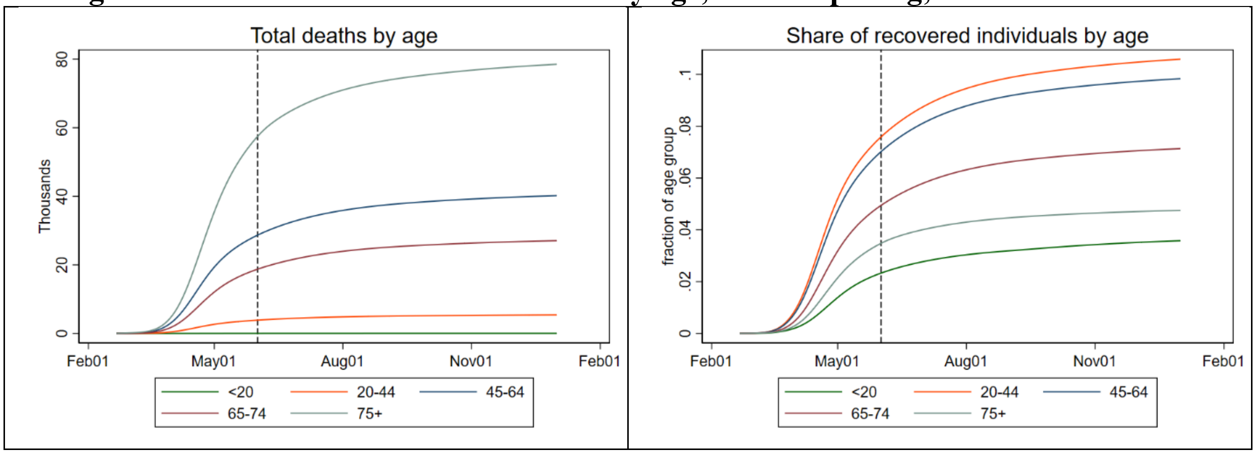
Notes: Each chart shows the level of weekly COVID-19 deaths, actual (black dashed) and simulated. The chart on the left shows the unemployment rate (measured by hours lost) and the chart on the right shows the level of quarterly GDP, indexed to February 2020 = 1. Bands denote +/- 1, 1.65, and 1.96 standard deviation bands arising from sampling uncertainty for the estimated parameters. The population-wide IFR is 0.6%, and the assumed quarantine rate and end-of-year cumulative death rate is given in the figure note. Source: Authors' calculations.

Figure 4. Fast reopening, restrictive baseline: Unemployment rate and GDP



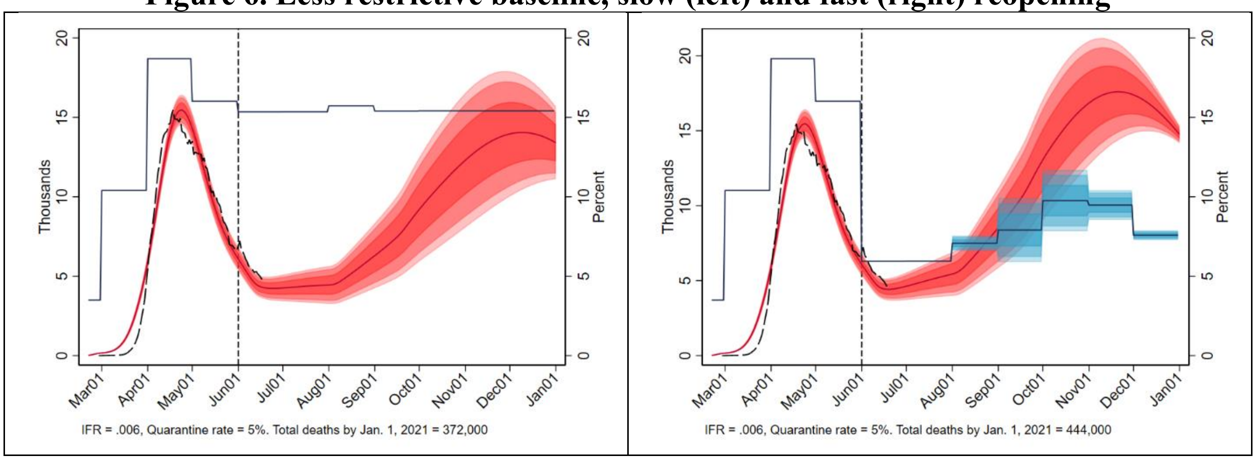
Notes: See the notes to Figure 3.

