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THE IMPACT OF VACCINES AND BEHAVIOR ON U.S. CUMULATIVE DEATHS FROM COVID-19

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ABSTRACT

The CDC reports that 1.13 million Americans have died of COVID-19 through June of 2023. I use a model of the impact over the past three years of vaccines and private and public behavior to mitigate disease transmission during the COVID-19 pandemic in the United States to address two questions. First, holding the strength of the response of behavior to the level of daily deaths from COVID-19 fixed, what was the impact of vaccines on cumulative mortality from COVID-19 up through June 2023? And second, holding the pace of deployment of vaccinations fixed, what would have been the impact of stricter or looser behavioral responses to COVID-19 deaths on cumulative mortality from COVID-19 over this same time period? In answering the first question, I find that vaccines saved 748,600 lives through June 2023. That is, without vaccines, cumulative mortality from COVID-19 would have been closer to 1.91 million over this time period. In answering the second question, I find that behavioral efforts to slow the transmission of the virus before vaccines became widely administered were critical to this positive impact of vaccines on cumulative mortality. For example, with a complete relaxation of these mitigation efforts, vaccines would have come too late to have saved a significant number of lives. Earlier deployment of vaccines would have saved many lives. I find that marginal changes in the strength of the behavioral response to COVID-19 deaths within the range of those responses estimated with the model have a significantly impact on cumulative COVID-19 mortality over this time period.

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Matlab Code to replicate results in the paper is available at
https://sites.google.com/site/andyatkeson/home/covid-work

1 Introduction

What impact did the deployment of vaccines together with public and private efforts to slow the spread of COVID-19 have on cumulative mortality from this disease in the United States over the three year period from early 2020 through June 2023?

There are a number of approaches one might take to answer this question.[1] In this paper, I take a structural modeling approach. Specifically, I present a parsimonious structural behavioral epidemiological model of the dynamics of COVID-19 deaths in the United States to assess the impact of vaccines and private and public responses to slow the transmission of COVID-19 on cumulative mortality from this disease in the United States from early 2020 through June 2023.[2] The model, with its baseline parameters, fits the dynamics of daily and cumulative COVID deaths in the United States very well. I then conduct several counterfactual exercises with the model to provide answers to the question above.

First, to assess the impact of the deployment of vaccines on cumulative mortality from COVID-19, I re-run the model with no vaccines. I find in this counterfactual exercise that an additional 748,600 Americans would have died from COVID-19 over the period from February 2020 through June 2023 over and above the 1,134,440 who are recorded by the Centers for Disease Control and Prevention (CDC) as having died from COVID-19 over this time period. In this modeling exercise, I leave unchanged the parameters governing the strength of the private and public disease mitigation responses to the level of daily COVID-19 deaths. Based on this counterfactual simulation, I conclude that the deployment of COVID-19 vaccines in 2021 and 2022 had a major impact on cumulative mortality from COVID-19 in the United States even when one takes into account that public and private efforts to mitigate disease transmission would have been stronger in the absence of vaccines.

Second, to assess the contribution of the endogenous private and public mitigation responses to slow transmission of COVID-19 to reducing cumulative mortality from the disease, I simply re-run the model with the parameters governing this endogenous mitigation response turned off. Here I leave in place the baseline parameters governing the timing and speed of the deployment of vaccines. Thus, I interpret this counterfactual simulation as assessing what would have happed had Americans made no private or public efforts to mitigate the spread of COVID-19. Here I find that an additional 751,600 Americans would have died from COVID-19 over the period from February 2020 through June 2023. That is, the cumulative mortality from COVID-19 in this simulation with vaccines but no efforts at mitigation would have been quite similar to what it would have been without vaccines.

I interpret these two findings as indicating that it was the combination of public and private mitigation efforts in response to the COVID epidemic together with the deployment of vaccines that resulted in a substantial reduction in cumulative COVID-19 mortality in the United States relative to what would have happened otherwise. I see this as the central finding of this modeling exercise.

Given that I pursue a structural modeling approach to addressing the two questions that motivate this paper, the reader might be concerned that the model itself is something of a

[1] For example, Barro (2022) examines cross section data on vaccination and epidemiological outcomes across regions of the United States to address these questions.

[2] The model is an update of the model in Atkeson (2021) to include the Delta and Omicron variants, incomplete and waning immunity, and the data on COVID-19 deaths through June 2023.

"black box" that is difficult to see inside and understand. How do the modeling assumptions and parameter choices impact the results of this modeling exercise? What data allow us to validate these results? To help address these questions, I start the paper a back-of-the envelope calculation intended to show the key model assumptions and key data that drive the two main quantitative model results.

Regarding the impact of vaccines on cumulative mortality from COVID-19, the key elements of the model calculation are as follows. Blood serology survey data from CDC that I review below indicate that a large majority of Americans, both those who have been vaccinated and those who have not, have been infected with COVID-19 as of late 2022. These data thus suggest that the deployment of vaccines did not dramatically reduce the number of Americans who eventually experienced a COVID-19 infection. The first modeling counterfactual result, the result that vaccines substantially reduced cumulative mortality, is then based not on an estimate that vaccines averted infections over the long run. Instead, to a large extent, this result is based on a model estimate of the number of Americans who avoided contracting COVID-19 before being vaccinated together with an estimate of the impact of having been vaccinated on the infection fatality rate for those contracting their first case of COVID-19.[3]

To help validate this model-based estimate of the number of Americans who were vaccinated before their first infection with COVID-19, I compare simulated model output for the dynamics of infections and vaccinations with the CDC blood serology survey data indicative of these dynamics over the course of 2021 and 2022. The fit of the model to these data provides external empirical support for the model's estimate that a large fraction of the American population got vaccinated before their first infection with COVID-19 — perhaps as much of half the U.S. population. In the model, the infection fatality rate for those who are vaccinated prior to their first infection with COVID-19 is substantially reduced relative to those who have not been vaccinated, an assumption that is in line with a considerable number of studies indicating that vaccination provided substantial protection against mortality from COVID-19.

Consider the following back-of-the-envelope calculation of the impact of vaccines on cumulative mortality from COVID derived from these assumptions. Assume that out of a population of 330 million Americans, 165 million (or half the population) contracted COVID for the first time before being vaccinated, with an infection fatality rate of 0.5% (or 50 basis points). Assume that the other 165 million contracted COVID after being vaccinated, with an infection fatality rate of 0.1% (or 10 basis points). These numbers would imply as a baseline estimate a total of 990,000 COVID-19 deaths with vaccines. Now consider a counterfactual alternative with no vaccines, but with the same total number of 330 million infections, with all infected suffering an infection fatality rate of 0.5%. In this alternative scenario, cumulative COVID deaths would be 1.65 million, or 660,000 higher than in our baseline with vaccines. The model is considerably richer (and has many more parameters) than this simple calculation, but this calculation illustrates the main forces at work in the model simulation and counterfactual exercises.

The model's second implication that the deployment of vaccines in 2021 and 2022 would

[3]There have been many studies of the impact of vaccination on the infection and fatality rate from COVID-19. See, for example Johnson, Amin, and Ali (2022), Johnson, Linde, and Ali (2023), and https://www.cdc.gov/coronavirus/2019-ncov/science/data-review/vaccines.html.

not have had much impact on cumulative COVID-19 mortality in the absence of observed private and public efforts to slow the spread of COVID-19 between early 2020 into 2022 then follows from its first implication above. The model predicts that, absent mitigation efforts, COVID-19 would have spread very rapidly through the US population in 2020. Since vaccines were not available until late 2020, this means that the model predicts that, absent mitigation efforts, most Americans would have contracted COVID-19 for the first time before being vaccinated. As a result, in this model counterfactual scenario, most Americans would have been at risk of the relatively high infection fatality rate for those infected for the first time with COVID-19 without the protection of vaccines. In this sense, under this scenario, vaccines are deployed too late to be of much benefit in reducing COVID-19 mortality.

The full structural model adds to these simple baseline calculations a richer dynamic framework for assessing not only stark counterfactuals of no vaccines or no mitigation, but also marginal changes in the timing and pace of deployment of vaccines and/or marginal changes in the strength of the endogenous response of private and public mitigation efforts to the evolving state of the epidemic. I consider a few such counterfactual scenarios.

The logic of the back-of-the-envelope calculation above suggests that had it been possible to advance the timing of the deployment of vaccines, a substantial number of lives could have been saved. I use the model to ask what cumulative COVID-19 mortality would have been had it been possible to advance the introduction of vaccines by six months (to early July 2020). Here I find that had this been possible, 406,760 additional COVID deaths might have been averted, as even more Americans would have had the benefit of being vaccinated before being infected with COVID-19.[4] Earlier deployment of vaccines would likely also have had substantial economic benefits as endogenous public and private mitigation efforts would have been reduced in the face of a lower daily death toll. I see this counterfactual exercise as confirming that speedy development and deployment of vaccines had a large impact on the cumulative mortality burden of COVID-19 and that the benefits of accelerating vaccine development even further would have been substantial.

The baseline specification of the model assumes that the strength of the endogenous response of private and public mitigation efforts in response to the level of daily COVID-19 deaths was quite strong in the period from early 2020 into the late fall of 2020 and was very much weaker after that point. This assumption in the model is required to match to waves of COVID-19 deaths associated with the initial variant and the Alpha, Delta, and Omicron variants. That is, if I assume that the strength of the behavioral response to the level of daily deaths in the initial wave of COVID-19 continued through the subsequent waves, the model does not match the patterns of daily deaths associated with Alpha, Delta, and Omicron variants. With this assumption about behavior, model-implied deaths in 2021 and 2022 are too low relative to the data. Likewise, if I assume that the relatively weaker behavioral response to the level of daily deaths in the waves associated with the Alpha, Delta, and Omicron also applied to the initial variant, then deaths in that initial wave would have been counterfactually high. I use this finding of a structural break in the strength of the endogenous response of mitigation efforts to the level of daily deaths to construct two counterfactual exercises to consider the impact of marginal changes in the strength of

[4]That is, the model simulation with early vaccine deployment predicts cumulative COVID-19 mortality from early 2020 through June 2023 of 755630 as opposed to the baseline predicted cumulative mortality of 1,162,300.

the endogenous response of public and private mitigation efforts on cumulative COVID-19 deaths.

The first counterfactual, which I call *strong behavioral response*, assumes that the strength of behavior observed from early 2020 into the late fall of that year had continued through June 2023. All other parameters, including the timing of vaccine deployment are held fixed. Here I find that a consistently strong behavioral response over this time period would have saved 283,570 lives, with most of these lives saved during the waves associated with the Alpha and Delta variants.[5]

The second counterfactual, which I call *weak behavioral response*, assumes that the strength of behavior observed from early 2020 into the late fall of that year was at the lower level observed after that time period. That is, it assumes that public and private mitigation efforts responded to the level of daily deaths in the initial wave in the weaker manner that they did to later waves. All other parameters, including the timing of vaccine deployment are held fixed. Here I find that a consistently weak behavioral response over this time period would have cost 172,300 additional lives.[6]

Of course, either of these alternative behavioral responses would have come at some economic cost or benefit as private and public mitigation efforts responded more strongly or less so to different waves of COVID-19 deaths. I leave it to further research to assess those counterfactual economic costs or benefits quantitatively.

The model is not well-suited to the analysis of the impact of specific private and public efforts to slow disease transmission. This is because the modeling of private and public behavior in the model is done in a very reduced-form fashion. Thus I cannot separately assess the impacts of private behavior and public policies on the evolution of the COVID epidemic and its cumulative mortality burden. Perhaps this framework can be extended to separately identify the impact of public and private mitigation efforts in future research.[7]

The remainder of this paper is presented as follows. Section 2 reviews the CDC Blood Serology Survey data referenced in the back-of-the-envelope calculations discussed above. Section 3 presents the key elements of the model with a complete description of the model and parameters given in the Appendix. Section 4 presents the baseline model results and the two counterfactual scenarios for the evolution of the COVID epidemic without vaccines and without mitigation efforts. Section 6 reviews a number of alternative counterfactual scenarios regarding marginal changes in mitigation behavior and Section 7 concludes.

2 CDC Data

In this section I review the data from the CDC on COVID-19 mortality and the Blood Donor Serology Survey data used in this paper.

