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May 5, 2021

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COVID-19 Modeling Consortium

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Overview

To support public health decision-making in Austin, Texas, we project COVID-19 healthcare demand as vaccines continue to roll out, and we provide retrospective estimates for in-hospital COVID-19 mortality during surge and non-surge periods of the pandemic. The projections indicate that a return to COVID-19 Alert Stage 2 in May 2021 would be unlikely to cause a healthcare surge that exceeds local ICU capacity. However, our retrospective estimates of in-hospital COVID-19 mortality suggest that even modest surges may increase the COVID-19 fatality rate and that, throughout the pandemic, in-hospital mortality has disproportionately occurred in communities with overlapping socioeconomic, occupational, and health risks. The analyses are based on multiple assumptions about the transmission rate, age-specific severity of COVID-19, and efficacy of vaccines, and thus do not represent the full range of uncertainty that the city of Austin may encounter. We are posting these results prior to peer review to provide insights regarding changing COVID-19 risks as vaccination coverage continues to increase and to guide the relaxation of COVID-19 mitigation measures in the spring and summer of 2021.

Healthcare Projections Following a Return to COVID-19 Alert Stage 2

The City of Austin uses a five-stage color-coded COVID-19 alert system, where each stage corresponds to a specific combination of social distancing measures and business restrictions [1]. Changes in alert stage are triggered based on the rolling seven-day average of COVID-19 hospital admissions across all area healthcare systems. Austin has been in stage 3 (yellow) since early March of 2021. Figure 1 projects COVID-19 hospitalizations and ICU patients under four retrospective scenarios for transitioning from stage 3 (yellow) to stage 2 (blue) during April of 2021. If the transition had occurred on April 7, then we estimate a 48% chance that COVID-19 patients will exceed local ICU capacity. That risk drops to 31%, 6%, and then 3%, respectively, if the transition to blue had occurred on April 14, 21, and 28. As vaccination coverage increases in Austin, particularly for high risk populations, it becomes safer to relax social distancing and cocooning.

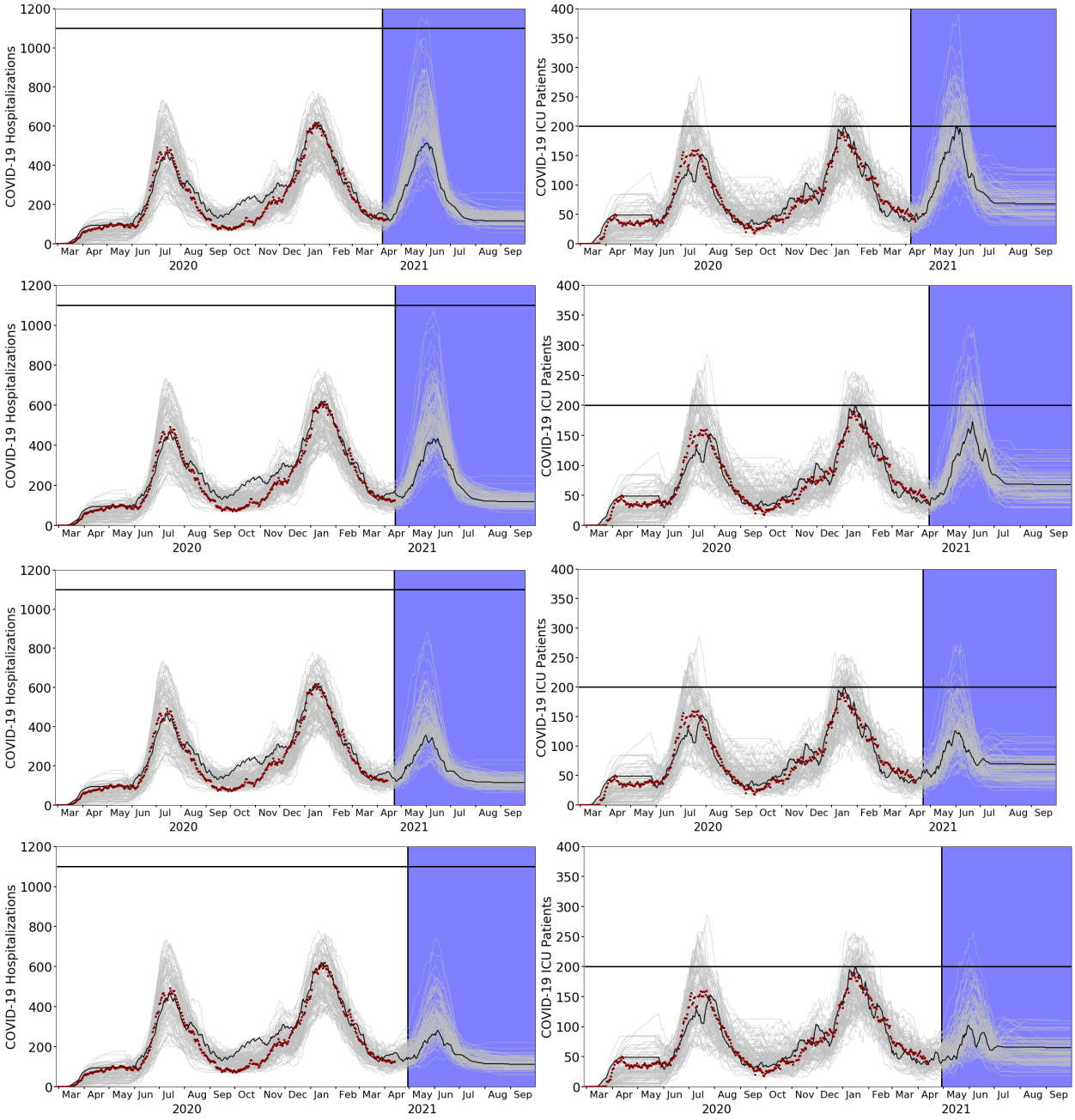

Figure 1: **Projected COVID-19 hospitalizations (left graphs) and ICU patients (right graphs) in the Austin-Round Rock MSA through September 30, 2021, assuming that Austin relaxes from Alert Stage 3 (yellow) to Stage 2 (blue).** From top to bottom, we assume that the relaxation occurs either on April 7, April 14, April 21 or April 28, as indicated by the blue shaded regions. The red points represent historical data, the black horizontal lines represent total hospital capacity (1100 beds) and ICU capacity (200 beds), the light curves indicate stochastic simulations (100 per graph), and solid lines illustrate a representative path. The fraction of scenarios that exceed ICU capacity is almost 50% when we assume an early April transition to the blue alert stage, but drops significantly for the late-April scenarios, given the rapid roll out of vaccines to those over 65 years old and in high-risk groups throughout the month. Specifically, the probability that COVID-19 ICU hospitalizations will exceed the estimated local ICU capacity is 48%, 31%, 6%, and 3% for the four different scenarios, respectively. If we assume that unvaccinated high-risk individuals continue to cocoon (i.e., adhere to cautionary social distancing measures), then the risks of an overwhelming ICU surge drop to 27%, 18%, 6%, and 3%, respectively (Appendix A, Figure 4). We assume that the vaccine uptake rate is 85% in the high-risk groups and in those aged 65 years and older, and that it is 70% for all other adults over 18 years of age.