Figure 5. Deaths and share of recovered by age, slow reopening, restrictive baseline



Source: Authors' calculations

Figure 6. Less restrictive baseline, slow (left) and fast (right) reopening



Notes: See the notes to Figure 3.

IV.B. Simulation of Alternative NPIs

We first consider mitigation of the second wave using policies that restrict economic activity, then turn to non-economic NPIs. We focus on the fast governor, whose situation is shown in the right panel of Figure 6.

ECONOMIC NPIs

The outcomes in Figure 6 for the slow and fast governor show that returning to a near-full economic shutdown reduces deaths substantially but does not stop the second wave. Here, we consider the effects of three more nuanced economic NPIs: relying more heavily on the Risk-to-GDP index, so that high-risk, low-value sectors are closed first; requiring all workers to work from home; and an age-based policy that requires all workers who are age 65+ (the most vulnerable working-age group) either to work from home if they are able or not to work at all.

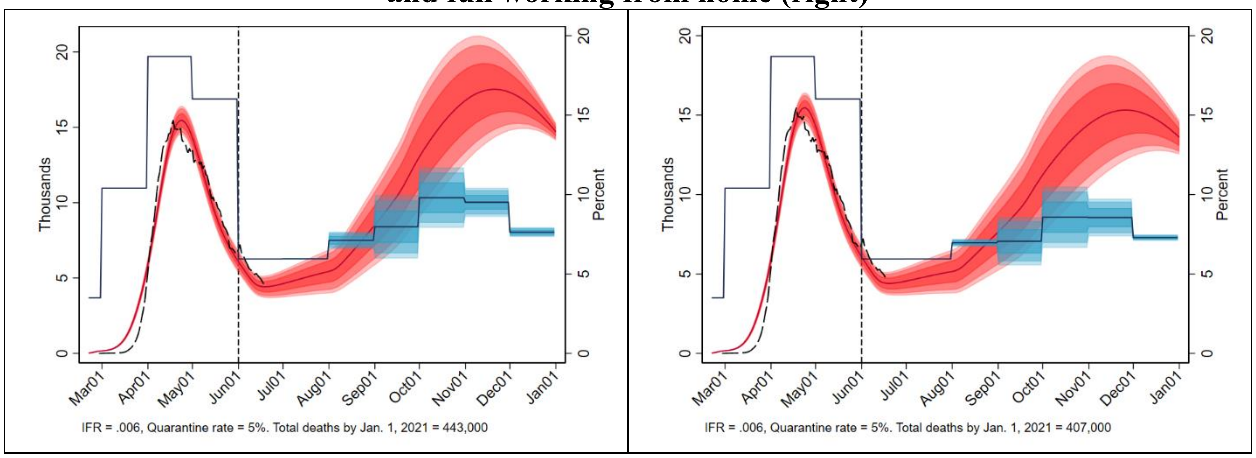
As discussed above, the scenarios so far make moderate use of the GDP-to-Risk index to phase a "smart" reopening. The left panel of Figure 7 illustrates a more aggressive use of the index. This scenario is calibrated so that the path of GDP is the as in Figure 6; thus any gains from this policy change are seen in lower deaths and a higher unemployment rate (holding GDP constant but prioritizing bringing back higher value workers results in fewer gains to employment). As it happens, this "smart" reopening/shutdown policy has very small effects, reducing deaths in this scenario by 1,000. This finding generalizes: we have explored the gains from phasing reopenings or shutdowns based on the GDP-to-Risk index and while doing so can reduce deaths, the gains are modest at best and, in scenarios in which deaths are being brought under control (as in the restrictive scenario), the effects of a nuanced reopening are nearly negligible. This finding has an important caveat that although our 66 sectors exhibit a large variation in the GDP-to-risk index, they average in the fat tail of economic contacts such as indoor professional sports, theaters, bars, and meat-processing plants with other lower-contact activities in their sectors. Judgement strongly suggests that such high-contact economic activity would appropriately be treated differently than broad-based reopening, and delayed, perhaps indefinitely until a vaccine is available. These very-high contact activities are a small fraction of economic activity, for example admissions to movie theaters, sports, and other live entertainment comprised less than 0.6% of personal consumption expenditures in 2019.

The right panel of Figure 7 considers the possibility of requiring those workers who are able to work from home to continue to so as businesses reopen. This policy reduces workplace contacts and consequently reduces total deaths by Jan. 1 from 446,000 to 407,000. This reduction in deaths allows the governor to implement less severe second-wave shutdowns, so the unemployment rate is lower (by approximately 1pp) during the fall than without the work from home order.[14]

[14] We note that there are plausibly effects on productivity from working at home, although *a-priori* the overall sign is unclear. Workers save time commuting, however they could have distractions such as from child care. Bloom et al. (2015) find that workers who work from home are more productive, however that is a pre-COVID19 study so there is plausibly selection in those results (see Mas and Pallais (2019) for a review). These potential productivity effects are not included in our calculations.