[5]That is, the model simulation with this strong behavioral response predicts cumulative COVID-19 mortality from early 2020 through June 2023 of 878730 as opposed to the baseline predicted cumulative mortality of 1,162,300.

[6]That is, the model simulation with this weak behavioral response predicts cumulative COVID-19 mortality from early 2020 through June 2023 of 1,335,000 as opposed to the baseline predicted cumulative mortality of 1,162,300

[7]See, for example Arias et al. (2023)

I begin with a review of the CDC data on COVID mortality. According to data tabulated by the CDC, just over 1.1 million Americans died from COVID-19 over the 3 1/3 -year period from early 2020 through June 2023.[8] I plot the dynamics of this measure of cumulative COVID-19 deaths in the United States over the time period from early 2020 through June 2023 as a dashed and a dotted red line in Figure 1. The dashed line is a daily measure of cumulative deaths and the dotted line is from weekly data on deaths. The blue line in the figure is the baseline prediction of the model used in this paper. The CDC data on cumulative COVID-19 deaths over this full time period is 1,134,440. The model estimate of cumulative COVID-19 deaths over this time period is 1,162,300.

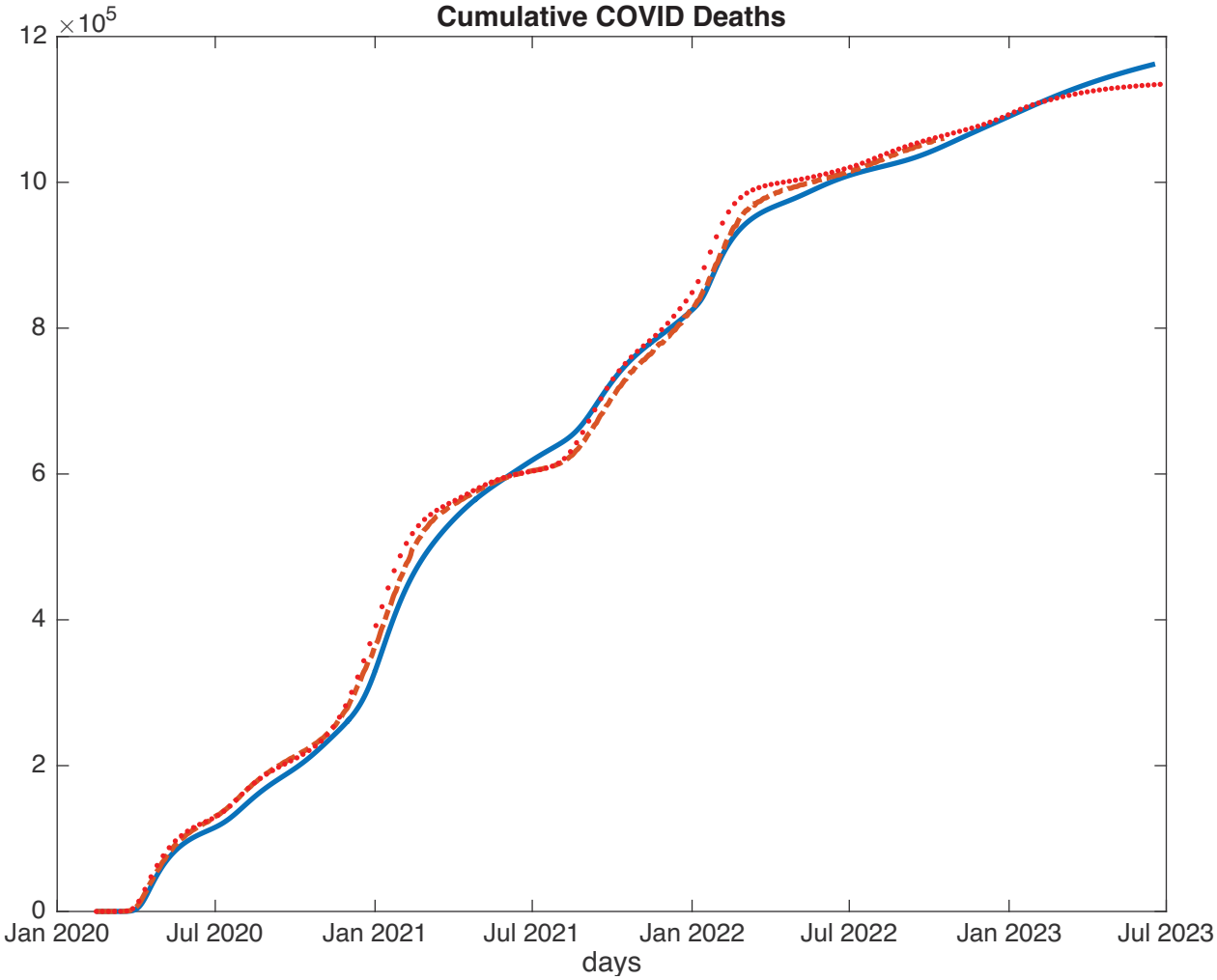

Figure 1: CDC Data and Model implications for cumulative COVID deaths with baseline parameter values

In Figure 2, I show the dynamics of the seven-day moving average of daily COVID-19

[8]See https://covid.cdc.gov/covid-data-tracker/#trends_totaldeaths_select_00 for CDC estimates of trends in cumulative deaths from COVID-19. This paper uses daily data on COVID deaths previously available at this website. The data now reported on this website is weekly. The CDC also compiles estimates of excess deaths here https://www.cdc.gov/nchs/nvss/vsrr/covid19/excess_deaths.htm.

deaths in the United States over this same time period as a red dashed line. The dotted red line is a daily average of weekly reported deaths data. Again, the blue line in the figure is the baseline prediction of the model used in this paper.

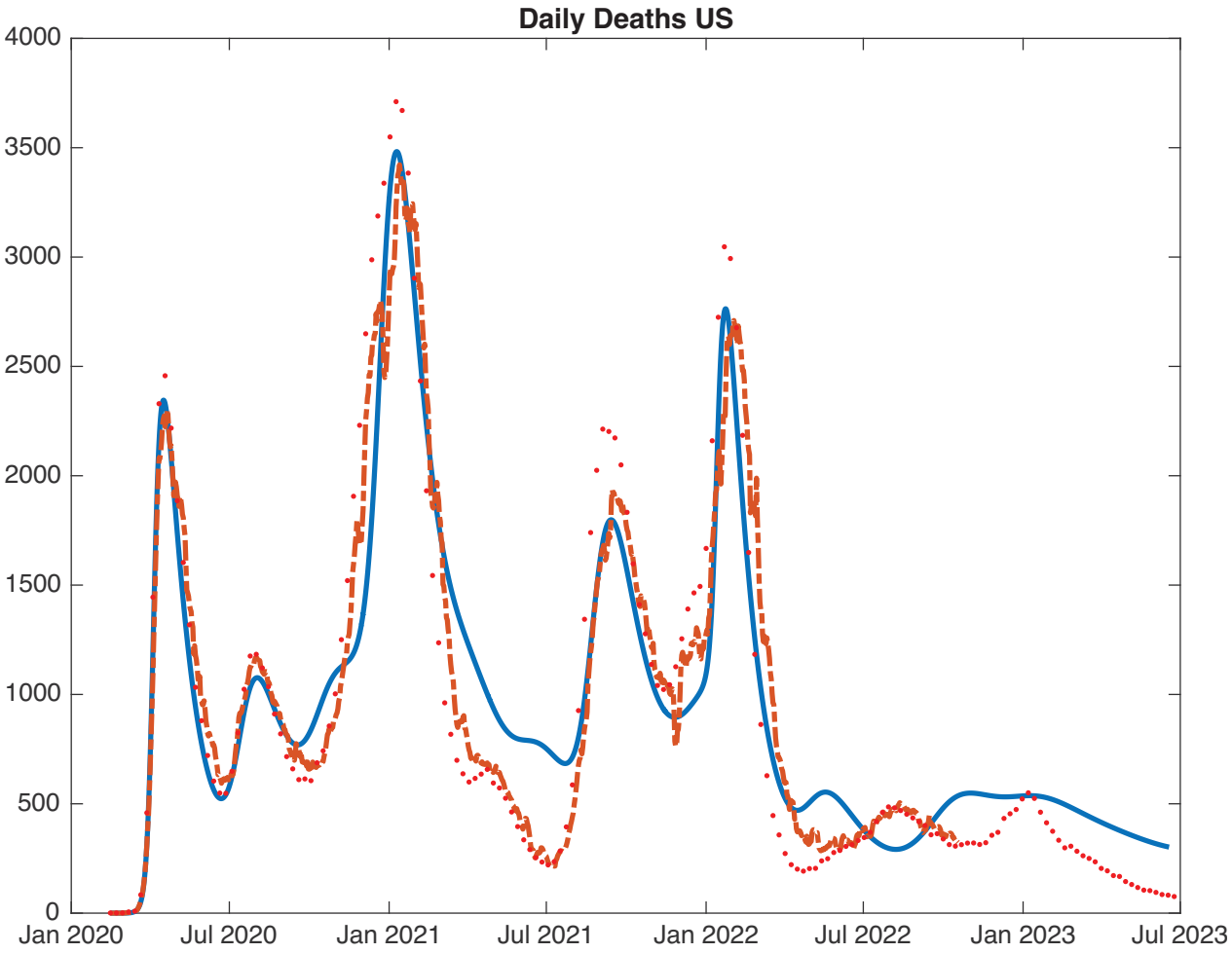

Figure 2: CDC Data and Model implications for daily COVID deaths with baseline parameter values.

As is evident in these figures, mortality from COVID-19 in the United States was extremely drawn out over this time period, with roughly 700,000 deaths being recorded after vaccines first became available to the U.S. public in late December of 2020. As I and others have argued elsewhere (Eksin, Paarporn, and Weitz (2019), Atkeson (2021) and Atkeson, Kopecky, and Zha (Forthcoming)), the prolonged evolution of the COVID-19 epidemic in the United States and in most other locations around the world strongly suggests private and public responses to slow the spread of COVID-19 had a powerful impact of the dynamics of this epidemic. In particular, these efforts appear to have slowed the transmission of COVID-19 allowing many Americans to avoid getting infected with the disease before they were able to get vaccinated.

To get a measure of the dynamics of the number of Americans having been infected with COVID-19 and/or vaccinated against the disease, I consult data from the CDC's Blood

Donor Serology Surveys covering the period from July 2020 through late 2022.[9] During this time period, the CDC collected serology survey data from blood donations across the country to assess the portion of those blood samples with antibodies consistent with past COVID infection and/or vaccination. This survey is used to measure seroprevalence, which is the fraction of a population of individuals who have antibodies to an infectious agent indicating past infection and/or vaccination. The survey reports two measures of seroprevalence: infection-induced seroprevalence and combined seroprevalence. Infection-induced seroprevalence estimates the portion of the population with evidence of one or more prior infections while combined seroprevalence estimates the portion of the population with antibodies indicative of either prior infection or vaccination or both. Both prior infection and the COVID vaccines in use in the United States result in production of anti-spike (anti-S) antibodies, but only infection results in the production of anti-N antibodies. I use the difference between the estimates of combined seroprevalence and infection-induced seroprevalence at a point in time as an indicator of the portion of the population that has been vaccinated but not infected with COVID-19.

I plot data from these seroprevalence surveys in Figure 3. Survey estimates of infection-induced seroprevalence are marked as purple crosses, while estimates of combined seroprevalence are marked as yellow circles. The implications of the model with its baseline parameters for cumulative infections is marked as a red line while those model implications for the combined total of cumulative infections and vaccinations is marked as a blue line. As is evident in this figure, in the data, the two measures of seroprevalence track each other very closely in 2020 as is expected given that vaccines were not available. We see however that in 2021, with the deployment of vaccines, combined seroprevalence climbs very rapidly relative to infection-induced seroprevalence, consistent with the hypothesis that during this time period, many American received at least one vaccine prior to having experienced their first COVID-19 infection. As the data continue into 2022, we see that combined seroprevalence levels off at a very high level, but that infection-induced seroprevalence continues to rise peaking at close to 80% in late 2022, consistent with the view that, in the long-run, a large majority of Americans ended up being infected with COVID-19, both those who were vaccinated and those who were not.