Geographic and Temporal Variation in In-hospital COVID-19 Mortality

As of April 26, 2021, Travis County has suffered 78 COVID-19 deaths per 100,000 residents. Almost 70% of those have occurred in hospitals. In comparison, the overall COVID-19 mortality rate across Texas is 169 deaths per 100,000 residents. The top left map in Figure 2 illustrates the disproportionate burden of in-hospital COVID-19 deaths across the 43 ZIP codes in Travis County, with some areas experiencing over three times the death rate of other areas. The top right map shows that ZIP codes in east Austin tend to have more vulnerable populations, according to the CDC's social vulnerability index (SVI) [2], a measure of poverty, lack of access to transportation, crowded housing and other factors that increase the likelihood of negative effects on communities caused by external stresses on human health. The scatter plot shows the strong correlation between social vulnerability and COVID-19 mortality. ZIP codes with high SVI scores tend to have experienced higher per capita COVID-19 deaths.

We also note strong temporal trends in the COVID-19 hospital experience. Figure 3 shows the in-hospital COVID-19 mortality rate and the length of COVID-19 hospitalizations through time, for the 17-49y, 50-64y and over 65y age groups. When compared to the overall hospital census (middle graph), we see that the mortality rate tends to increase and the hospital stays tend to get longer, as the overall number of hospitalized COVID-19 patients increases. The weeks leading up to the summer 2020 and winter 2020-2021 surges were particularly deadly across all age groups. The daily estimates are based on all COVID-19 patients admitted to Austin area hospitals within a 60-day rolling window.

There are several possible explanations for the apparent correlation between COVID-19 hospital census and COVID-19 patient outcomes. First, surges in COVID-19 hospitalizations may directly undermine the quality of care and worsens patient outcomes. High influxes of new patients, high overall patient loads, and high patient to staff ratios can cause delayed or insufficient administration of time-sensitive medical interventions. Second, hospitals may be less likely to admit mildly or moderately ill COVID-19 cases during periods of high demand. This could cause the average severity of admitted cases to increase during surges, which would be expected to increase in-hospital mortality rates. Third, demographic shifts in COVID-19 incidence can influence the vulnerability of patients admitted to hospitals, for example, episodic outbreaks in long term care facilities might drive declines in patient outcomes (although our analysis accounts for age groups). Finally, the emergence and spread of more contagious and deadly SARS-CoV-2 variants can simultaneously amplify transmission and exacerbate in-hospital mortality.

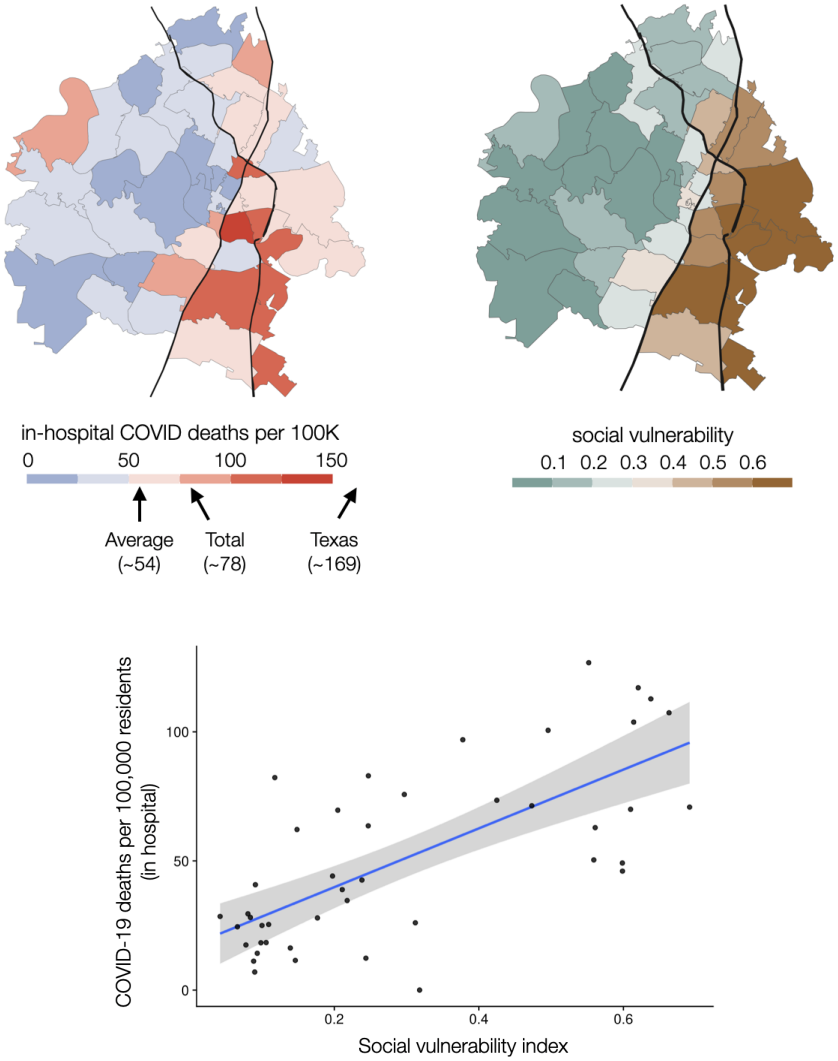

Figure 2: **Geographic variation of social vulnerability and COVID-19 mortality in Austin's 43 ZIP codes through April 26, 2021.** The top-left map indicates the in-hospital COVID-19 mortality rate per 100,000 residents, based on comprehensive data from all three major healthcare systems. ZIP codes are colored by whether their mortality rate is below (blue) or above (red) the city-wide average mortality rate of 54 per 100,000 residents. The map is based on COVID-19 deaths occurring in hospitals and does not include deaths that occur in other settings, such as hospices. The overall in-hospital COVID-19 mortality rate for Travis County is 54 per 100,000, whereas the rate including out-of-hospital deaths is 78 per 100,000. For Texas, the overall COVID-19 mortality rate is 169 per 100,000. The top-right map indicates the social vulnerability index (SVI) of each ZIP code [2]. ZIP codes are colored by whether their SVI rate is below (blue) or above (brown) the city-wide average. Black lines represent Austin's two major highways, I-35 and US-183. Most ZIP codes east of I-35 have higher SVI's and COVID-19 mortality rates than those west of I-35. The scatter plot shows a strong correlation between social vulnerability and in-hospital COVID-19 deaths across the city (bottom). An increase in SVI of 0.01 is associated with an increase in mortality rate of 1.1 (95% CI: 0.8–1.5) per 100,000 residents.