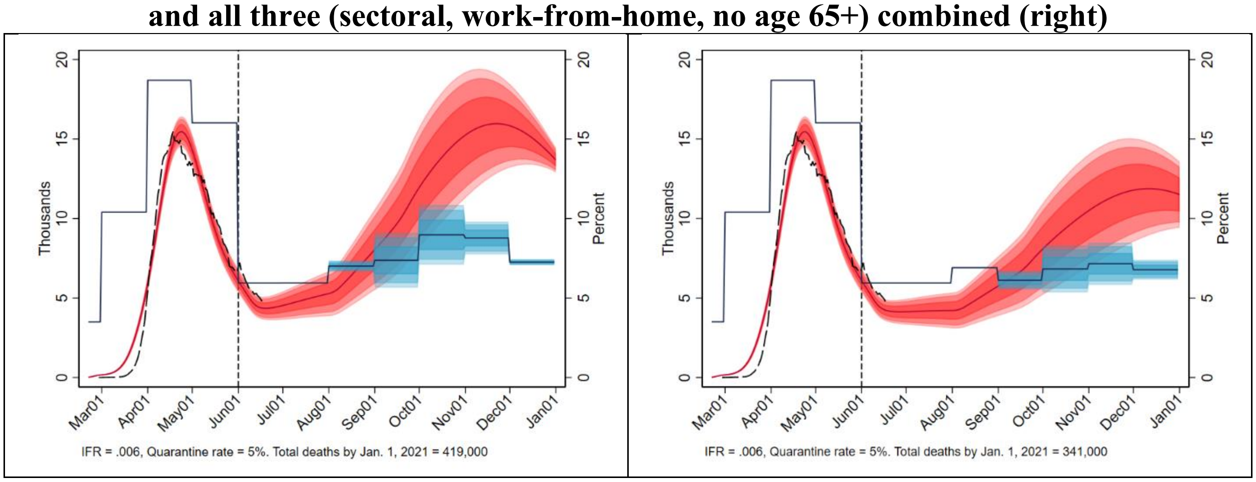
Figure 8 (left) considers an age-based policy, in which only workers under age 65 are required to work from home, if they are able, or not at all. The effect of this NPI on employment and contagion varies by sector, depending on the age distribution of workers, personal proximity in the workplace, and the extent to which that sector admits working from home. This policy reduces total deaths from 446,000 to 419,000. Although some of the over-65 workers are unemployed under this policy, the overall unemployment rate is lower than in the base case because the reduced deaths allow the governor to have a somewhat lighter shutdown in the fall.

Figure 7. Economic NPIs: Greater use of the GDP-to-Risk index (left) and full working from home (right)



Notes: See the notes to Figure 3.

Figure 8. Economic NPIs: No on-site workers age 65+ (left) and all three (sectoral, work-from-home, no age 65+) combined (right)



Notes: See the notes to Figure 3.

The right panel of Figure 8 considers the combined effects of these three economic NPIs: leaning more heavily on phasing by sector, requiring working from home, and laying off workers age 65+ who are not able to work from home. These instruments are complementary and between them they reduce deaths by just over 100,000. Yet, they do not prevent nor quell the second wave, just limit its damage, and they also result in elevated unemployment rates, even under the fast governor. When the slow governor is given these same tools, the unemployment rate remains just above 15% at the end of the year (see the online Appendix for results) and although deaths are lower, neither does the slow governor avert the second wave.

Compared to the full shutdown, the three more nuanced economic NPIs have the virtue of both reducing deaths and supporting overall employment. That said, the main conclusion from these simulations is that while a full economic shutdown (Figure 6, left) and the more nuanced economic NPIs considered in Figure 7 and Figure 8 reduce deaths, none are potent enough, by themselves, to stop the second wave.

NON-ECONOMIC NPIs

We now turn to four non-economic NPIs that could mitigate the second wave: not allowing schools to reopen in the fall; undertaking enhanced protections for ages 75+, especially the most vulnerable in long-term care facilities; increasing the quarantine rate, which would entail directing resources towards increased testing and contact tracing; and revoking Phase III non-economic relaxation, such as returning to prohibitions on large group gatherings and enhanced mask-wearing and personal distancing.