[9]These data are available here (for 2020 and 2021) https://covid.cdc.gov/covid-data-tracker/#nationwide-blood-donor-seroprevalence and here (for 2022) https://covid.cdc.gov/covid-data-tracker/#nationwide-blood-donor-seroprevalence-2022. The data are reported monthly in 2020 and 2021 and quarterly in 2022. I show end-of-quarter data throughout. A fuller description of these data and their limitations is available here https://jamanetwork.com/journals/jama/fullarticle/2784013 and here https://www.cdc.gov/mmwr/volumes/72/wr/mm7222a3.htm.

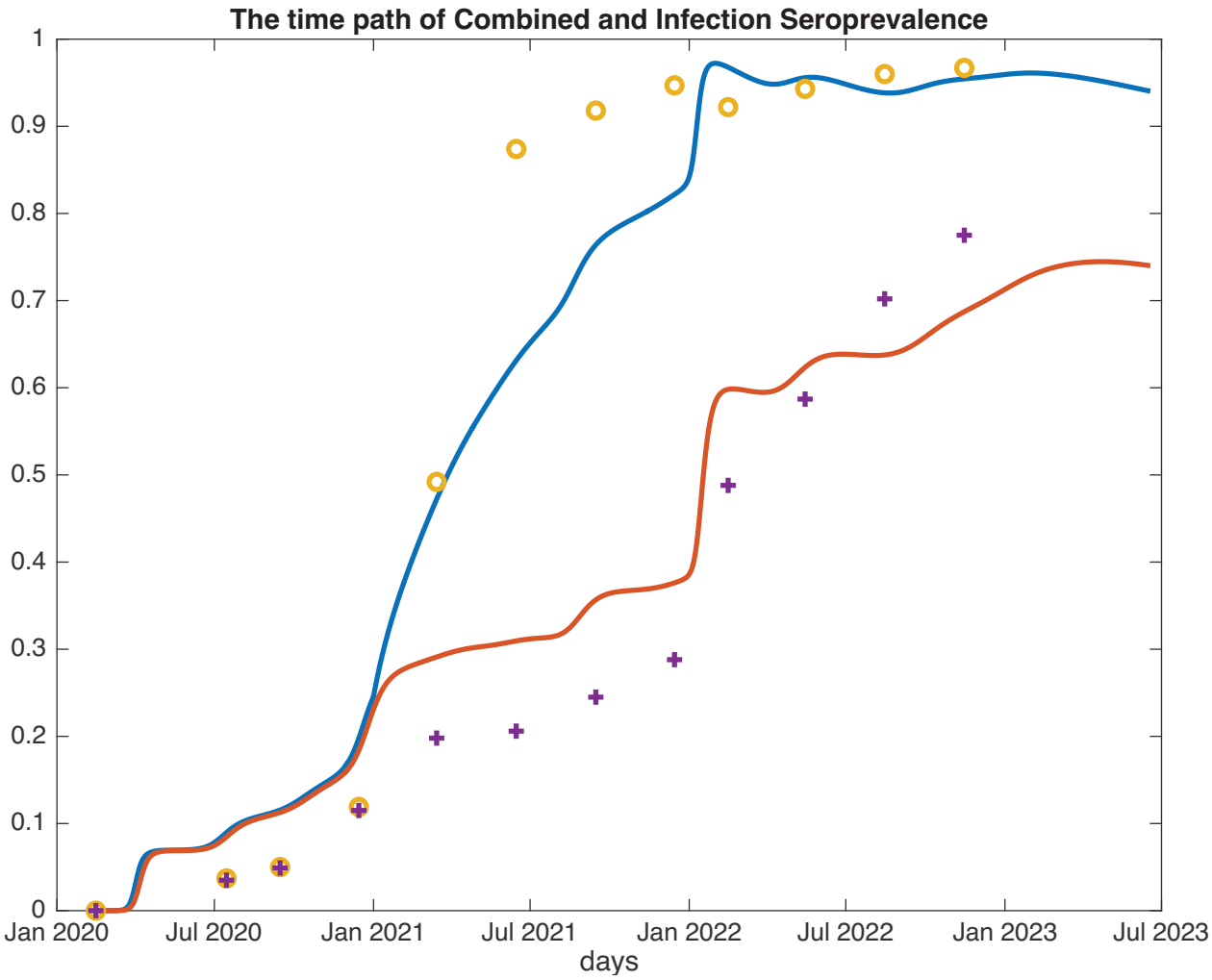

Figure 3: Infection-Induced and Combined Seroprevalence, CDC data and model baseline

To relate the data in Figure 3 to the back-of-the-envelope calculation presented in the introduction, observe that in June of 2021, infection-induced seroprevalence reported in this figure was close to 20% but combined seroprevalence was nearly 90%. Since the difference between these two numbers is an indication of the portion of Americans who had received a vaccine but had not yet been infected with COVID-19, these data are consistent with the view that as of June 2021, the portion of vaccinated but not yet infected individuals was quite high. Then consider that infection-induced seroprevalence climbs from roughly 20% in June of 2021 to nearly 80% at the end of 2022. These data are consistent with the hypothesis that a large number of vaccinated Americans ended up getting infected with COVID-19 after June 2021. These observations, together with an estimate that the infection fatality rate for vaccinated individuals was much lower than for those without a vaccine, then suggest that the deployment of vaccines did saved a large number of lives not by averting infections but instead by reducing the infection fatality rate for those infected with COVID-19.

I next present the model I use to build on this back-of-the-envelope calculation and to conduct counterfactual exercises to assess the impact of vaccines and the strength of private and public mitigation responses on the cumulative mortality from COVID-19.

3 Model

I summarize the main features of the model here. A full description of the model equations and parameters is given in the Appendix.

Disease dynamics are described by an SEIR model (with compartments for agents who are susceptible, S, exposed, E, infectious, I, and recovered and hence removed R) modified to include a compartment for those infected agents who end up with serious disease. I refer to this compartment as H, for hospitalized. Agents who die from COVID are assumed to transition from infection I to death, D, through this compartment H. The expected time that agents spend in this compartment is set 30 days to capture the delay between serious illness that leads to death, and the reporting of that death.

To accommodate four alternative variants of COVID (the original, Alpha, Delta, and Omicron), I index the exposed and infected compartments E_i and I_i with subscripts indicating these variants. I assume that the flow rates per unit time from the exposed to infected and from the infected to hospitalized or recovered compartments are the same for all variants. Variants differ in their inherent transmissibility as described below. The first three variants are assumed to have the same infection fatality rate. Omicron is assumed to differ from previous variants not only in its infection fatality rate but also in that agents infected with Omicron can infect those with prior immunity (in the removed compartment R). Vaccines are modeled as a flow of individuals from the S compartment directly to the R compartment at a rate $\lambda(t)$ reflecting the speed of deployment of vaccines. Waning immunity is modeled as a flow rate of agents back from the removed compartment R to the susceptible compartment S.

In the model, for the original, Alpha, and Delta variants, individuals who have entered the R compartment either through vaccination or prior infection are assumed to be protected from infection and death as long as they remain in that compartment. Once immunity to these variants has waned, individuals who have transitioned back to the S compartment have the same risk of infection and death from these variants as those who have no immunity. It is in this manner that vaccination or prior infection reduces mortality risk from further COVID-19 infections to the extent that waning immunity is slow. For the Omicron variant, the model allows for breakthrough infections and potentially death. Omicron is assumed to have a lower infection fatality rate for those in the S compartment than prior variants and an even lower infection fatality rate for breakthrough infections of those in the R compartment.

To understand the implications of these model assumptions for its implications for the dynamics of the COVID-19 epidemic, consider the blue line in Figure 3. This line shows the model's implications for the portion of the population in the R compartment. Starting in early 2022, this blue line levels off at a high level (roughly 95% of the population). But model-implied deaths from COVID-19 shown in Figure 2 continue through June 2023. This is because Omicron continues to circulate infecting those in both the S and R compartments, leading to a persistent flow of COVID-19 deaths in 2022 and early 2023.[10]

Behavior in this model is assumed to respond to daily death rates as they are reported. It is assumed that behavior does not respond immediately to new infections as these are not

[10] As of mid-2023, the flow of COVID-19 deaths appears to be falling below the levels implied by the model, offering some hope that mortality associated with this now endemic disease will remain low going forward.

directly observed. As discussed by John Cochrane[11], Atkeson (2021) and Weitz et al. (2020) the delay between infection and death introduced by this compartment H implies that this simple behavioral model has oscillatory endogenous dynamics that are helpful in allowing the model to reproduce the deaths data.

In the United States, we have seen public authorities tighten and loosen COVID mitigation policies in tandem with changes in the prevalence of this disease. I interpret this correlation between public policies and disease prevalence as arising from a public behavioral response to shifting political calculations as disease prevalence rises and falls, that is, as a social choice behavioral response. I interpret private behavioral responses as arising from rising concern over personal infection risk with rising disease prevalence. I thus interpret the reduced form behavioral response of transmission rates to disease prevalence as resulting from a combination of private and public reactions to disease prevalence. I do not attempt to distinguish the relative importance of these two responses.

To be more specific, the reduced-form for the behavioral response of the rate at which infected agents transmit the disease is given by

$$\beta_i(t) = \bar{\beta}_i \exp\left(-\kappa(t)\frac{dD(t)}{dt} + \psi(t)\right) \tag{1}$$

where the parameters $\bar{\beta}_i$ control the baseline transmissibility of the original and subsequent variants of COVID, the parameter $\psi(t)$ is set to be a cosine function of time to introduce seasonality in transmission, and $\kappa(t)$ is the semi-elasticity of transmission with respect to the level of daily deaths. Note that the relative transmissibility of each variant for any level of daily deaths and point in the seasonal cycle is given by $\bar{\beta}_i/\bar{\beta}$. Furthermore, note that behavior is assumed to have the same proportional impact on the transmission rate of all variants.

The reduced form response of the transmission rates of the original and new variants of the virus to daily deaths assumed in the model can be understood as arising from the combined responses of private and public actors to disease prevalence as follows. Conider a two-equation system in which the transmission rate is given as a function of activity $Y(t)$ with

$$\beta_i(t) = \bar{\beta}_i Y(t)^{\alpha} \exp(v(t) + \psi(t))$$

and activity is given as a declining function of daily deaths

$$Y(t) = \exp\left(-\frac{\kappa_p(t)}{\alpha}\frac{dD(t)}{dt} + u(t)\right)$$

In the first of these two equations, the parameters $\bar{\beta}_i$ are fixed coefficients that capture features of the virus and the population determined prior to the epidemic that might impact transmission of the original and more transmissible variants. Factors considered in the literature include population density, modes of transportation (subway vs. car, etc.), household and demographic structure, cultural norms (bowing vs. shaking hands or kissing), temperature and humidity, etc. The parameter α captures the elasticity of transmission with respect to activity. The parameter $v(t)$ represents a potentially time-varying shock to the

[11] See https://johnhcochrane.blogspot.com/2020/05/an-sir-model-with-behavior.html

region-specific relationship between activity and transmission that may represent the impact of policy over time. I normalize $v(0) = 0$. When interpreting variation in $v(t)$ as representing the impact of policies, here I am thinking about policies such as mask-wearing, ventilation, physical distancing, redesign of workspaces, or other measures implemented after the start of the epidemic that reduce transmission given a fixed level of activity.

I normalize the level of activity at the start of the pandemic to $Y(0) = 1$. Given this normalization, the parameter $\bar{\beta}_i$ sets the transmission rate of the virus at the start of the epidemic. Specifically, $\bar{\beta}_i$ together with the flow rates σ and γ determine the *basic reproduction number* of the original and more transmissible variants at the peak of the seasonal cycle of transmissibility.

In the second of these two equations, I model individuals' decisions to engage in activity at time t, $Y(t)$, as a declining function of the level of daily deaths, $\dot{D}(t)$. The parameter $\frac{\kappa_p(t)}{\alpha}$ is the semi-elasticity of private behavior with respect to daily deaths. The variable $u(t)$ in this second equation represents a time-varying shock to the region-specific relationship between deaths and activity. I interpret $u(t)$ as reflecting public policies such as lockdowns or closures that would reduce activity below what agents might choose in a decentralized fashion.