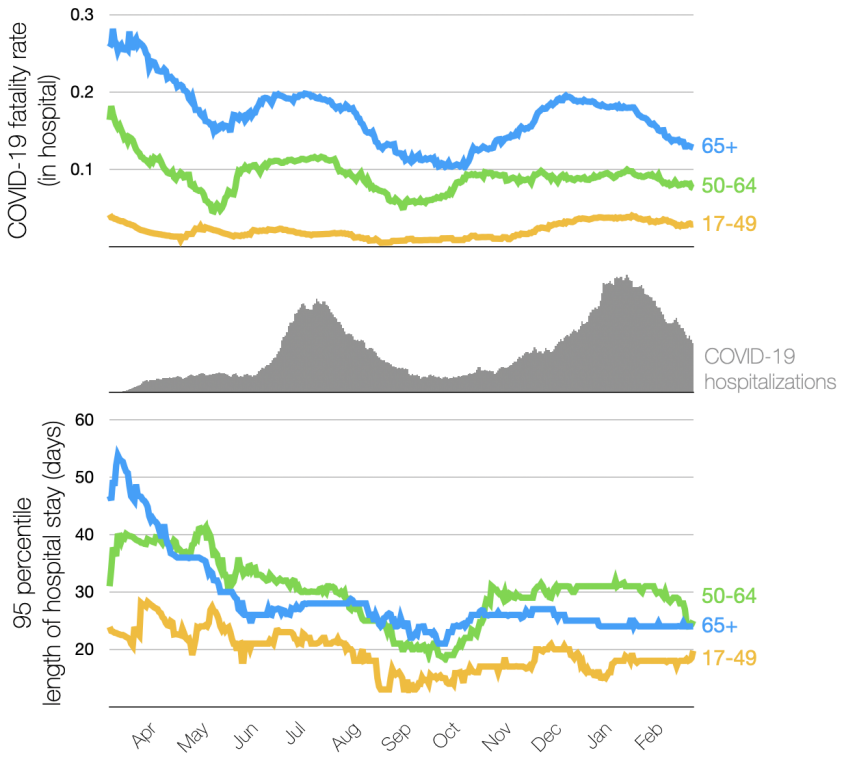

Figure 3: **In-hospital COVID-19 mortality (top) and duration of hospital stays (bottom) throughout the pandemic, by age group, compared to overall COVID-19 hospital census (middle), through March 1, 2021.** The top graph indicates the average fatality rate for COVID-19 hospital patients each age group (orange: 17-49y, green: 50-64y, blue: over 65), based on all patients admitted into Austin area hospitals within 30 days before or after the given date. The bottom graph indicates the 95th percentile for length of a COVID-19 hospital stay for each age group, also based on data from patients admitted within a 60-day rolling window. The middle graph indicates the total number of COVID-19 patients in area hospitals on each day. During the first two months of the pandemic in Austin, the in-hospital fatality rate declines sharply, in all age groups. During the summer 2020 and winter 2020-2021 pandemic surges, COVID-19 fatality rates and lengths of hospital stay tended to increase as the overall number of COVID-19 patients increased.

Appendix

Appendix A provides projections of hospitalizations and ICU utilization when we assume high-risk groups and those over 65 years of age cocoon. Appendix B details how we used Texas Department of State Health Services (DSHS) data on the vaccine roll-out to estimate how many people in each age-risk group are vaccinated in our analysis. Appendix C describes the enhanced SEIR model we used in our analysis, Appendix D details parameters used in the model along with methods for estimating or selecting those parameters.

A Projections of COVID-19 Hospitalizations and ICU Hospitalizations

Using a high-fidelity SEIR (susceptible-exposed-infectious-recovered) epidemiological simulation model for the five-county Austin MSA, we project total hospitalizations and intensive care unit (ICU) hospitalizations through September, 2021 under the vaccination schedule sketched in Appendix B. Key parameters of the SEIR model are fit using data from Austin-area hospitals on daily COVID-19 admissions, the daily census in ICU and general-ward beds, and deaths. The estimated reduction in disease transmission at different time periods from March 2020–April 2021 inform the estimates of transmission associated with various levels (red, orange, yellow, blue) in Austin's staged alert system, and we use transmission values tied to these stages in the projections that we provide here.

Figure 4 repeats the analysis of Figure 1 in the main text, but optimistically assumes those 65 years and older, and those with high-risk to severe COVID-19 outcomes, are cocooning. As a result 27%, 18%, 6%, and 3% of sample paths exceed the ICU capacity when Austin moves to the blue stage on April 7, 14, 21 and 28, respectively. The analogous values are 48%, 31%, 6%, and 3% (main text) without effective cocooning. All plots show 100 stochastic simulations (gray spaghetti lines) as well as COVID-19 hospitalization data (red dots) and a single projection (black line).

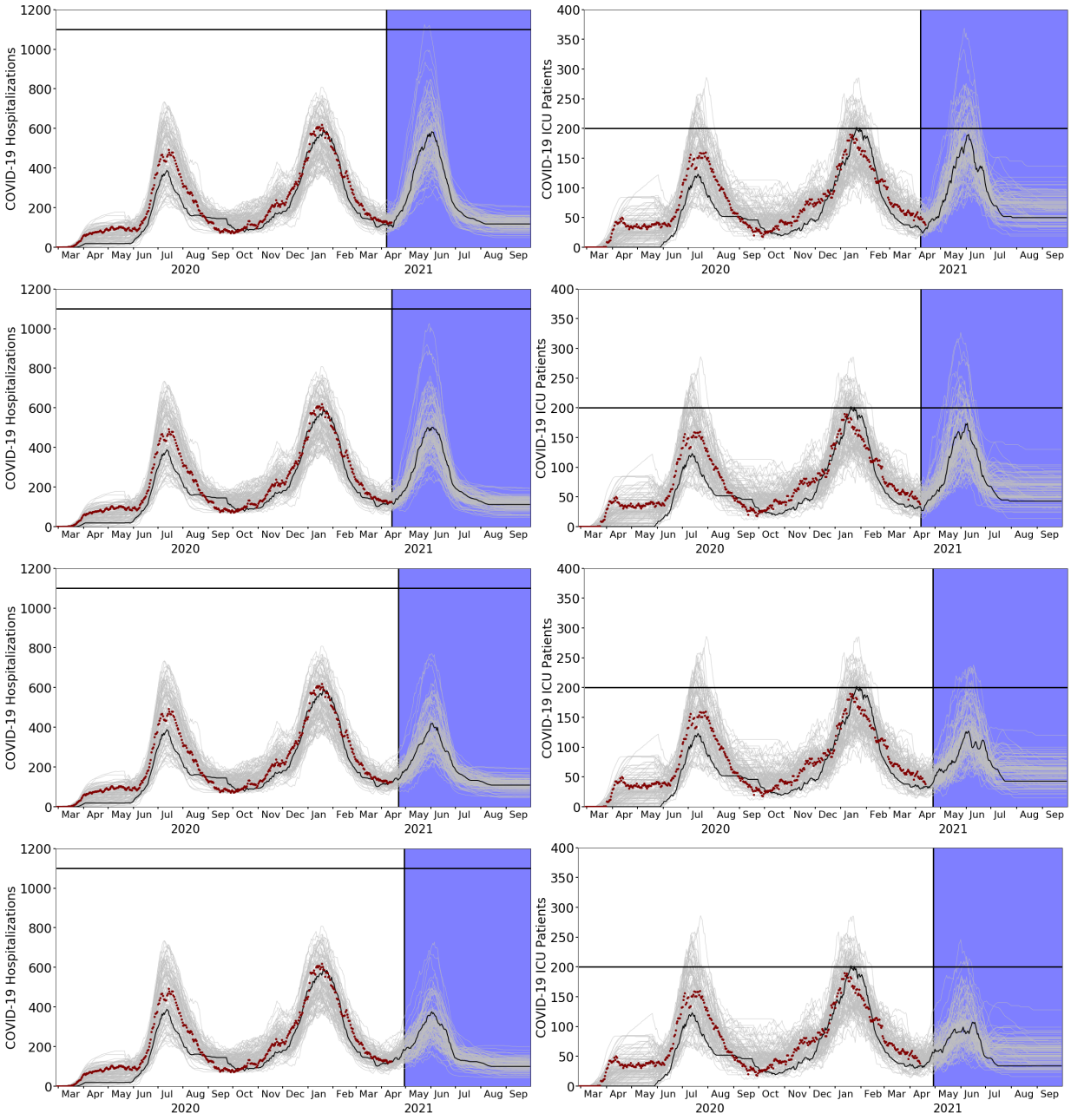

Figure 4: **Projected COVID-19 hospitalizations (left graphs) and ICU patients (right graphs) in the Austin-Round Rock MSA through September 30, 2021, assuming that Austin relaxes from Alert Stage 3 (yellow) to Stage 2 (blue) and unvaccinated high-risk individuals continue to cocoon.** From top to bottom, we assume that the relaxation occurs either on April 7, April 14, April 21 or April 28, as indicated by the blue shaded regions. The red points represent historical data, the black horizontal lines represent total hospital capacity (1100 beds) and ICU capacity (200 beds), the light curves indicate stochastic simulations (100 per graph), and solid lines illustrate a representative path. The fraction of scenarios that exceed ICU capacity is over 25% when we assume an early April transition to the blue alert stage, but drops significantly for the late-April scenarios, given the rapid roll out of vaccines to those over 65 years old and in high-risk groups throughout the month. Specifically, the probability that COVID-19 ICU hospitalizations will exceed the estimated local ICU capacity is 27%, 18%, 6%, and 3% for the four different scenarios, respectively. We assume that the vaccine uptake rate is 85% in the high-risk groups and in those aged 65 years and older, and that it is 70% for all other adults over 18 years of age.