We begin with the option of not reopening elementary and secondary schools in the fall, which is shown in the left panel of Figure 9. Not sending children to school reduces contacts among children and between children and their teachers, and thus reduces the spread of the virus. As discussed in Section II, however, contacts with children appear to be less effective in spreading the virus than contacts among adults, so deaths by January 1 only fall by 22,000. Moreover, if schools are closed then some workers will be constrained in their labor supply because they must provide child care; as a result, the unemployment rate remains elevated through the fall at just above 10%. In addition, closing schools has the additional undesirable affect of retarding schoolchildren's education, especially for those least able to learn in an online environment. So not reopening schools imposes considerable economic and non-economic costs while not solving the problem of the second wave.

Because the elderly have the highest death rates from COVID-19, one possible policy is to devote additional resources focused on protecting the elderly. Current CDC guidelines for nursing homes[15] recommend virus testing for all residents and staff but does not specify testing frequency. The CDC also recommends that visitors wear cloth masks and to restrict their visit to their relative's room. The Centers for Medicare and Medicaid Services guidelines for reopening long-term care facilities recommends weekly testing of staff, providing staff with personal protective equipment, and delaying outside visitors until the state enters federal Phase III reopening (CMS (2020)). In theory, these are strong and protective steps, however it is unclear how the testing and additional staff needed to implement these guidelines will be paid for and how nursing homes will have the institutional capacity to implement these measures.

Figure 9 (right) examines the effects of enhanced protections for the elderly, modeled as restricting visits in Nursing Homes and enhancing other protections to reduce contacts with infected individuals (e.g., by regular staff testing, see the top and rightmost columns of the contact matrix in Figure 1) and to reduce transmission if a contact is infected (additional distance and PPE). The reduction in deaths is considerable, from 444,000 in the base case to 335,000; this is a reduction of one-third of projected cases under the baseline from June 25 through January 1. This significant saving in life is consistent with the findings in a similar calculation in Acemoglu et al (2020), although their gains are larger because they start from a much higher baseline number of deaths. The reduced number of deaths provides room for the governor to be less restrictive, and although under this policy the economy still has a W-shaped recession, the second dip is much less deep.

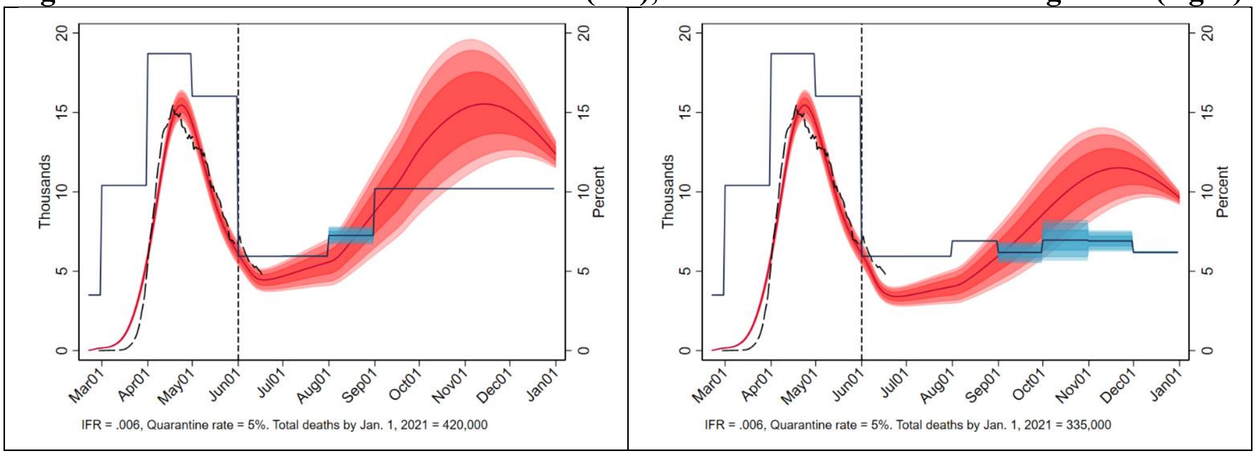
The roadmaps generally stress the importance of widespread testing and quarantine. Until recently, testing has been noteworthy mainly because of its absence. Tests are now becoming more widely available, but still fall far short of what is recommended in the roadmaps to facilitate widespread case identification. Our enhanced quarantine scenario has a 10% effective quarantine rate, that is, 10% of infected individuals are sent into perfect quarantine at some point during their infection.[16] Without legally enforceable quarantine, even a 10% effective quarantine rate evidently would require a significant increase in testing, plus incentives to quarantine. That

[15] https://www.cdc.gov/coronavirus/2019-ncov/hcp/nursing-homes-testing.html, accessed June 20, 2020.