I consider government policies that are "behavioral" in that they are responsive to the prevalence of the disease as measured by daily deaths as well as policies that depend only on time. To model the behavioral component of government policies, assume that public policies impacting the relationship between activity and transmission $v(t)$ and between daily deaths and activity $u(t)$ are responsive to the level of daily deaths. Specifically, assume that

$$v(t) = -\eta_v \frac{dD(t)}{dt}$$

$$u(t) = -\frac{\eta_u}{\alpha} \frac{dD(t)}{dt}$$

With these assumptions, we have that the behavioral decline in activity and disease transmission with daily deaths can be interpreted as arising either from a change in private behavior or public mandates that are conditioned on the prevalence of the disease. Specifically, with these assumptions, we obtain the reduced-form relationship between daily deaths and disease transmission in equation (2) with the overall semi-elasticity of transmission with respect to daily deaths given as a compound parameter capturing both private and public responses to daily deaths

$$\kappa = \kappa_p + \eta_v + \eta_u$$

The parameter $\psi(t)$ corresponds to changes in disease transmission that are unrelated to the level of daily deaths. In the baseline model, this variation is pure seasonal variation in disease transmission.

In fitting the model to the data, I introduce several shocks.

First, I introduce a one-time change in behavior modeled as a reduction in the semi-elasticity of the transmission rate with respect to the daily death rate from an initial level to a new, permanently lower level. I refer to this second shock as the onset of pandemic fatigue. When I fit the model to the United States, I assume that pandemic fatigue sets in late in 2020. In updating the model for 2021, I find that I do not need to incorporate any

further changes in the semi-elasticity of the transmission rate with respect to the daily death rate. That is, I find that I can account for the data on daily deaths in 2021 with a single behavioral parameter.

Second, I model the introduction of the variants Alpha, Delta, and Omicron. Alpha is introduced to the United States on December 1, 2020. The transmissibility of this variant is set to be 50% higher than the original variant. Delta is introduced on April 25, 2021. The transmissibility of this variant is set to be 75% more transmissible than the Alpha variant. Omicron is introduced to the United States on November 6, 2021. I assume that this variant can transmitted to those in the recovered compartment R (corresponding to those with immunity from infection with prior variants and/or vaccines) at 1/25th the rate at which it is transmitted to those in the susceptible compartment S. The transmissibility of Omicron to susceptibles is very high — 2.45 times that of Delta. With this combination of ability to infect those with prior immunity and this underlying transmissibility, the Omicron variant rapidly displaces Delta and prior variants.

Third, I introduce vaccines on January 1, 2021. I model the impact of vaccines as moving agents from the susceptible compartment S directly to the removed compartment R at a rate $\lambda(t) = 0.004$ per day after they are introduced. With this assumption, I impose that the vaccine blocks both transmission by the vaccinated and disease in the vaccinated.

I assume that the infection fatality rate for the original, Alpha, and Delta variants is constant over time at 0.5% (0.005). I assume that Omicron has an infection fatality rate of 0.002 (or 2/5 the level of prior variants) for those with neither prior infection or vaccines (in the S compartment). I assume that the infection fatality rate for Omicron is substantially lower at 0.00004 (or 1/125th the level of the earlier variants) for those with immunity from prior infection or vaccine (in the R compartment). I assume that the protection offered by vaccines and prior infection in terms of reducing the infection fatality rate wanes at a rate corresponding to expected protection of 3 years for all variants.

The model allows for variation over time in the parameter $\kappa(t)$ governing the semi-elasticity of transmission with respect to the level of daily deaths, with a higher value of $\kappa(t)$ denoting a stronger endogenous equilibrium response of disease transmission to changes in the level of daily deaths. It turned out that the fit of the model with its baseline parameters is obtained with a parsimonious specification of the evolution of this parameter over time as shown in Figure 4.

As we see in this figure, the model estimates that the endogenous equilibrium response of disease transmission to the level of daily deaths was substantially stronger from the start of the epidemic through late Fall of 2020 than the estimate of that response for the rest of that pandemic (the parameter $\kappa(t)$ drops to 35% of its initial value). After that period, the model matches the peaks of daily deaths associated with the Alpha variant (in January of 2021), the Delta variant (in Fall of 2021), and the Omicron variant (in January of 2022) quite closely with the parameter $\kappa(t)$ governing the strength of the behavioral response to the level of daily deaths held constant through these three waves. I interpret this finding as a validation of the model estimate of the strength of this behavioral response of private and public mitigation efforts to slow disease transmission to the level of daily deaths as it seems quite plausible that the introduction of more transmissible variants can be considered as exogenous shocks.

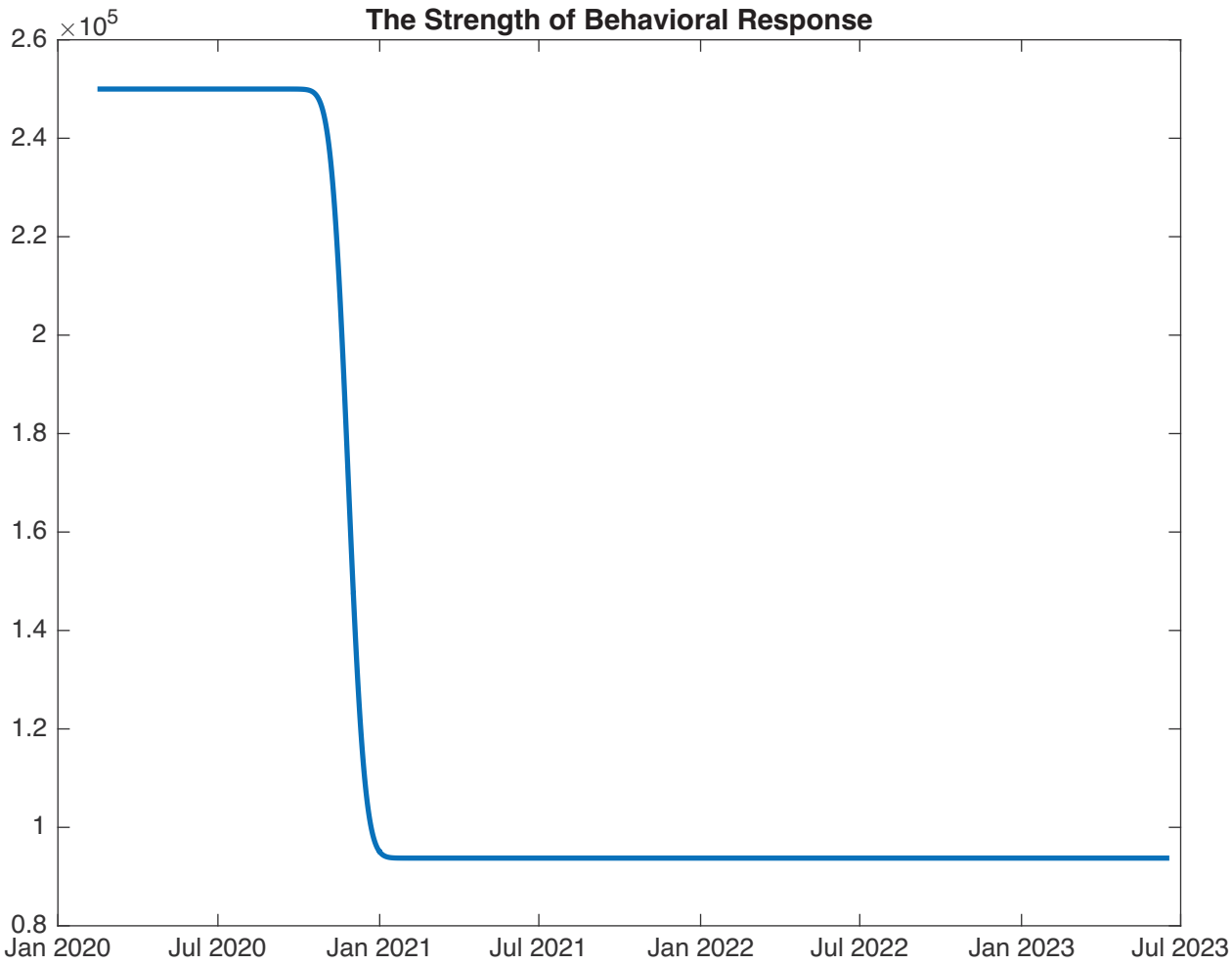

Figure 4: Semi-elasticity of behavioral response baseline model

In the baseline simulation, and in each counterfactual simulation, the differential equations of the model are simulated starting from an initial condition of a small number of individuals infected with the initial variant introduced into the United States on February 15, 2020. In each simulation, these differential equations are solved for a time period corresponding through June of 2023. The dates at which the Alpha, Delta, and Omicron variants are introduced, as well as the parameters governing their transmissibility and infection fatality rates are held constant across all simulations. In the counterfactual simulations, I alter only the parameters governing the deployment of vaccines or the strength of the endogenous response of mitigation to daily deaths as captured by the parameter $\kappa(t)$.

4 Model Baseline and Two Main Counterfactuals

The implications of the model with its baseline parameters for the dynamics of cumulative and daily deaths from COVID-19 are shown in Figures 1 and 2 above. In these figures, the model implications are shown as blue lines, while the mortality data from the CDC is shown as red dashed lines. We see in this figures that the model matches the dynamics of

COVID-19 mortality in the United States quite well. These data were used in choosing model parameters.

In Figure 3, I compare the implications of the model for infection-induced and cumulative seroprevalence to the data from the CDC Blood Donor Serology Survey. The solid blue line in the figure corresponds to the model estimate of combined-seroprevalence. It corresponds to one minus the fraction of the population currently in the susceptible compartment S.[12] The red line in the figure is the model's implication for cumulative infections taking into account waning immunity for those previously infected. Note that these serology data were not used in choosing model parameters. We see in this figure that the model implications for the dynamics of COVID infections and vaccinations is roughly consistent with those found in the CDC Blood Donor Serology Survey in that the model implies that a large portion of the population is vaccinated before they are first infected with COVID-19.

4.1 No Vaccines

To model counterfactual outcomes with no vaccines, I set the parameter $\lambda(t)$ governing the pace of vaccine deployment to zero for all dates t. The model results for the dynamics of COVID-19 deaths in this no-vaccine counterfactual together with the CDC data on COVID-19 mortality are shown in Figures 5 and 6, with the model implications shown as solid blue lines and the CDC data as dashed red lines.

We see in Figure 5 that model-implied cumulative mortality from COVID-19 in this no-vaccine scenario rises far above actual mortality starting in early 2021, consistent with the view that vaccines started to have a measurable impact on COVID-19 mortality at this time. We see in Figure 6 that, in the absence of vaccines, daily deaths in 2021 would have consistently exceeded the first peak level of deaths in the Spring of 2020. The model has this implication because of the model estimate that the endogenous behavioral response of private and public mitigation efforts to the level of daily deaths was much weaker in 2021 than it was in the Spring of 2022.

We also see in Figure 6 that the model implied level of daily deaths in the absence of vaccines falls substantially in 2022. The model has this implication because the Omicron wave infects a large number of individuals early on in 2022, raising the model-implied combined seroprevalence close to 95%, just as in the baseline scenario shown in Figure 3.

Based on a comparison of this counterfactual no-vaccine model simulation with the CDC data on COVID-19 deaths and the results of the baseline model simulation shown in Figures 1 and 2, I derive this model-based estimate that the introduction and deployment of vaccines saved roughly 748,600 lives in the United States over the period from February 15, 2020 through June 2023, with most of this impact of vaccines on COVID-19 mortality occurring during 2021.

[12] I do not consider the impact of births and deaths over the nearly three years of the COVID epidemic in computing model implications for fractions of the population in various compartments. Note that the blue line in Figure 3 levels off at roughly 95% after January 2022 as, in the model, waning immunity from either prior infection or vaccines refreshes the pool of susceptibles. The antibodies detected in a serology survey also wane over time, so that a previously vaccinated or infected person might be recorded as not having antibodies after a long enough interval. It is not clear whether waning immunity and the waning of antibodies happen at the same rate.