B COVID-19 Vaccine Allocation

We consider a vaccine that provides 80% and 90% reduction in susceptibility 14 days after the first dose and second dose, respectively [3]. We model daily vaccination efforts starting on January 10, 2021, but we account for earlier vaccinations, effective on January 10th. We use Texas Department of State Health Services (DSHS) data to estimate how vaccines were allocated across multiple age-risk groups from January 10 to April 15, 2021. In particular, we use data regarding the *first-dose vaccine administration* from DSHS [4] to estimate the number of vaccinated individuals for each age and risk group, across ten such groups: ages 0-4 years-old, 5-17 yo, 18-49 yo, 50-64 yo, and 65 years and older, each with low risk and high risk for severe COVID-19 outcomes. After April 15, 2021 we assume 4% of the population in the Austin MSA is vaccinated each week in accordance with the DSHS vaccine-allocation data between April 1 and 15, 2021. We further assume that every individual who receives a first dose of the vaccine, receives a second dose 21 days later. We assume an uptake rate of 85% in high-risk groups and those over 65 years-old, a 70% uptake rate for low-risk groups 18-49 yo and 50-64 yo, and our analysis assumes vaccines are not allocated to those under 18 years old. In the rest of this section we provide further details on how we estimate who was vaccinated when based on DSHS data.

The COVID-19 vaccination effort in states across the US is using a phased roll-out. In Phase 1a, health-care providers and residents of long-term care facilities (LTCF) received vaccines. To account for these vaccinations in our analysis, we assume that healthcare providers are only in age groups 18-49 yo and 50-64 yo and follow a demographic structure like the rest of Austin. We assume LTCF residents are in age group 65 years and older, and the proportion of LTCF residents with high-risk conditions is the same as Austin's overall high-risk proportions in that age group.

Under the Phase 1b vaccine allocation policy in Texas, those 65 years and older and those 18-64 years old with high risk were prioritized. From DSHS data we have for each week how many individuals 65 years and older received a first-dose vaccine. We assume pro rata allocation among high and low risk individuals over 65 years old.

On March 3 2021, Texas expanded vaccine eligibility to personnel working in schools and child care facilities. We ignore this fact in our modeling and assume only high risk groups are vaccinated in the 18-64 yo age groups until March 15, 2021. On March 15, Texas expanded eligibility to 50-64 years of age. We assume vaccines are administered to low and high risk groups pro rata among the 50-64 yo age group during March 15-20, 2021. We assume vaccine uptake is 85% for the high-risk groups for those 18 years and older and for all individuals 65 years and older. As a result, as of March 20, 85% of the 50-64 yo high-risk group are vaccinated, and we thus assume that the 50-64 yo age group with low risk begin receiving vaccines after March 20. Similarly, as of March 15, 2021 85% of those in the 18-49 yo high-risk group are vaccinated according to our assumptions, and we therefore assume that the 18-49 yo age group with low-risk receive all of the corresponding vaccines after March 15, with vaccines again allocating pro rata across the two age groups, 18-49 yo and 50-64 yo.

Texas opened up vaccination to all individuals 16 year and older on March 29. As stated earlier, we use DSHS vaccine data until April 15. For vaccinations after April 15, we assume vaccines are administrated pro rata among remaining 18-64 yo low risk groups and the 65+ yo age group. Vaccination of those over 65 years old ends on April 26, 2021 when 85% of that population is vaccinated. All vaccination efforts end on May 22, 2021 when 70% of the 18-64 yo low-risk groups are vaccinated.

We assume that vaccine uptake is higher for individuals who are at higher risk of severe COVID-19 outcomes. Among the 18-64 yo high-risk groups and the 65+ yo age group, vaccine uptake is assumed to be 85%, whereas for 18-64 low risk groups vaccine uptake is assumed to be 70%. According the CDC, estimated vaccine hesitancy is 15% in Travis and Williamson counties, 16% in Hays county and 18% in Bastrop and Caldwell counties [5]. Thus assuming a 70% uptake rate for the 18-64 low-risk groups may be pessimistic.

C Epidemiological Model Overview

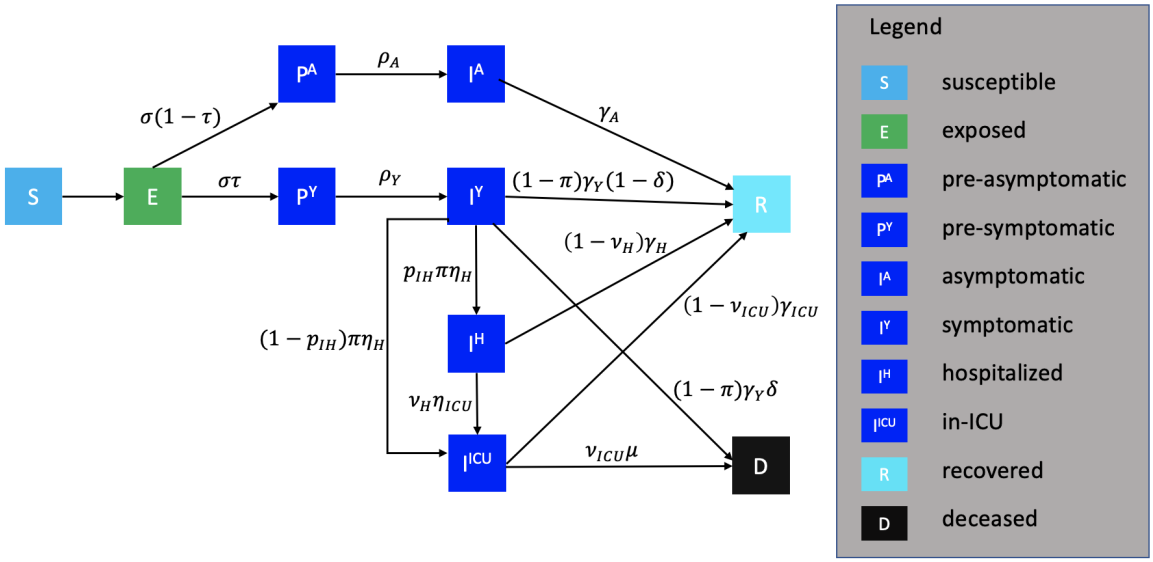

Figure 5: **Compartmental model of COVID-19 transmission in the Austin MSA.** Each subgroup is defined by age and risk as well as vaccine status (vaccinated with two doses, vaccinated with one dose, unvaccinated), and is modeled with a separate set of compartments. Upon infection, susceptible individuals (S) progress to exposed (E) and then to either pre-symptomatic infectious (P^Y) or pre-asymptomatic infectious (P^A) from which they move to symptomatic infectious (I^Y) and asymptomatic infectious (I^A), respectively. All asymptomatic cases eventually progress to a recovered state, where they are assumed to remain protected from future infection (R); symptomatic cases are either hospitalized (I^H), recover or deceased. Mortality (D) varies by age group and risk group.