[16] We consider this effective quarantine rate as ambitious but achievable. Current estimates of the asymptomatic rate vary from less than 40% to approximately 80%. Yang, Guji, and Xiong (2020) estimate a 42% asymptomatic rate for a sample of Wuhan residents. Data in Guðbjartsson et al (2020) suggest a comparable asymptomatic rate in Icelandic testing, and Poletti et al. (2020) suggest a 70% asymptomatic rate among those less than 60. As a calibration, suppose that 40% of the infected (a high fraction of the symptomatic) get tested, get their results back while they are still infectious, and are advised to self-isolate, that half of those comply, and that those who comply reduce their contacts by 50%. This results in a 10% effective quarantine rate.

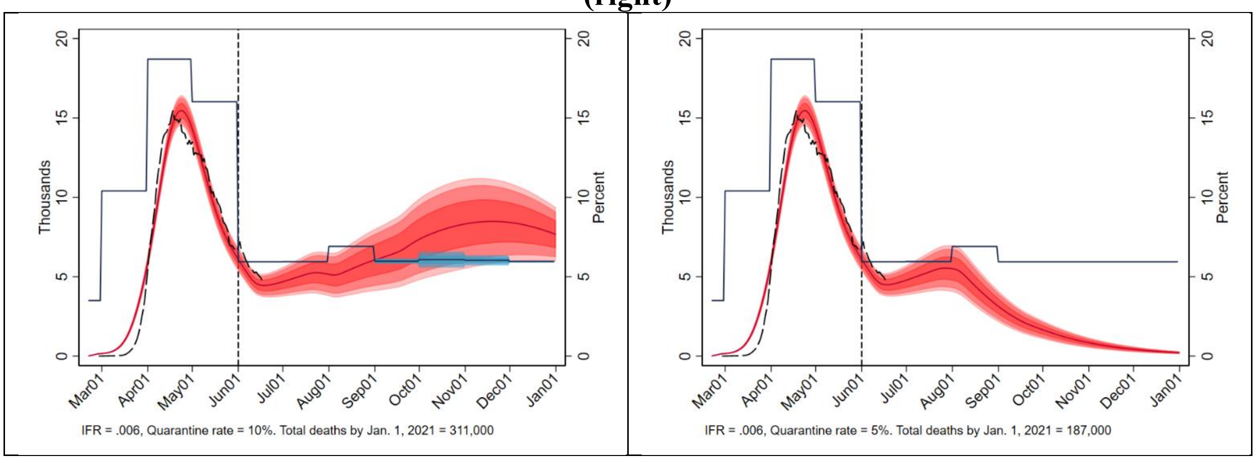
testing need not be random, but instead could be focused on populations who are both at a highest risk of getting the virus and are most likely to spread it.

Figure 9. Non-Economic NPIs: No School (left), Enhanced Protections for Ages 75+ (right)



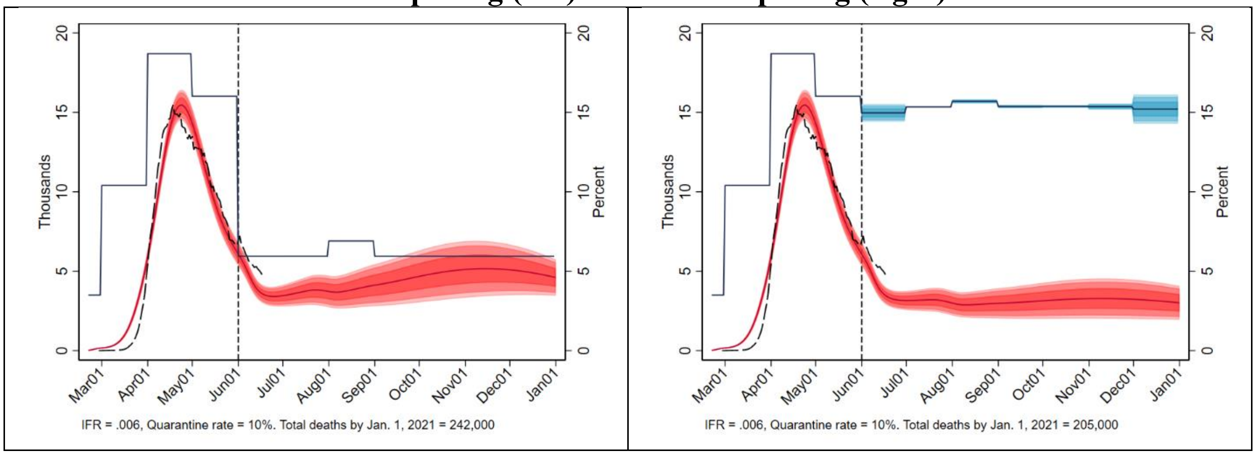
Notes: See the notes to Figure 3.