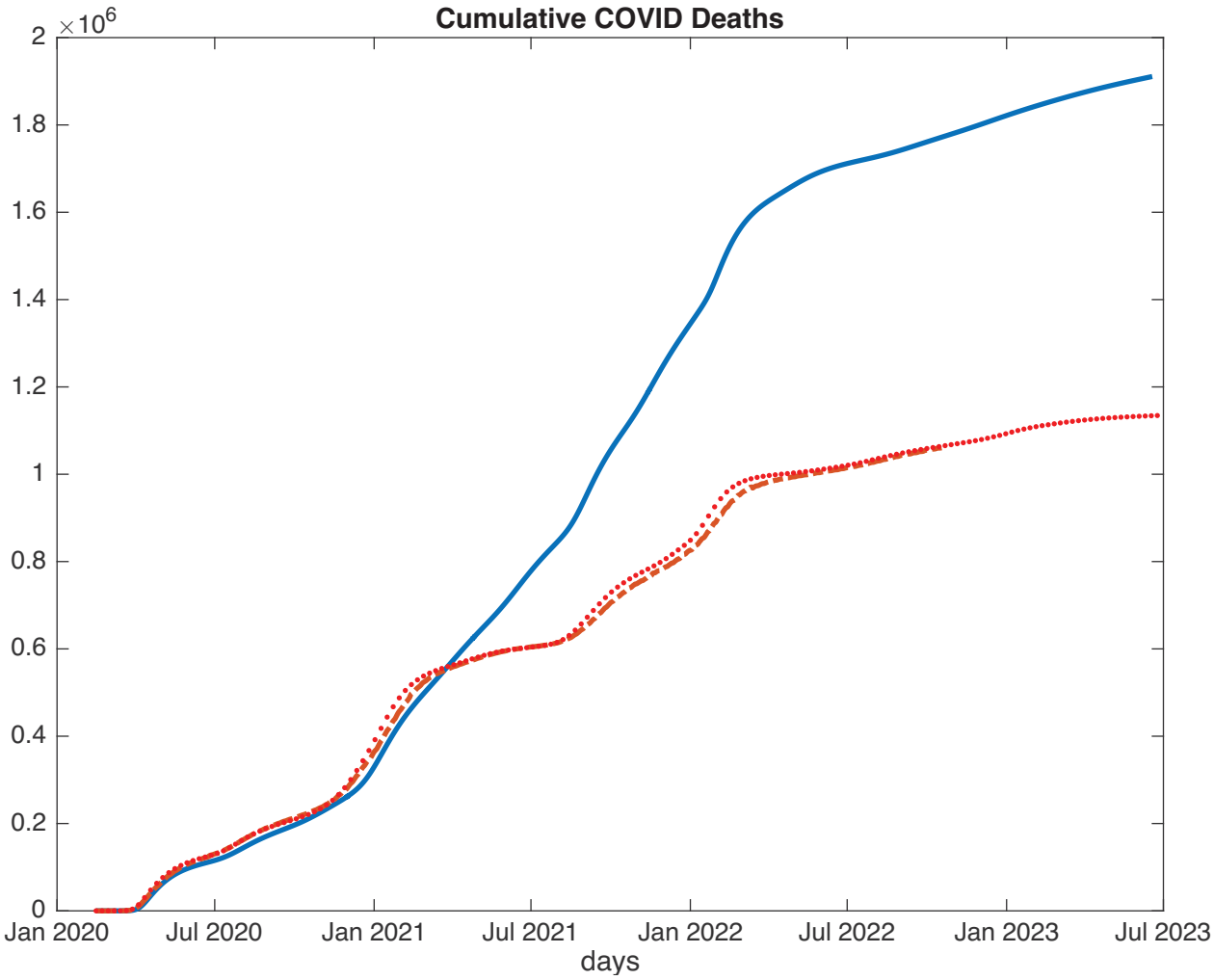

Figure 5: CDC Data and Model implications for cumulative COVID deaths with no vaccines

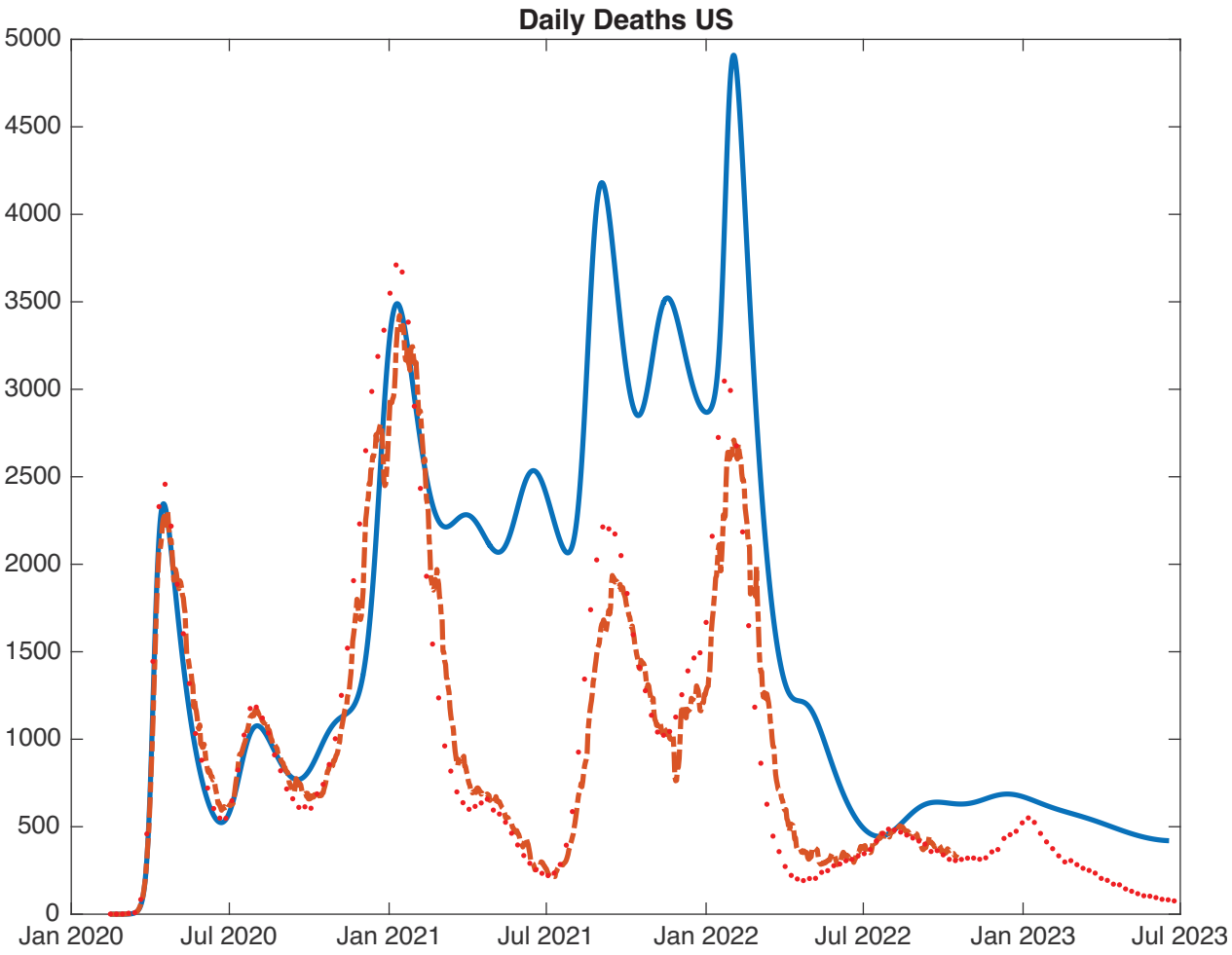

Figure 6: CDC Data and Model implications for daily COVID deaths with no vaccines

4.2 No Mitigation

To model counterfactual outcomes with vaccines but with no public or private efforts to mitigate disease transmission, I set the parameter $\kappa(t)$ governing the strength of that behavioral response to zero for all dates, with all other parameters including $\lambda(t)$ set to their baseline values. In this counterfactual scenario, the model implies cumulative deaths well above the actual total that occurred and close to the total in the case with no vaccines shown in Figure 5.

This finding that vaccines have virtually no impact on cumulative mortality in the absence of a behavioral response can be understood by examining the model's implication for the timing of COVID-19 deaths under this counterfactual scenario of no behavioral response to the epidemic shown as the blue line in Figure 7. In this figure we see that the model implies that, absent mitigation, the large majority of COVID-19 deaths would have occurred well before vaccines were introduced in late 2020.

Based on a comparison of the model implications for this counterfactual scenario with no mitigation efforts to the data on COVID-19 deaths and the model baseline implications for these data shown in Figures 1 and 2, I conclude that mitigation efforts in 2020 and 2021

were essential for the success of vaccines in saving lives.

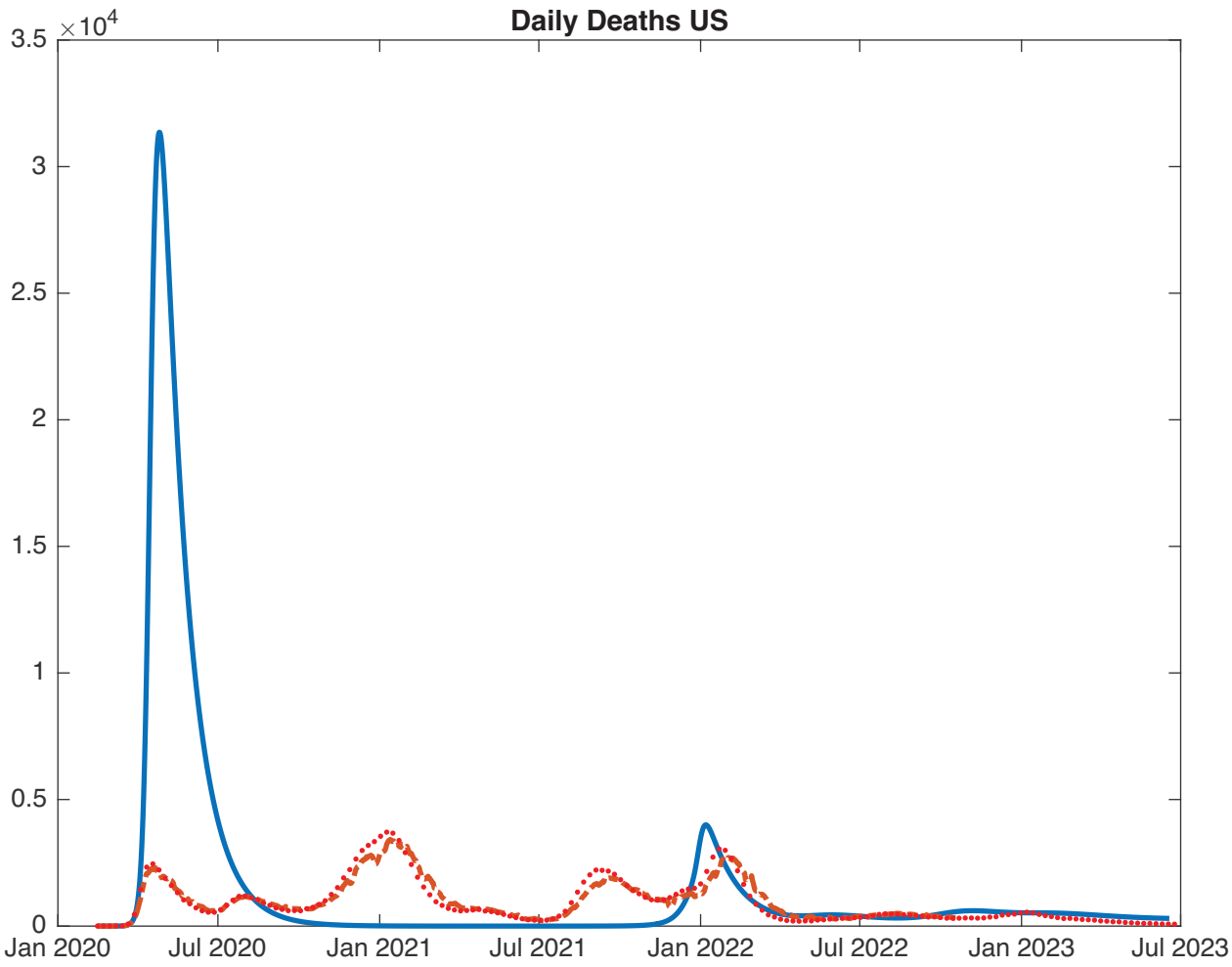

Figure 7: CDC Data and Model implications for daily COVID deaths with no mitigation

5 Early Vaccines

The argument that vaccines saved lives to the extent that Americans were able to get vaccinated before their first infection with COVID-19 suggests that a considerable number of American lives could have been saved if it had been possible to deploy vaccines earlier. To investigate this hypothesis, I use the model to calculate counterfactual cumulative mortality from COVID-19 over the period February 2020 through June 2023 under the scenario that vaccines were deployed 180 days earlier than they actually were. In Figure 8, I plot the model's implications for the dynamics of daily deaths from COVID-19 in this scenario with early vaccines. In this counterfactual scenario with early vaccines, the model predicts cumulative mortality over this time period of 755,630. This predicted cumulative mortality is considerably smaller than the model prediction of 1,162,300 deaths under the baseline scenario. That is, early deployment of vaccines might have saved over 400,000 lives.