Notation:

Indices and Sets

$t \in \mathcal{T}$	set of time periods $\{1, 2, \ldots, \lvert\mathcal{T}\rvert\}$ [day]
$t \in \mathcal{T}_0$	$\mathcal{T} \cup \{0\}$
$a \in \mathcal{A}$	set of age groups {0-4y, 5-17y, 18-49y, 50-64y, 65y+}
$v \in \mathcal{V}$	set of vaccination status {1 (unvaccinated), 2 (received first dose), 3 (received second dose) }
$r \in \mathcal{R}$	risk groups $\{low, high\}$
$i \in \mathcal{I}$	predefined alert stages $\{1\,(\text{red}), 2\,(\text{orange}), 3\,(\text{yellow}), 4\,(\text{blue})\}$ governing transmission rates
$\omega \in \Omega$	set of simulated spread scenarios

Parameters

Epidemiological parameters:

β	unmitigated transmission rate
λ_1	vaccine effectiveness after first dose
λ_2	vaccine effectiveness after second dose
t^e	number of days between vaccination and when vaccine effect starts
t^s	number of days between first and second doses of vaccine
β_v	unmitigated transmission rate for vaccine status v ($\beta_1 := \beta$ (unvaccinated), $\beta_2 := \beta(1-\lambda_1)$ (first dose),

	$\beta_3 := \beta(1-\lambda_2)$ (second dose))
σ	rate at which exposed individuals become infectious
τ	proportion of exposed individuals who become symptomatic
ρ_A	rate at which pre-asymptomatic individuals become asymptomatic
ρ_Y	rate at which pre-symptomatic individuals become symptomatic
γ_A	recovery rate from asymptomatic compartment
γ_Y	recovery rate from symptomatic compartment
γ_H^a	recovery rate from hospitalized compartment for age group a
γ_{ICU}^a	recovery rate from ICU compartment for age group a
P	proportion of pre-symptomatic transmission
$YHR^{a,r}$	percent of symptomatic infectious that go to the hospital for age-risk group a, r
η_H	hospitalization rate after symptom onset
ω_A	infectiousness of individuals in IA relative to IY
$\omega_P^{a,r}$	$\frac{P}{1-P}\frac{\tau(YHR^{a,r}/\eta_H+(1-YHR^{a,r})/\gamma_Y)+(1-\tau)\omega_A/\gamma_A}{\tau/\rho_Y+(1-\tau)\omega_A/\rho_A}$: infectiousness of pre-symptomatic individuals relative to IY for age-risk group a, r
$\pi^{a,r}$	$\frac{\gamma_Y \cdot YHR^{a,r}}{[\eta_H-(\eta_H-\gamma_Y)YHR^{a,r}]}$: rate-adjusted proportion of symptomatic individuals who go to the hospital for age-risk group a, r
p_{IH}	percent of patients directly going to the general ward of the hospital
δ	percent of out-of-hospital deaths
$HICUR$	percent of general ward patients who get transferred to ICU
η_{ICU}^a	ICU admission rate after admission to the general ward for age group a
ν_H^a	$\frac{\gamma_H^a \cdot HICUR}{[\eta_{ICU}^a-(\eta_{ICU}^a-\gamma_H^a)HICUR]}$: rate-adjusted proportion of general ward patients transferred to ICU for age group a
μ^a	rate from ICU to death for age group a
$ICUFR^a$	percent of hospitalized that die for age group a
ν_{ICU}^a	$\frac{\gamma_{ICU}^a \cdot ICUFR^a}{[\mu^a-(\mu^a-\gamma_{ICU}^a)ICUFR^a]}$: ICU fatality rate-adjusted proportion for age group a
$\phi_{i,t}^{a',r',a,r}$	expected number of daily contacts from (a', r') to (a, r) at time t under stage i
$N^{a,r}$	population of age-risk group a, r
C_t	vaccine supply at time t
Variables	
Epidemiological variables (for scenario $\omega \in \Omega$):	
$S_{t,\omega}^{a,r,v}$	number of susceptible people of age group a, risk group r, and vaccine status v at time t [persons]
$dS_{t,\omega}^{a,r,v}$	$S_{t,\omega}^{a,r,v} - S_{t+1,\omega}^{a,r,v}$ [persons]
$E_{t,\omega}^{a,r,v}$	number of exposed people of age group a, risk group r, and vaccine status v at time t [persons]
$PA_{t,\omega}^{a,r,v}$	number of pre-asymptomatic people for a, r, v, t [persons]
$PY_{t,\omega}^{a,r,v}$	number of pre-symptomatic people for a, r, v, t [persons]
$IA_{t,\omega}^{a,r,v}$	number of infectious-asymptomatic people for a, r, v, t [persons]
$IY_{t,\omega}^{a,r,v}$	number of infectious-symptomatic people for a, r, v, t [persons]
$IH_{t,\omega}^{a,r,v}$	number of infected-hospitalized people in the general ward for a, r, v, t [persons]
$ICU_{t,\omega}^{a,r,v}$	number of infected-hospitalized people in the ICU for a, r, v, t [persons]
$R_{t,\omega}^{a,r,v}$	number of recovered people for a, r, v, t [persons]
$D_{t,\omega}^{a,r,v}$	number of deceased people for a, r, v, t [persons]
$H_{t,\omega}$	daily hospital admissions, from infectious-symptomatic to the general ward and ICU, at time t [persons/day]
$\overline{H}_{t,\omega}$	seven-day moving average of $H_{t,\omega}$ [persons/day]

$U_{t,\omega}$	daily ICU admissions (from infectious-symptomatic and the general ward) at time t [persons/day]
$Y_t^{a,r}$	number of vaccinated individuals at time t for a, r [persons] ($\sum_{a\in\mathcal{A}}\sum_{r\in\mathcal{R}} Y_t^{a,r} \leq C_t$)

Indicator variables:

$X_{i,t,\omega}$	1 if the system is in alert stage i at time t for scenario ω; 0 otherwise

We refer to Table 6 for further details on model parameters. We first define the epidemiological transition dynamics in the following equations for all $\omega \in \Omega$. These dynamics largely follow the formulation used in [6] with the addition of three compartments to improve model fidelity and to distinguish beds in the ICU and general ward. The initial conditions specify a single infectious individual in the 18-49 age group with low risk. The age-risk groups are initialized with the rest of the population in their respective susceptible compartments. Eqs. [1a]-[1m] below then provide a sample path, indexed by ω, for the progression of the disease in the community. For the moment, the indicator variables $X_{i,t,\omega} \in \{0, 1\}$ are taken as input, and select the current stage and, in turn, the expected number of daily contacts via $\phi_{i,t}^{a',r',a,r}$. The contact matrices are indexed by t because they capture whether school is currently open and if so, the school calendar; they further capture weekdays versus weekends and the level of cocooning, which can vary with time; and they capture contacts at school, home, work, and another catch-all category. We assume that sufficient precautions are taken in hospitals so that hospitalized cases do *not* contribute to infecting others via Eq. [1m]. However, we assume an infected vaccinated individual can infect the unvaccinated as much as an infected unvaccinated individual. The most significant updates of the model from that in [6] and [7] are in additional compartments. We use constructs similar to He et al. [8] for a pre-symptomatic period to more accurately model the profile of infectiousness of individuals by including pre-symptom onset transmission. We also model the ICU compartment explicitly for two reasons. First, patients in the ICU have different durations in the hospital than those in the general ward, and second it allows us to account for ICU capacity as a resource. We let p_{IH} denote the probability a hospitalized patient is admitted to a general ward bed and the remaining fraction go directly to the ICU. As Fig. 5 and Eq. [1h] indicate, it is possible to transfer general ward patients to the ICU later if needed. In order to better estimate the recorded deaths for possible vaccination scenarios, we consider in-hospital and out-of-hospital deaths. As Fig. 5 and Eq. [1l] indicate, deaths are recorded either from the ICU (in-hospital) or from the symptomatic individuals that are not hospitalized (out-of-hospital).