Figure 10. Non-Economic NPIs: 10% Quarantine (left), Reimpose Personal distancing (right)



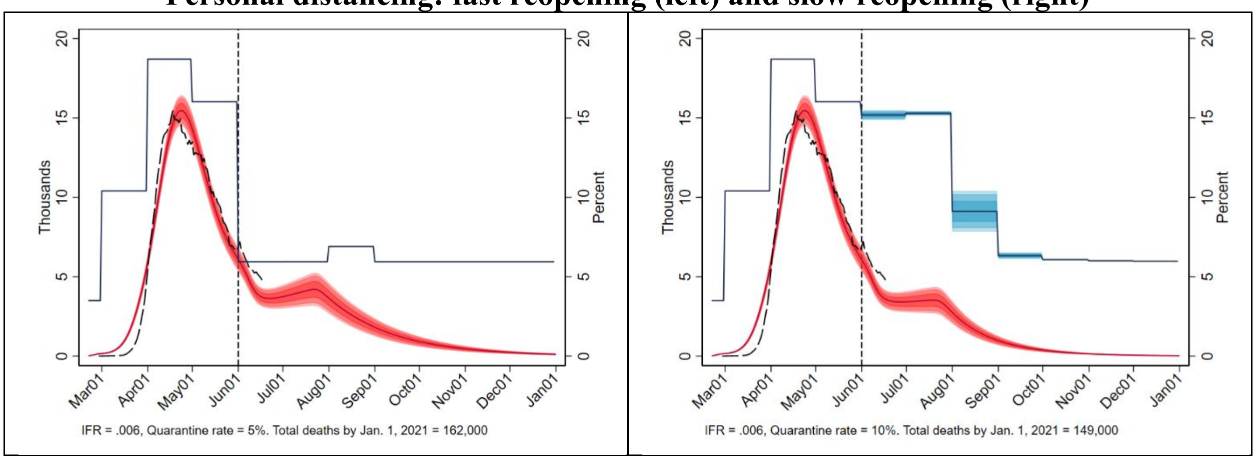
Notes: See the notes to Figure 3.

Figure 11. Non-Economic NPIs: 10% Quarantine + Enhanced 75+ Protections: fast reopening (left) and slow reopening (right)



Notes: See the notes to Figure 3.

Figure 12. Non-Economic NPIs: 10% Quarantine + Enhanced 75+ Protections + Strong Personal distancing: fast reopening (left) and slow reopening (right)



Notes: See the notes to Figure 3.

The effect of a 10% quarantine rate (up from 5% in the baseline) is shown in Figure 10 (left). This increase in the quarantine rate has the effect of (nearly) flattening the death curve, reducing total deaths from 444,000 to 311,000. This flattening-the-curve is sufficient for the governor to implement only a brief and shallow partial re-closing of the economy.

These scenarios all envision phased-in lifting of restrictions on non-economic activities, such as basketball games, large group gatherings, and religious services, as well as partial relaxation of personal protections such as wearing masks. (Recall that none of these relax safety standards at the workplace, which remain strict under all scenarios.) An option available to the governor is to revoke the Phase II reopenings and to call for, successfully, increased wearing of masks and personal distancing. We therefore consider a case in which the governor does so on July 20, upon seeing the reversal of the previously-declining trend in deaths. That said, these reversals are not complete, and personal distancing is less complete than our empirical estimates for mid-May.

Figure 10 (right) considers this enhanced personal distancing policy. Unlike any of the actions we have considered, this policy brings R^{eff} below 1, and deaths decline; the second wave is kept small and brief. Total deaths by the end of the year are only 187,000, and the economy is near full employment.

The remaining two cases examine the combined some of these non-economic NPIs. Given the negative consequences of closing schools for both children and parents who must otherwise provide child care, and the relatively small effect that we estimate of closing schools on deaths, we suppose that schools are opened on August 24.

Figure 11 (left) considers the combined effect of 10% quarantine and enhanced protections for the elderly. Together, these two policies flatten the curve, but do not decrease deaths. Figure 11 (right) places the slow-reopening governor in this environment. Whereas the fast-reopening governor takes advantage of the plateau in deaths, at a low level, to fully reopen the economy, the slow-reopening governor institutes a second round of closings in response to the plateau. This second round reduces deaths substantially, by 38,000 compared to the fast governor in the same situation, but fails to bring R^{eff} below 1 so deaths do not decline. The slow governor ends the year with a recession which, at that point, looks L-shaped.