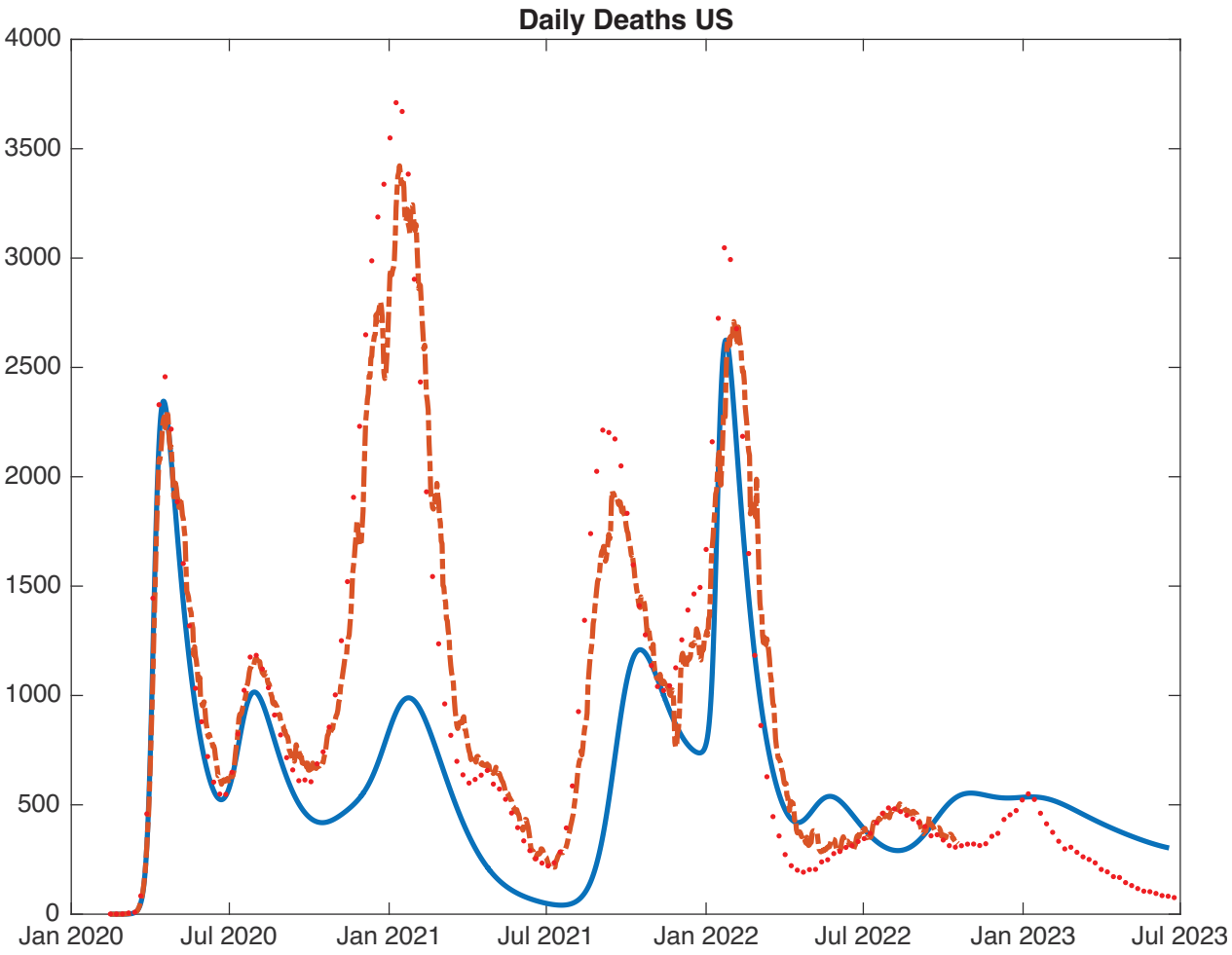

Figure 8: CDC Data and Model implications for daily COVID deaths with early vaccines

6 Marginal Changes in Behavior

In Figure 4 above, I display the model estimate of how the strength of the endogenous equilibrium response of public and private behavior impacting disease transmission to daily deaths varied over the course of the epidemic. We see in this figure that this response is estimated to have been substantially stronger before late Fall 2020 than it was afterwards. I now use the model to conduct two counterfactual exercises regarding the impact of marginal changes in behavior motivated by this estimate of the change in the strength of the behavioral response to the level of daily deaths in the early and subsequent phases of the COVID-19 epidemic.

6.1 Strong Behavior Throughout

In the first of these exercises, I use the model to calculate the counterfactual dynamics of deaths from COVID-19 under a scenario in which the strength of the endogenous response of private and public efforts to mitigate disease transmission to the level of COVID-19 deaths

had remained at its initially high level throughout the time period considered. I refer to this scenario as strong behavior response. I report the model's implications for the dynamics of daily COVID-19 deaths in this counterfactual behavior of strong behavior throughout in Figure 9.

Here I find that a consistently strong behavioral response over this time period would have saved about 283,570 lives, with most of these lives saved during the waves associated with the Alpha and Delta variants. That is, the model simulation with this strong behavioral response predicts cumulative COVID-19 mortality from early 2020 through June 2023 of 878,730 as opposed to the baseline predicted cumulative mortality of 1,162,300.

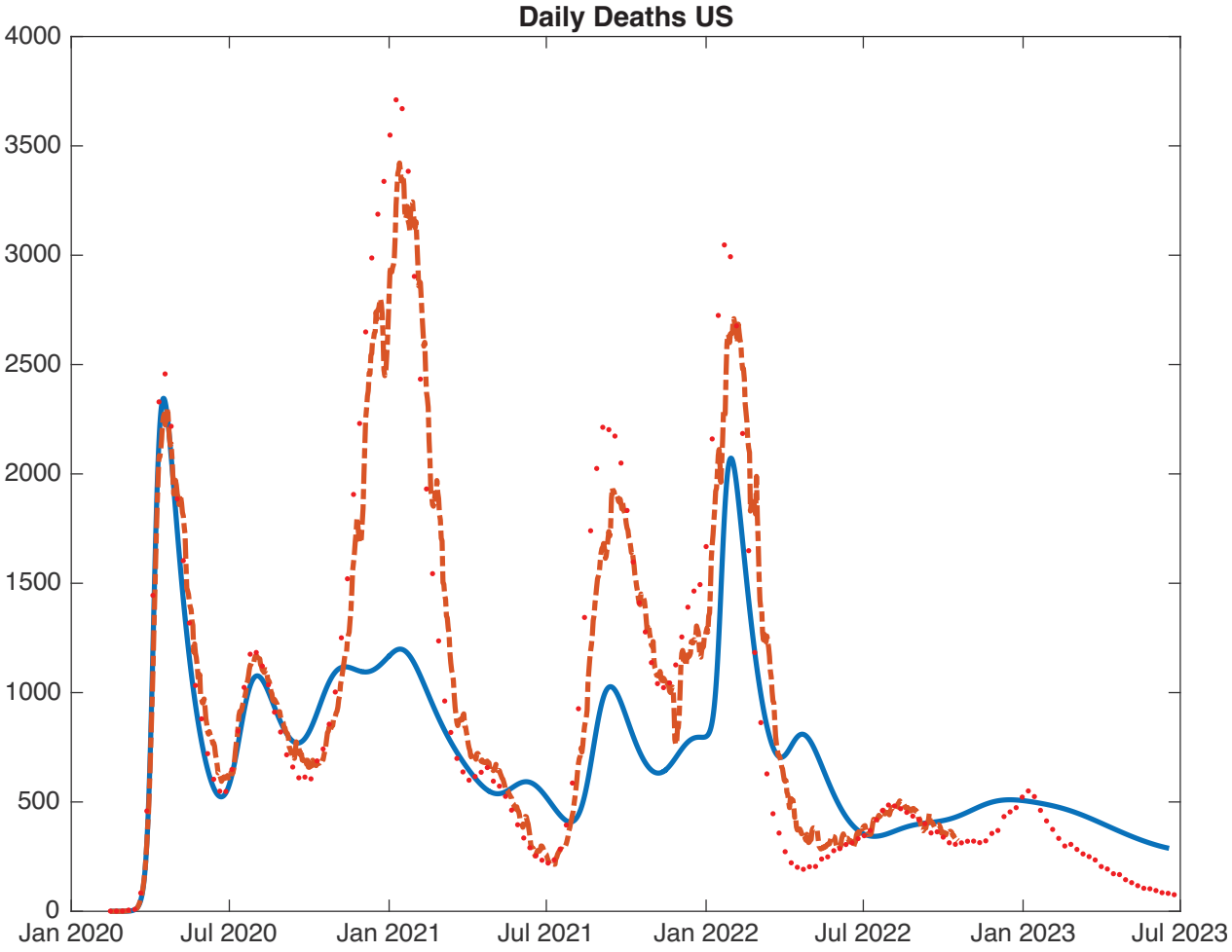

Figure 9: CDC Data and Model implications for daily COVID deaths with strong behavior throughout.

Note that this counterfactual simulation should not be considered as an evaluation of any specific public or private mitigation effort. Furthermore, it cannot be considered as an evaluation of specific data-driven rule for interventions by public health authorities as the endogenous response of disease transmission to the level of daily deaths is the result of the composite of private and public efforts. Further research is needed to identify the separate impacts of public and private actions to reduce disease transmission.

6.2 Weak Behavior Throughout

In the second of these exercises, I use the model to calculate the counterfactual dynamics of deaths from COVID-19 under a scenario in which the strength of the endogenous response of private and public efforts to mitigate disease transmission to the level of COVID-19 deaths had been constant at its low level after the late Fall of 2020 throughout the time period considered. That is, with this simulation, I consider what might have been the impact on cumulative COVID-19 mortality had the endogenous response of disease transmission to daily deaths started out at is subsequent, weaker, level. I refer to this scenario as *weak behavioral response*. I report the model's implications for the dynamics of daily COVID-19 deaths in this counterfactual behavior of weak behavior throughout in Figure 10.

Here I find that a consistently weak behavioral response over this time period would have cost about 172,700 additional lives. That is, the model simulation with this strong behavioral response predicts cumulative COVID-19 mortality from early 2020 through mid-October 2022 of 1,335,000 as opposed to the baseline predicted cumulative mortality of 1,162,300. This increase in cumulative mortality occurs largely in this first wave of the pandemic. In this scenario, more Americans would have gotten their first COVID-19 infection before they were vaccinated.