For simplicity, we write the finite-difference Eqs. [1] in a deterministic form. They become stochastic, and require indexing by ω, because binomial random variables replace terms like $\sigma E_{t,\omega}^{a,r,v}$; here the binomial random variable has parameter $n = E_{t,\omega}^{a,r,v}$ and σ serves as the "success" probability. This construct is pervasive throughout right-hand side terms in Eqs. [1]. In addition to these "micro" stochastics there are "macro" stochastics because we model σ, ω_A, γ_A, and γ_Y as random variables that are subject to a Monte Carlo draw at time 0 of the simulation.

The following equations hold for all $\forall t \in \mathcal{T}_0, a \in \mathcal{A}, r \in \mathcal{R}, v \in \mathcal{V}$:

$$S^{a,r,v}_{t,\omega} - S^{a,r,v}_{t,\omega} = - dS^{a,r,v}_{t,\omega} \quad [1a]$$

$$E^{a,r,v}_{t+1,\omega} - E^{a,r,v}_{t,\omega} = dS^{a,r,v}_{t,\omega} - \sigma E^{a,r,v}_{t,\omega} \quad [1b]$$

$$PA^{a,r,v}_{t+1,\omega} - PA^{a,r,v}_{t,\omega} = \sigma(1-\tau)E^{a,r,v}_{t,\omega} - \rho_A PA^{a,r,v}_{t,\omega} \quad [1c]$$

$$IA^{a,r,v}_{t+1,\omega} - IA^{a,r,v}_{t,\omega} = \rho_A PA^{a,r,v}_{t,\omega} - \gamma_A IA^{a,r,v}_{t,\omega} \quad [1d]$$

$$PY^{a,r,v}_{t+1,\omega} - PY^{a,r,v}_{t,\omega} = \sigma\tau E^{a,r,v}_{t,\omega} - \rho_Y PY^{a,r,v}_{t,\omega} \quad [1e]$$

$$IY^{a,r,v}_{t+1,\omega} - IY^{a,r,v}_{t,\omega} = \rho_Y PY^{a,r,v}_{t,\omega} - (1-\pi^{a,r})\gamma_Y IY^{a,r,v}_{t,\omega} - \pi^{a,r}\eta_H IY^{a,r,v}_{t,\omega} \quad [1f]$$

$$IH^{a,r,v}_{t+1,\omega} - IH^{a,r,v}_{t,\omega} = p_{IH}\pi^{a,r}\eta_H IY^{a,r,v}_{t,\omega} - (1-\nu^a_H)\gamma^a_H IH^{a,r,v}_{t,\omega} - \nu^a_H\eta^a_{ICU} IH^{a,r,v}_{t,\omega} \quad [1g]$$

$$ICU^{a,r,v}_{t+1,\omega} - ICU^{a,r,v}_{t,\omega} = (1-p_{IH})\pi^{a,r}\eta_H IY^{a,r,v}_{t,\omega} + \nu^a_H\eta^a_{ICU} IH^{a,r,v}_{t,\omega} - \quad [1h]$$

$$(1-\nu^a_{ICU})\gamma^a_{ICU} ICU^{a,r,v}_{t,\omega} - \nu^a_{ICU}\mu^a ICU^{a,r,v}_{t,\omega} \quad [1i]$$

$$R^{a,r,v}_{t+1,\omega} - R^{a,r,v}_{t,\omega} = \gamma_A IA^{a,r,v}_{t,\omega} + (1-\pi^{a,r})\gamma_Y\delta IY^{a,r,v}_{t,\omega} + (1-\nu^a_H)\gamma^a_H IH^{a,r,v}_{t,\omega} + \quad [1j]$$

$$(1-\nu^a_{ICU})\gamma^a_{ICU} ICU^{a,r,v}_{t,\omega} \quad [1k]$$

$$D^{a,r,v}_{t+1,\omega} - D^{a,r,v}_{t,\omega} = \nu^a_{ICU}\mu^a ICU^{a,r,v}_{t,\omega} + (1-\pi^{a,r})\gamma_Y(1-\delta)IY^{a,r,v}_{t,\omega} \quad [1l]$$

$$dS^{a,r,v}_{t,\omega} = S^{a,r,v}_{t,\omega} \sum_{a'\in\mathcal{A}}\sum_{r'\in\mathcal{R}}\sum_{v'\in\mathcal{V}}\sum_{i\in\mathcal{I}} \frac{\beta_v \phi^{a',r',a,r}_{i,t} X_{i,t,\omega}}{N^{a',r'}} \Big(IY^{a',r',v'}_t + \omega_A IA^{a',r',v'}_t + \omega^{a',r'}_P \omega_A PA^{a',r',v'}_t + \omega^{a',r'}_P PY^{a',r',v'}_t \Big). \quad [1m]$$

The initial conditions have all variables indexed by $t = 0$ as zero except the following:

$$IY^{\text{18-49},low}_{0,\omega} = 1, S^{\text{18-49},low}_{0,\omega} = N^{\text{18-49},low} - 1, \text{and } S^{a,r}_{0,\omega} = N_{a,r} \forall (a,r) \in \mathcal{A}\times\mathcal{R} \setminus \{(\text{18-49}, low)\}. \quad [2]$$

We assume vaccine is administered only to susceptible individuals and provides protection 14 days after vaccination and second doses are administered 21 days after the first dose in Eqs. [3]:

$$S^{a,r,1}_{t,\omega} \leftarrow S^{a,r,1}_{t,\omega} - Y^{a,r}_{t-t^e} \qquad \forall t \in \mathcal{T}_0, a \in \mathcal{A}, r \in \mathcal{R} \quad [3a]$$

$$S^{a,r,2}_{t,\omega} \leftarrow S^{a,r,2}_{t,\omega} + Y^{a,r}_{t-t^e} \qquad \forall t \in \mathcal{T}_0, a \in \mathcal{A}, r \in \mathcal{R} \quad [3b]$$

$$S^{a,r,2}_{t,\omega} \leftarrow S^{a,r,2}_{t,\omega} - Y^{a,r}_{t-t^e-t^s} \qquad \forall t \in \mathcal{T}_0, a \in \mathcal{A}, r \in \mathcal{R} \quad [3c]$$

$$S^{a,r,3}_{t,\omega} \leftarrow S^{a,r,3}_{t,\omega} + Y^{a,r}_{t-t^e-t^s} \qquad \forall t \in \mathcal{T}_0, a \in \mathcal{A}, r \in \mathcal{R} \quad [3d]$$

D Model Parameters

Table 1 partitions the population of the Austin MSA based on age groups (0-4 years old, 5-17 years old, 18-49 years old, 50-64 years old, and 65 years and older) and risk groups (low risk and high risk). The high-risk group proportions are estimated based on the population with chronic conditions listed by the CDC 500 cities data [9]. Population data processing is detailed in the appendix of [6] and here we present only the final numbers used for this paper's analysis.