Figure 12 considers the combined effect of 10% quarantine, enhanced protections for the elderly, and enhanced personal distancing implemented on July 20, and examines the behavior of both the fast (left) and slow (right) governor. These three non-economic NPIs collectively stem the second wave. The fast governor takes advantage of the plateau and decline in deaths to reopen the economy quickly. The slow governor reacts more cautiously, and keeps many businesses closed during the summer as an additional tool against the second wave (in effect, returning to Phase I of the economic reopening through August); but when the death rate starts to fall and gets very low, even the slow governor reopens the economy, having achieved a death count that is lower than that of the fast governor, although only by 13,000 deaths.

COST PER LIFE

A standard approach in the economics literature on the pandemic is to view NPIs through the lens of cost per life saved. There are technical reasons to object to this calculation: standard estimates of the value of life refer to marginal consumption losses whereas the current losses are non-marginal, and the true cost of a shutdown-induced recession depends on the path of recovery which is highly uncertain. More importantly, the preceding simulations underscore that the value-of-life framing is too narrow for many of these calculations, in which the NPI reduces lives *and* improves economic outcomes.

With these caveats, one component of a cost-benefit analysis of economic NPIs is the economic cost, measured by lost output, relative to lives saved. The paths of the fast and slow governors allow us to compute the value of lost output per death averted as a result of a slow reopening (or aggressive closing), relative to the fast governor, over the period of the simulation, holding constant all other NPIs.[17] These values vary substantially across NPI scenarios, from $12 million/death averted to more than $50 million/death averted. The lowest costs per death averted occur when deaths are high, as in Figure 7; the higher costs occur when non-economic NPIs have already brought the epidemic under control, as in Figure 12.

IV.C. Nonlinear Input-Output Calculations

Our counterfactual GDP estimates use the approximation (11) known as Hulten's (1978) theorem. Hulten's theorem is an equilibrium first-order approximation for small shocks. Given that the sectoral reductions in hours associated with lockdowns are very large, it is natural to question the validity of this approximation. As shown by Baqaee and Farhi (2019, 2020a,b), the quality of the approximation depends on the size of the sectoral shocks and how sectoral labor income shares vary with the shocks, which in turn depends on the elasticities of substitution in consumption and in production. When all the elasticities are equal to one, the economy is Cobb-Douglas, the sectoral labor shares are constant, and Hulten's theorem applies globally and not only as a first-order approximation. However, if the elasticities are less than one, so that there are complementarities, then the quality of the approximation can quickly deteriorate when the shocks get large. This is potentially important given that the empirical literature typically finds that inter-sectoral elasticities are significantly below one.

To gauge the importance of these nonlinearities for our calculations, we consider the counterfactual sectoral reductions in hours in 2020Q3 in the economic lockdown scenario of Figure 6 (left). We explore different values within the plausible set of inter-sectoral elasticities (σ, θ, e, η), where σ is the elasticity of substitution in consumption, θ is the elasticity of

[17] This calculation misses differences in lives saved and costs incurred in 2021, outside the simulation window.

substitution across intermediates in production, e is the elasticity of substitution between value added and intermediates in production, and η is the elasticity of substitution between capital and labor in production. We consider low elasticities given the short horizons involved. When $(\sigma, \theta, e, \eta) = (1, 1, 1, 1)$, so that Hulten's theorem applies globally, the reduction in real GDP is 6.0%. When $(\sigma, \theta, e, \eta) = (0.95, 0.001, 0.7, 0.5)$ the reduction in real GDP is 6.4%. When $(\sigma, \theta, e, \eta) = (0.7, 0.001, 0.3, 0.2)$, the reduction in real GDP is 7.6%. Finally, when $(\sigma, \theta, e, \eta) = (0.5, 0.001, 0.3, 0.2)$, the reduction in real GDP is 8.1%. Hence, empirically plausible complementarities in consumption and in production can amplify real GDP losses, relative to what we have reported, by somewhere between 10% and 40%.

VII. Discussion

The modeling presented here goes beyond what is in the literature by incorporating an age-base SEIQRD model into a sectoral economic model with multiple explicitly-specified NPIs, calibrated and estimated to current US conditions using the most recently available data. Still, multiple caveats are in order. One is that the situation differs by state, with northeastern states currently seeing a very sharp decline in infections and deaths but other parts of the United States seeing expansions in infections and deaths. The national modeling here abstracts from these differences. In addition, there is considerable uncertainty over some key epidemiological parameters, such as the infection fatality ratio. Additional simulation results in the online Appendix explore the sensitivity of the modeling results to some of the key epidemiological parameters. Although numerical values differ, for example under all control scenarios deaths are higher if a higher value of the IFR is assumed, the conclusions from Section VI are robust.