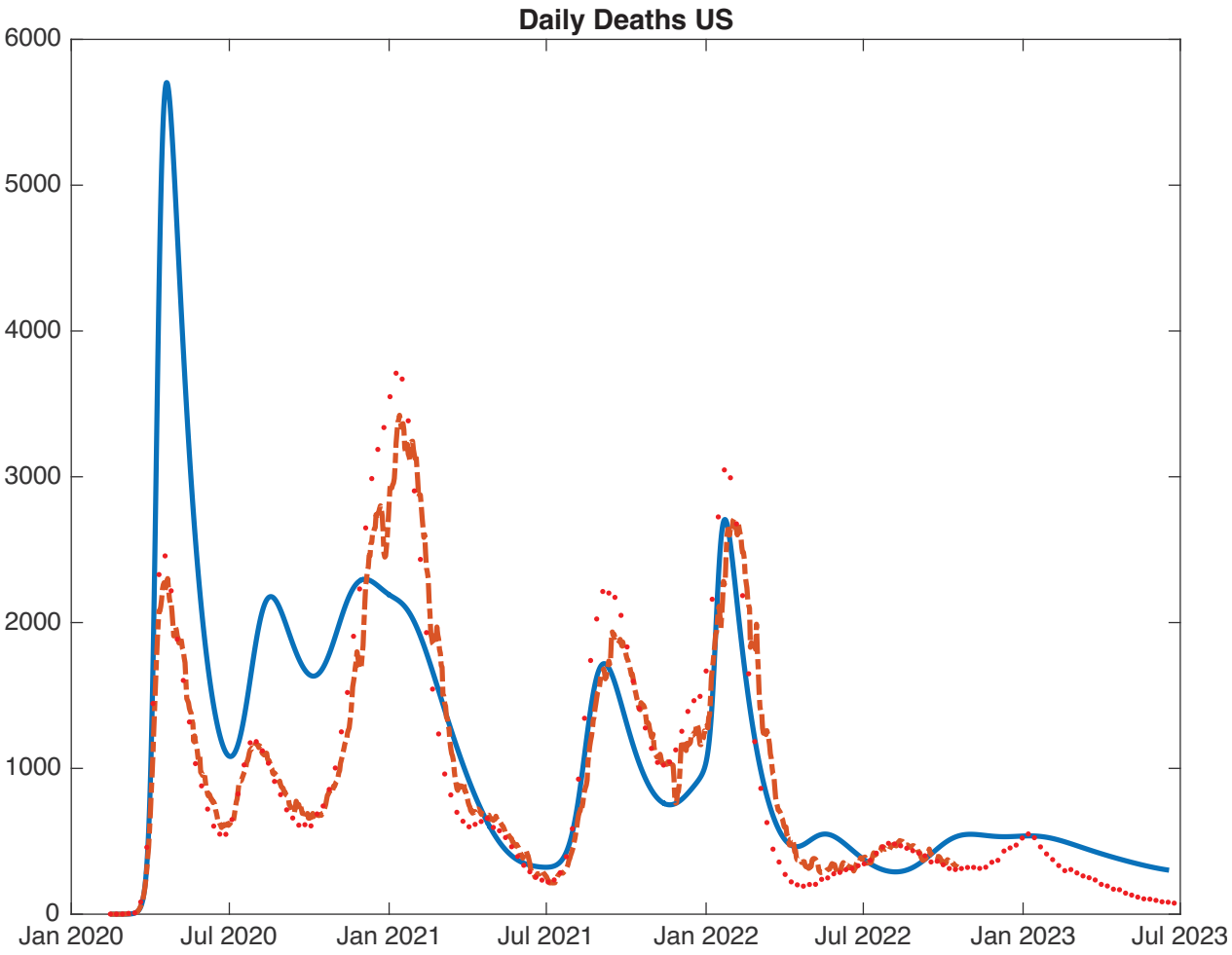

Figure 10: CDC Data and Model implications for daily COVID deaths with weak behavior throughout.

Further research is needed to evaluate the tradeoff between lives lost and economic and other benefits that might have arisen had the behavioral response been marginally weaker in the first phase of the epidemic.

7 Conclusion

In this paper, I have presented a parsimonious behavioral epidemiological model to evaluate the impact on cumulative mortality from COVID-19 over the period February 2020 and June 2023 of the introduction and deployment of vaccines and of alternative behavioral responses to the level of daily COVID-19 deaths. I find that vaccines, in combination with mitigation efforts during 2020 and 2021, dramatically reduced the cumulative death toll from COVID-19. I find that vaccines alone, without these mitigation efforts, would not have had much impact on cumulative COVID-19 mortality as, in this case, most people would have been infected with COVID-19 prior to being vaccinated.

The approach taken in this paper highlights the importance of considering the equilibrium dynamics of behavior together with that of the COVID-19 epidemic itself to assess the impact

of changes in the timing of vaccine deployment and/or changes in the strength of public responses to the dynamics of this epidemic. I leave it to future research to separately analyze the role of public policy and private behavior in shaping cumulative mortality from COVID-19.

One important shortcoming of this modeling effort is that I do not disaggregate the model by age. Given the strong evidence that infection fatality rates from COVID-19 were much higher for the elderly than for other groups, a more precise answer to the questions raised in this paper might require an examination of the rate at which the elderly were vaccinated before their first infection with COVID-19. There is some evidence on this question from the CDC Blood Donor Serology surveys that disaggregate results by age. But incorporating separate age groups into the model would require modeling of different behavioral responses of different age groups. See, for example Glover et al. (2023) and Eichenbaum et al. (2023) .

8 Model Appendix

This appendix presents the model and parameters used in this paper. This model is an update of the model presented in the appendix to "Behavior and the Dynamics of Epidemics" by Andrew Atkeson for the Brookings Panel on Economic Activity Spring 2021. This model is based closely on that presented in "A Parsimonious Behavioral SEIR Model of the 2020 COVID Epidemic in the United States and United Kingdom" which is available as NBER working paper 28434 and as Federal Reserve Bank of Minneapolis Staff Report 619. This appendix discusses the model extended to include vaccines and the potential for waning immunity, as well as the arrival of the Delta and Omicron variants. It is applied to the United States.

This appendix has three parts. In section 8.1, I present the equations of the model. I also compare the structure of this model with that of a simpler behavioral SIRD model as analyzed in Atkeson, Kopecky, and Zha (2021)[13] and Droste and Stock (2021)[14] .

In section 8.2, I discuss the values of the parameters. The model is fit to US data on daily deaths from COVID. Several parameters are set to match recommendations from the Center for Disease Control for modeling of COVID-19. Other parameters, in particular, the basic reproduction number of the original variant of the virus, the original semi-elasticity of the transmission rate to the level of daily deaths, and the size of the seasonal fluctuation in transmission, are chosen through a process of trial and error. It would be useful to make these parameter choices more systematic.

In section 8.3 I describe the files used in the code for the model and what steps a user must take to run the model and the counterfactual experiments.

8.1 Model

The model is as follows.

The SEIHR model extends the SIR model by adding both the exposed state E and the hospitalized state H. In this version of the model the total population N is given by the sum of susceptible agents in state S, exposed in state E, infected in I, hospitalized in H, recovered in R, and dead in D.

The compartments E and I are further broken down by variant i, where i indexes the original variant, and the Alpha, Delta, and Omicron variants. The rate at which agents leave the E_i compartmenst for both the normal and more transmissible variants is σ and the rate at which agents leave the I_i compartments for all variants is γ. I also include compartments E_i and I_i corresponding to those experiencing breakthrough Omicron infections. These individuals are modeled as having immunity to previous variants but not to Omicron. The mean generation time for the model is then $1/\sigma + 1/\gamma$. As discussed below, the choice of these parameters is guided by CDC recommendations for these disease parameters.

As agents leave the I_i compartment, fraction η_i go into the hospitalized compartment H

[13] Atkeson, Kopecky, and Zha "Behavior and the Transmission of COVID-19" forthcoming, *American Economic Review Papers and Proceedings* with the longer version available here https://www.minneapolisfed.org/research/staff-reports/behavior-and-the-transmission-of-covid19

[14] Droste and Stock "Adapting to the Pandemic" forthcoming, *American Economic Review Papers and Proceedings*

and $1-\eta_i$ transition directly to the recovered compartment R_i. The rate at which agents leave the H compartment is ζ. I assume that all agents leaving the H compartment die. Thus, the overall infection fatality rate for variants is given by η_i and the mean time in the H compartment corresponding to illness and delays in reporting deaths is $1/\zeta$. Note that with these assumptions, it is not appropriate to compare the model's predictions for hospitalizations to data. Instead, this H compartment simply serves to introduce a delay between infection and death.

The transmission rate of the original variant is denoted by $\beta(t)$. Those for the new variants are denoted by $\beta_i(t)$. New variants are introduced by setting $\bar{E}_i(t) = 1/population$ in the equations below for two days on a specified date t_i and equal to zero otherwise. This corresponds to the introduction from abroad of a single individual carrying this more transmissible variant. Note that this quantity is subtracted off of the change in the R compartment simply to keep the population constant. Since this shift is only one person for one day, it does not impact the quantitative implications of the model for large populations.

For the Omicron variant, I assume that those infected with Omicron transmit their infection to those in the removed compartment R at a fraction ν_O of the rate at which they transmit their infection to those in the susceptible compartment S. The infection fatality rate from Omicron for those with no prior infection or vaccination is η_O while that for those infected with Omicron but with prior immunity (i.e. coming out of the R compartment) is η_{OR}. I include separate compartments for those exposed to and infected with Omicron depending on whether they came out of the S compartment or the R compartment to allow for these separate infection fatality rates. I assume that those infected with Omicron who do not die transit to a separate compartment removed compartment R_O indicating immunity from prior infection with Omicron. I assume that this protection against serious disease wanes at the same rate ξ as assumed for other variants.

I assume that prior infection with Omicron confers immunity against both Omicron and other prior variants.

I do not consider population growth in the model.

The dynamics of the model are given by

$$\frac{dS(t)}{dt} = -\left(\beta(t)I(t) + \sum_{i=A,D,O,OR} \beta_i(t)I_i(t)\right)S(t) - \lambda(t)S(t) + \xi R(t) + \xi R_O(t)$$

where $R_O(t)$ denotes those who have recovered from a breakthrough infection of Omicron (i.e. they were infected while in the R compartment)

$$\frac{dE(t)}{dt} = \beta(t)I(t)S(t) - \sigma E(t)$$

For $i = A, D, O$

$$\frac{dE_i(t)}{dt} = \beta_i(t)I_i(t)S(t) - \sigma E_i(t) + \bar{E}_i(t)$$

Here the terms $\bar{E}_i(t)$ are used to introduce agents infected with new variants on particular dates. In the code, these terms are zero except for a two day window in which the new variant is introduced with this term equal to 1/330,000,000 in this two-day time window.

For $i = OR$

$$\frac{dE_{OR}(t)}{dt} = \beta_{OR}(t)I_{OR}(t)\nu_O R(t) - \sigma E_{OR}(t)$$

$$\frac{dI(t)}{dt} = \sigma E(t) - \gamma I(t),$$

For $i = A, D, O, OR$

$$\frac{dI_i(t)}{dt} = \sigma E_i(t) - \gamma I_i(t)$$

$$\frac{dH(t)}{dt} = \eta\gamma(I(t) + \sum_{i=A,D} I_i(t)) + \eta_O\gamma I_O + \eta_{OR}\gamma I_{OR} - \zeta H(t)$$

Recall that the parameters η_i denote the infection fatality rate for different variants since all agents who flow into the H compartment eventually die. As mentioned above η is a single number of the original, Alpha, and Delta variances and then is different for Omicron and Omicron breakthrough infections.

$$\frac{dR(t)}{dt} = (1-\eta)\gamma(I(t) + \sum_{i=A,D} I_i(t)) - \sum_{i=A,D,O} \bar{E}_i(t) + \lambda(t)S(t) - \xi R(t)$$

Here $\lambda(t)$ denotes the flow of susceptibles into R due to vaccination. $\lambda(t) = 0$ prior to the introduction of vaccines and is set to a constant rate after that date.

$$\frac{dR_O(t)}{dt} = (1-\eta_O)\gamma I_O + (1-\eta_{OR})\gamma I_{OR} - \xi R_O(t)$$

All those who do not die of Omicron flow into the recovered from Omicron compartment. Finally, deaths are recorded as agents flow out of the H compartment

$$\frac{dD(t)}{dt} = \zeta H(t)$$

To measure the model's implications for the fraction of the population that show combined immunity from either prior infection or vaccination, I use $1 - S(t)$. To measure the model's implications for the fraction of the population that show infection-induced immunity, I use a running total $CI(t)$ that starts equal to zero, with

$$\frac{dCI(t)}{dt} = (1-\eta)\gamma(I(t) + \sum_{i=A,D} I_i(t)) - \sum_{i=A,D,O} \bar{E}_i(t) + (1-\eta_O)\gamma I_O + (1-\eta_{OR})\gamma I_{OR} - \xi CI(t)$$

The reduced-form for the behavioral response of the transmission rate to the level of daily deaths is given by

$$\beta(t) = \bar{\beta}\exp(-\kappa(t)\frac{dD(t)}{dt} + \psi(t)) \tag{2}$$

and for variants

$$\beta_i(t) = \bar{\beta}_i\exp(-\kappa(t)\frac{dD(t)}{dt} + \psi(t))$$

where the parameters $\bar{\beta}$ and $\bar{\beta}_i$ control the baseline transmissibility of the original and subsequent variants of COVID, the parameter $\psi(t)$ is used to introduce seasonality in transmission,

and $\kappa(t)$ is the semi-elasticity of transmission with respect to the level of daily deaths. Note that the relative transmissibility of each variant for any level of daily deaths and point in the seasonal cycle is given by $\bar{\beta}_i/\bar{\beta}$.