$N^{a,r}$	0-4	5-17	18-49	50-64	65 and older
Low risk	128527	327148	915894	249273	132505
High risk	9350	37451	156209	108196	103763

Table 1: Austin age-risk group populations.

We define four baseline contact matrices, $\mathcal{H}, \mathcal{S}, \mathcal{W}$, and $\mathcal{O}$, to describe the contact frequency between age groups at home, at school, at work, and at other locations. These *baseline* matrices assume there is no difference in contacts among the low- and high-risk groups. Each row and column represents an age group, in the order of 0-4 years old, 5-17 years old, 18-49 years old, 50-64 years old, and 65 years old and above, with the row-column value corresponding to a "from-to" transmission contact:

$$\mathcal{H} = \begin{bmatrix} 0.5 & 0.9 & 2.0 & 0.1 & 0.0 \\ 0.2 & 1.7 & 1.9 & 0.2 & 0.0 \\ 0.2 & 0.9 & 1.7 & 0.2 & 0.0 \\ 0.2 & 0.7 & 1.2 & 1.0 & 0.1 \\ 0.1 & 0.7 & 1.0 & 0.3 & 0.6 \end{bmatrix} \qquad \mathcal{S} = \begin{bmatrix} 1.0 & 0.5 & 0.4 & 0.1 & 0.0 \\ 0.2 & 3.7 & 0.9 & 0.1 & 0.0 \\ 0.0 & 0.7 & 0.8 & 0.0 & 0.0 \\ 0.1 & 0.8 & 0.5 & 0.1 & 0.0 \\ 0.0 & 0.0 & 0.1 & 0.0 & 0.0 \end{bmatrix}$$

$$\mathcal{W} = \begin{bmatrix} 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.1 & 0.4 & 0.0 & 0.0 \\ 0.0 & 0.2 & 4.5 & 0.8 & 0.0 \\ 0.0 & 0.1 & 2.8 & 0.9 & 0.0 \\ 0.0 & 0.0 & 0.1 & 0.0 & 0.0 \end{bmatrix} \qquad \mathcal{O} = \begin{bmatrix} 0.7 & 0.7 & 1.8 & 0.6 & 0.3 \\ 0.2 & 2.6 & 2.1 & 0.4 & 0.2 \\ 0.1 & 0.7 & 3.3 & 0.6 & 0.2 \\ 0.1 & 0.3 & 2.2 & 1.1 & 0.4 \\ 0.0 & 0.2 & 1.3 & 0.8 & 0.6 \end{bmatrix}.$$

The contact matrices $\phi_{i,t}^{a',r',a,r}$ are calculated in the same way as Table S6 in [6], considering the effect of weekends, holidays, school closures, and social distancing and cocooning of high-risk populations based on the risk stage. Stages correspond to distancing stages of different strictness, which govern the reduced number of daily contacts people make relative to baseline. In our model, this is reflected by a coefficient $\kappa_i, i \in \mathcal{I}$, where $\kappa_i = 0.75$ would reduce the expected number of contacts to 25% of the baseline value. For the age group of 65 years and older and for the high-risk group, we use reductions based on cocooning, which are represented by coefficients $c_i, i \in \mathcal{I}$:

$$\phi_{i,t}^{a',r',a,r} = \begin{cases} (1-\kappa_i)\left[(1-1_{\{\text{off day}\}})\cdot(1-1_{\{\text{school closure}\}})\cdot\mathcal{S}_{a',a} + \right. & \text{if } a', a \in \{\text{0-4yr, 5-17yr, 18-49yr, 50-64yr}\}, \\ \quad \left.(1-1_{\{\text{off day}\}})\cdot\mathcal{W}_{a',a} + \mathcal{H}_{a',a} + \mathcal{O}_{a',a}\right] & \quad r', r \neq \text{high-risk} \\ (1-c_i)\left[(1-1_{\{\text{off day}\}})\cdot(1-1_{\{\text{school closure}\}})\cdot\mathcal{S}_{a',a} + \right. & \\ \quad \left.(1-1_{\{\text{off day}\}})\cdot\mathcal{W}_{a',a} + \mathcal{H}_{a',a} + \mathcal{O}_{a',a}\right] & \text{otherwise.} \end{cases} \quad [4]$$

The indicator $1_{\{\text{off day}\}}$ takes value 1 if the day is a weekend or holiday and is otherwise 0, and a similar indicator accounts for school closures. When a high-risk group, along with those 65 years and older, is involved either on the "giving" or "receiving" end of a contact, Eq. [4] assumes reduced transmission via the cocooning coefficient, c_i.

The following are key dates during the pandemic in Texas, and some define time blocks, which we use in estimating time-varying transmission reduction factors and other key model parameters as we describe shortly:

- February 28, 2020: Seed date for simulation of Austin, assuming seeding by a single symptomatic individual age 18-49y. This corresponds to 14 days prior to the first detected COVID-19 case in Austin on March 13, 2020.
- March 24, 2020: Austin's Stay Home-Work Safe Order is enacted at midnight [10].
- May 1, 2020: The Governor of Texas relaxed social distancing orders statewide [11].
- May 21, 2020: Just prior to Memorial Day Weekend.
- June 26, 2020: The Governor of Texas issued an executive order limiting service at bars and restaurants, and Travis County (which includes Austin) banned gatherings of more than 100 people [12; 13].

- July 17, 2020: Time point in hospitalization data suggesting a change in dynamics.
- August 9, 2020: The last day of observed data from the hospital system used in estimating changes in ICU dynamics.
- August 20, 2020: First day students returned to residence halls at the University of Texas at Austin.
- October 29, 2020: Apparent COVID-19 fatigue leads to rise in cases
- November 29, 2020: Right after Thanksgiving holiday.
- December 30, 2020: Right before Christmas break end.
- January 10, 2021: The initial day of vaccination in the model.
- March 13, 2021: Austin moves down stage 3.
- April 12, 2021: The last day of observed data used in estimating model parameters.
- April 15, 2021: The last day of observed data used in historical vaccine allocations.

We assume that there are ten time blocks denoted by $\mathcal{T}_j$ for $j \in \{1, \ldots, 11\}$ as defined in Table 2. They guide fitting of transmission-reduction parameters, κ and c, and certain dynamics in use of the ICU and hospital duration, as detailed below.

Time Block	Start Date	End Date	Definition
$\mathcal{T}_1$	2/28/20	3/23/20	unmitigated transmission before first stay-home order
$\mathcal{T}_2$	3/24/20	5/20/20	effective period for first stay-home order
$\mathcal{T}_3$	5/21/20	6/25/20	relaxed period starting with Memorial Day weekend
$\mathcal{T}_4$	6/26/20	7/16/20	period of effective social distancing
$\mathcal{T}_5$	7/17/20	8/19/20	period distinguished by changes in ICU dynamics
$\mathcal{T}_6$	8/20/20	10/28/20	period of effective social distancing
$\mathcal{T}_7$	10/29/20	11/29/20	period of effective social distancing
$\mathcal{T}_8$	11/30/20	12/30/20	period of effective social distancing
$\mathcal{T}_9$	12/31/20	01/11/21	period of effective social distancing
$\mathcal{T}_{10}$	01/12/21	03/12/21	period of effective social distancing and vaccination
$\mathcal{T}_{11}$	03/13/21	04/12/21	period of effective social distancing and vaccination

Table 2: The nine time blocks, $\mathcal{T}_1$, $\mathcal{T}_2$, $\mathcal{T}_3$, $\mathcal{T}_4 \cup \mathcal{T}_5$, $\mathcal{T}_6$, $\mathcal{T}_7$, $\mathcal{T}_8$, $\mathcal{T}_9$, $\mathcal{T}_{10}$, and $\mathcal{T}_{11}$ correspond to different rates of spread, as estimated using transmission-reduction factors κ and c. The fourth and fifth time blocks, $\mathcal{T}_4$ and $\mathcal{T}_5$, differ only in dynamics involving the ICU, both the admission probability and the sojourn time in the general ward prior to ICU admission.