For convenience, we have called the decision-maker in the model the governor. This is a simplification of a complex decision-making environment in which federal guidelines, state requirements and guidelines, local implementation, and individual decisions combine to influence the spread of the virus. There is now a compelling body of work that much of the decline in economic activity in March and April was not directly caused by government intervention but instead was an endogenous self-protective response by consumers and, more recently, that official reopenings had limited if any direct causal effect on spending (see Bartik et al. (2020) and Gupta et al (2020) in this volume). If so, one might think of consumers as more akin to our slow governor. Under this interpretation, our results align with the reduced-form evidence that the key to reviving the economy is providing a setting in which consumers and workers are comfortable returning to economic activity, that is, in which deaths are low and declining.

The main conclusion from the simulations in Section VI is that aggressive use of non-economic NPIs can lead to a reduction in deaths and a strong economic reopening. If a second wave emerges, a second round of economic shutdowns would be both costly and ineffective, compared to non-economic NPIs. A key such non-economic NPI is returning to Phase-I level restrictions on non-economic social activities, combined with widespread adoption of measures to reduce transmission such as masks and personal distancing. When combined with other measures, such as ramped-up testing and quarantine and enhanced protection of the elderly, especially in nursing homes, these non-economic NPIs can provide a powerful force to control a second wave and, based on our modeling, make room for bringing the large majority of those currently not working back to work.

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Appendix Table 1
Standardized Index of Relative Industry Contributions θ

NAICS	Sector	θ
61	Educational svcs	-0.736
485	Transit and ground passenger transportation	-0.735
445	Food and beverage stores	-0.718
HS	Housing	-0.706
722	Food svcs and drinking places	-0.697
525	Funds, trusts, and other financial vehicles	-0.686
624	Social assistance	-0.683
452	General merchandise stores	-0.681
4A0	Other retail	-0.675
713	Amusements, gambling, and recreation inds	-0.672
623	Nursing and residential care facilities	-0.636
23	Construction	-0.583
622	Hospitals	-0.566
711AS	Performing arts, sports, museums, and related atvs	-0.560
441	Motor vehicle and parts dealers	-0.541
621	Ambulatory health care svcs	-0.524
721	Accommodation	-0.493
81	Other svcs, exc govmt	-0.455
339	Misc manufacturing	-0.446
493	Warehousing and storage	-0.426
561	Administrative and support svcs	-0.415
481	Air transportation	-0.395
3361MV	Motor vehicles, bodies and trailers, and parts	-0.392
337	Furniture and related products	-0.354
483	Water transportation	-0.331
ORE	Other real estate	-0.326
311FT	Food and beverage and tobacco products	-0.324
321	Wood products	-0.294
512	Motion picture and sound recording inds	-0.234
313TT	Textile mills and textile product mills	-0.072
323	Printing and related support atvs	-0.063
326	Plastics and rubber products	-0.019
3364OT	Other transportation equipment	-0.004
327	Nonmetallic mineral products	0.004
22	Utilities	0.061
322	Paper products	0.093
521CI	Federal Reserve banks, credit intermed, and related atvs	0.103
111CA	Farms	0.106
562	Waste mgmt and remediation svcs	0.108

333	Machinery	0.141
487OS	Other transportation and support atvs	0.142
514	Data processing, internet publishing, and other info svcs	0.154
532RL	Rental and leasing svcs, lessors of intangibles	0.167
332	Fabricated metal products	0.258
482	Rail transportation	0.280
315AL	Apparel and leather and allied products	0.309
335	Electrical equipment, appliances, and components	0.355
212	Mining, exc oil and gas	0.367
113FF	Forestry, fishing, and related atvs	0.428
513	Broadcasting and telecommunications	0.507
325	Chemical products	0.520
331	Primary metals	0.530
213	Support atvs for mining	0.563
486	Pipeline transportation	0.618
324	Petroleum and coal products	0.771
484	Truck transportation	0.850
42	Wholesale trade	1.295
334	Computer and electronic products	1.515
5412OP	Misc professional, scientific, and technical svcs	1.707
511	Publishing inds, exc internet (includes software)	2.221
524	Insurance carriers and related atvs	4.411
5415	Computer systems design and related svcs	6.662
211	Oil and gas extraction	9.175
5411	Legal svcs	22.350
523	Securities, commodity contracts, and investments	22.516
55	Mgmt of companies and enterprises	38.636

The index is standardized to have median zero and unit interquartile range. The non-standardized values of θ have median 0.92 and 25th and 75th percentiles 0.36 and 1.50.