To model seasonality in the transmission of the virus, we set

$$\psi(t) = seasonalsize * (\cos((t + seasonalposition) * 2\pi/365) - 1)/2$$

where *seasonalsize* controls the magnitude of the seasonal fluctuations in transmissibility holding behavior fixed and *seasonalposition* controls the location of the seasonal peak in transmission. Note that t is indexed to $t = 0$ on February 15, 2020.

To model the change in $\kappa(t)$, I set

$$\kappa(t) = \bar{\kappa} * (1 - normcdf(t, fatiguemean, fatiguesig))+$$

$$fatiguesize * \bar{\kappa} * normcdf(t, fatiguemean, fatiguesig)$$

where $\bar{\kappa}$ sets the initial semi-elasticity of transmission with respect to daily deaths, $fatiguesize$ sets the percentage reduction in this semi-elasticity in the long run, *normcdf* is the normal CDF, $fatiguemean$ sets the date at which the transition in $\kappa(t)$ from its initial to new long run level is halfway complete, and $fatiguesig$ sets the speed with which that transition occurs.

Initial conditions for all simulations are $E(0) > 0$, $E_i(0) = I(0) = I_i(0) = R(0) = R_O(0) = H(0) = D(0) = 0$, $S(0) = 1 - E(0)$. For the United States, $E(0) = 33$ on February 15 out of a population of 330 million.

8.2 Parameters

In this section I discuss the choice of parameters and shocks to the model. Most of the parameters are the same as those used in the Spring 2021 version of this paper. The new parameters in this version of the model pertain to the dates of introduction and the transmission rates and infection fatality rates for the Delta and Omicron variants as well as the speed of waning immunity. I first discuss these new parameter choices in subsection 8.2.1 and then I review the choices for parameters made in the Spring 2021 version of this paper in 8.2.2.

Note that this model is highly non-linear and that the choice of parameter values is not done in a systematic manner. A systematic review of parameter choices would be useful as a subject for future research.

All parameters except the date of introduction of vaccines are set in the MATLAB file *Omicronv1.mlx*. I indicate line numbers in those files where these values are set. The date of introduction of vaccines is set in the MATLAB file *omicronodefile.m*. I indicate the line number in that file below.

The model simulation starts at $t = 0$ corresponding to February 15, 2020 (line 117) and is run for 3.34×365 days (line 7) ending in late June 2023.

8.2.1 New Parameters

The new parameter of the model pertain to the Delta and Omicron variants and waning immunity.

I assume that the Delta variant is introduced by a single individual on April 25, 2021 (lines 92 and 93). The transmissibility of this variant is set to be 75% more transmissible than the Alpha variant (i.e. $\bar{\beta}_D = 1.75\bar{\beta}_A$ on line 54). I assume that Delta has the same infection fatality rate as prior variants. (This infection fatality rate η is set on line 48)

This assumed transmission rate for Delta relative to Alpha was chosen by trial and error. The model predictions for the height of the peak of daily deaths due to Delta and the timing of that peak are very sensitive to the choice of this transmission rate.

For waning immunity, I set $\xi = 1/(3 * 365)$ (line 66 and line 27 for Omicron) which corresponds to an expected time to loss of immunity of 3 years. Note that this rate corresponds to a 29% loss of immunity in one year. This parameter was set with reference to estimates of the timing of waning immunity from vaccines from the IHME group at the University of Washington that were summarized in Figures 2 and 3 of a post https://www.healthdata.org/special-analysis/omicron-and-waning-immunity. Estimates of the timing of waning immunity from prior infection with COVID were shown in Table 2 of the same post. These estimates showed a wide range of estimates of the speed of waning immunity with protection from infection estimated to wane faster than protection from serious disease and death. Unfortunately, this post is no longer available online.

The third shock is the introduction of the Omicron variant. This variant is introduced by a single individual on November 1, 2021 (lines 34 and 35). I assume that this variant can transmitted to those in the recovered compartment R (corresponding to those with immunity from infection with prior variants and/or vaccines) at 1/25th the rate at which it is transmitted to those in the susceptible compartment S (line 10). The transmissibility of the Omicron variant from infected to susceptibles is set on line 100 and its transmissibility relative to Delta is set at 2.45 as reported on line 101. This combination of inherent transmissibility and ability to infect those with immunity to prior variants were chosen to match data on the growth in Omicron cases relative to that for Delta cases in Gautang South Africa in November of 2021 (this calculation is done on lines 99 and 100) . With this combination of ability to infect those with prior immunity and this underlying transmissibility, the Omicron variant rapidly displaces Delta and prior variants.

I assume that prior infection or vaccination offers substantial protection against death from Omicron. In particular, I set the infection fatality rate from Omicron for those with prior immunity to 1/50th the infection rate for Omicron for those without prior immunity ($\eta_{OR} = 0.02\eta_O$) (line 19). I set the infection fatality rate from Omicron for those without prior immunity to 40% that of prior variants. That is $\eta_O = 0.4\eta = 0.002$ (line 15).

8.2.2 Old Parameters

The following repeats the discussion of model parameters used in the Spring 2021 prior version of this paper. Please see that prior version of this paper for a review of the sensitivity of model result to those parameter choices.

I group the old parameters of the model into three sets.

The first set are those set from CDC model recommendations for the generation time of infections and the infection fatality rate. As is standard in an SIR model, the basic reproduction number, which is a ratio of two rates and is thus unitless, determines the overall shape of the epidemic. The generation time then determines the time-scale over which the

epidemic plays out.

This first set of parameters is set as follows: $\gamma = 0.4$ (line 44) and $\sigma = 0.425$ (line 46). The parameter σ corresponds to an expected time before an exposed agent becomes infectious of 2.35 days and the parameter γ corresponds to an expected time for which an infected individual is infectious of 2.5 days. The generation time is defined as the average time between which one infected individual shows symptoms and a person infected by that individual shows symptoms. These two parameters together imply an average generation time of $1/\sigma + 1/\gamma = 4.85$ days.[15] As mentioned above, this generation time sets the time-scale of the epidemic implied by the model. There is some evidence that the generation time for Omicron is shorter than for previous variants. I have not yet incorporated this into the model.

In the model, tthe hospitalization compartment H serves only to introduce a delay between infection and death. Thus, I assume that all people who enter the compartment H die. Accordingly, the infection fatality rate for the original variant is the fraction of individuals flowing out of the infected compartments in the the H compartment. The infection fatality rate $\eta = 0.005$ (line 48) is appleid to the original, Alpha, and Delta variants. As discussed above, I allow for lower infection fatality rates for the Omicron variant.

The second set of parameters is comprised of the rate ζ at which those hospitalized flow to death. This rate ζ is chosen to have an average stay in compartment H of 30 days (line 40), which corresponds to an average stay in the hospital of two weeks for those with serious illness and a reporting delay of deaths of two weeks.[16] This assumption combined with the average generation time assumed above implies that roughly six generations of infections pass on average before reported daily deaths rise provoking a behavioral response. The delay between infection and reported death introduced by this compartment H implies that this simple behavioral model has oscillatory endogenous dynamics that are helpful in allowing the model to reproduce the data with only a few shocks.

The basic reproduction number of the original variant of the virus at peak seasonal transmissibility is $\mathcal{R}_0(t) = \bar{\beta}/\gamma$. For the United States, I set $\bar{\beta} = 3\gamma$ (line 50) giving a peak basic reproduction number at pre-pandemic levels of behavior in Winter of 3. This number is well within the range of estimates of this parameter from the early phase of the pandemic.[17] As discussed in the Spring 2021 version of this paper, this parameter was chosen by trial and error. In that prior version of this paper, I show how changes in the parameter impact the model predictions for daily deaths.

For the Alpha variant, I set $\bar{\beta}_A = 1.5\bar{\beta}$ (line 52) making this variant 50% more transmissible than the original variant at any point in the seasonal cycle and at any level of behavior. The basis for this parameter choice is discussed in the Spring 2021 version of this paper.

The initial semi-elasticity of transmission with respect to daily deaths (measured as a fraction of the population) for the United States is $\bar{\kappa} = 250000$ (line 56). As discussed in the

[15] See https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html. On that webpage, the CDC notes a mean time of approximately six days between symptom onset in one person to symptom onset in another person infected by that individual.

[16] See https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html. On that webpage, the CDC notes a median time from symptom onset to death of approximately two weeks and a median time from death to reporting just under three weeks.

[17] See https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html.

Spring 2021 version of this paper, this parameter was chosen by trial and error.

To model seasonality of transmission in the United States, I set $seasonalsize = 0.35$ (line 74) and $seasonalposition = 20$ (line 77). This seasonal variation in the parameter $\psi(t)$ leads to variation over time in the basic reproduction number of the virus as discussed in the Spring 2021 version of this paper.

The model has several shocks in addition to the seasonal fluctuation in transmission rates. These include pandemic fatigue, the introduction of a new variant on December 1, 2020, the introduction of vaccines, and the counterfactuals of extra mitigation measures that are not dependent on disease prevalence and of waning immunity. I describe the specification and impact of these shocks and counterfactual experiments here.

The initial semi-elasticity of transmission with respect to daily deaths (measured as a fraction of the population) for the United States is $\bar{\kappa} = 250000$. To model the onset of pandemic fatigue in the United States, I set $fatiguesize = 0.375$, (line 81) $fatiguemean = 285$ (line 84) and $fatiguesig = 15$ (line 85). As discussed in the Spring 2021 version of this paper, this semi-elasticity is assumed to fall to 37.5% of its original level late in the year.

To model the impact of vaccines, I set $\lambda(t) = 0.004$ (line 62) starting on January 1, 2021 (this date is set on line 56 of *omicronodefile.m*). I assume that vaccinations are offered to the general population. This implies that in a population of 330 million, the daily number of vaccines administered is close to 1.3 million. In comparing this number to data on vaccinations, one must take into account that most of the vaccines administered require two or three doses for full effect. This assumption implies that roughly 51% of the population is fully vaccinated by July 1, 2021.

8.3 Code

The MATLAB code to run this model and create all of the figures in this document and the main text is comprised of the following files. *Omicronv1.mlx* is a Matlab live script that is the main file. This file calls four Matlab scripts *omicronodefile.m* is a function with all the differential equations described above, *omicronrunthemodel.m* contains the code to solve these differential equations starting from the initial conditions described above with various parameter configurations, and *usdata.m* and *usdataw.m* contains the CDC data on daily COVID and weekly deaths in the United States used in the plots.

To run this code, one should put all four files in the same directory. One need only run the MATLAB Live Script *Omicronv1.mlx*. Note the lines of the baseline parameters in the description above.

To run the counterfactual simulation with no vaccines, uncomment line 64 in *Omicronv1.mlx* to set $\lambda(t) = 0$ for all dates. Be sure to comment that line again to run other counterfactuals with vaccines.

To run the counterfactual simulation with no behavioral response, uncomment line 58 in *Omicronv1.mlx* to set $\kappa(t) = 0$ for all dates. Be sure to comment that line again to run other counterfactuals with behavior.

To run the counterfactual simulation with early vaccines, comment out line 56 in *omicronodefile.m* and uncomment line 58 in that file to move the introduction of vaccines up by 180 days. Be sure to restore the original comments (so line 56 runs and line 58 is comment out) for alternative counterfactuals.

To run the counterfactual simulation with strong behavior throughout, uncomment line 83 in *Omicronv1.mlx* to set the variable *fatiguesize* to 1 so that the resulting $\kappa(t)$ is constant at its initial value throughout. (That should appear in Figure 7 on line 215).

To run the counterfactual simulation with weak behavior throughout, leave line 83 uncommented so that *fatiguesize* to 1 and also uncomment line 60 to reduce the initial value of κ to 0.375 times its baseline value. Be sure to restore default comments to run the baseline version of the model again.

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