We model the hospitalization dynamics, including proportions of hospitalized requiring the ICU, durations in the general ward and ICU, and ICU mortality rate using data from a multi-facility hospital system serving the central Texas region, including Austin, Texas ("hospital system data"). While we model differences based on five age groups, we assume the same hospital dynamics in different hospital systems after a patient is admitted across Austin due to similar medical standards. Conditional on being admitted to the hospital, we observe a decreasing trend in the probability a patient is admitted to the ICU throughout the time horizon, which holds for both direct admissions to the ICU and patients who are first admitted to the general ward. Among patients who enter the general ward and are then admitted to the ICU, their duration of stay in the general ward, determined by η_{ICU}, grows over time. For each time block,

$\mathcal{T}_j$, we assume a constant $\eta_{ICU,j}$ and further assume a constant daily decrease, r_j, on both of the fractions, p_{IH} and $HICUR$:

$$p_{IH,t+1} = r_j p_{IH,t} \qquad \forall j \in \{1,\ldots,11\}, t \in \mathcal{T}_j \qquad \text{[5a]}$$

$$HICUR_{t+1} = r_j HICUR_t \qquad \forall j \in \{1,\ldots,11\}, t \in \mathcal{T}_j, \qquad \text{[5b]}$$

along with a similar decrement across boundaries of the blocks. We use duration times for each time block from the hospital system data to estimate $\eta^a_{ICU,j}$ and fit r_j, with the estimated parameters in Table 3.

	age group	$\mathcal{T}_1$	$\mathcal{T}_2$	$\mathcal{T}_3$	$\mathcal{T}_4$	$\mathcal{T}_5 \cup \cdots \cup \mathcal{T}_{11}$
$\eta^a_{ICU,j}$	0-4 yr	0.5882	0.5882	0.3885	0.2640	0.2589
	5-17 yr	0.5882	0.5882	0.3885	0.2640	0.2589
	18-49 yr	0.5882	0.5882	0.3885	0.2640	0.2589
	50-64 yr	0.6273	0.6273	0.4143	0.2815	0.2761
	$\geq$ 65 yr	0.6478	0.6478	0.4278	0.2907	0.2851
r_j		0.9973	0.9973	0.9932	0.9921	1

Table 3: Estimates of ICU admission probability parameters, η_{ICU}, p_{IH}, and $HICUR$; see Fig. 5 and accompanying parameter definitions. For each age group, a, and each time block, j, we specify η_{ICU}, and we give the daily decrement factor, r_j, used in Eq. [5].

Using the hospital system data, and consistent with the transition diagram in Fig. 5, we define the ICU duration for a patient as the time between their admission to the ICU and their discharge from the hospital. The reality is more complex as ICU patients typically return to the general ward prior to discharge from the hospital, and iterations between the two units, driven by a patient's health status, can also occur. Therefore, the reported duration in the ICU leads to over estimating ICU utilization and under-estimating that of the general ward. To handle this in our model, we introduce three constant parameters, α_{ICU}, α_H and α_D, to better estimate durations in the ICU and general ward and ICU mortality rate and better represent their respective utilization:

$$\begin{aligned}
\gamma_H &= (1-\alpha_H)\gamma^0_H \\
\gamma_{ICU} &= (1+\alpha_{ICU})\gamma^0_{ICU} \\
\mu &= (1+\alpha_D)\mu^0,
\end{aligned}$$

where γ^0_H, γ^0_{ICU}, and μ^0 are obtained from the hospital system data, with each row corresponding to an age group in ascending order:

$$\gamma^0_H = \begin{bmatrix} 0.2399 \\ 0.2399 \\ 0.2399 \\ 0.2222 \\ 0.2124 \end{bmatrix}, \; \gamma^0_{ICU} = \begin{bmatrix} 0.0700 \\ 0.0700 \\ 0.0700 \\ 0.0575 \\ 0.0518 \end{bmatrix}, \; \mu^0 = \begin{bmatrix} 0.0749 \\ 0.0749 \\ 0.0749 \\ 0.0766 \\ 0.0799 \end{bmatrix},$$

with units of day^{-1}.

The bulk of the epidemiological and hospitalization parameters are specified above or are detailed in Tables 6 and 7, with the latter obtained from the literature or information collected from local healthcare agencies. The time blocks are specified in Table 2. Given these, we estimate 25 parameters, but with 11 degrees of freedom, as we detail below. We perform the fit of the deterministic SEIR model in Eqs. [1] using: (i) daily COVID-19 admissions, denoted H_t; (ii) a daily COVID census in the general ward, IH_t; (iii) a daily COVID census in the ICU, ICU_t; (iv) daily

COVID-19 in-hospital deaths, D_t^H; and (v) daily COVID-19 out-of-hospital deaths obtained from [14], D_t^{OH}, all on day t. By minimizing a weighted sum of least-square errors, we estimate $\hat{\kappa}_j$ and $\hat{c}_j$, $j = 1, 2, \ldots, 11$, α_H, α_{ICU}, α_D and δ, using SciPy/Python [15] via `scipy.optimize.least_squares`.

We minimize

$$\sum_t (IH_t - \widehat{IH}_t)^2 + w_{ICU}^2 \sum_t (ICU_t - \widehat{ICU}_t)^2 + w_H^2 \sum_t (H_t - \widehat{H}_t)^2 + w_D^2 \sum_t (D_t^H - \widehat{D}_t^H)^2 + w_D^2 \sum_t (D_t^{OH} - \widehat{D}_t^{OH})^2,$$

where $\widehat{IH}_t$, $\widehat{ICU}_t$, $\widehat{H}_t$, $\widehat{D}_t^H$, and $\widehat{D}_t^{OH}$ denote the estimated IH_t, ICU_t, H_t, D_t^H, and D_t^{OH} obtained through Eqs. [1]; w_{ICU}, w_H, and w_D are scaling constants; and the sum is over $t \in \mathcal{T}_1 \cup \cdots \cup \mathcal{T}_{11}$. We assume $w_{ICU} = 1.50$, $w_H = 7.58$, and $w_D = 10 w_H$, as those values approximate magnitudes relative to that of the general ward. To obtain a parsimonious model, we use $\hat{c}_1 = 0$, $\hat{c}_2 = \hat{c}_3 = \hat{\kappa}_2$, $\hat{c}_4 = \hat{c}_5 = \hat{\kappa}_4 = \hat{\kappa}_5$, $\hat{c}_6 = \hat{c}_8 = \hat{\kappa}_4$, $\hat{c}_7 = \hat{\kappa}_2$, $\hat{c}_9 = \hat{\kappa}_9$, $\hat{c}_{10} = \hat{\kappa}_{10}$ and $\hat{c}_{11} = \hat{\kappa}_{11}$ which reduces the number of estimated parameters from 25 to 14.

We use the trust region reflective algorithm (`trf`) in `scipy.optimize.least_squares`, with lower and upper bounds on each parameter of 0 and 1, respectively. The algorithm obtains locally optimal values of the parameters, the quality of which has been validated by comparing projections with the observed data. All the remaining parameters are set to their default values (see above and Tables 6 and 7). The fitted values for $\hat{\kappa}_j$ and $\hat{c}_j$ and α_H, α_{ICU} and α_D are given in Table 4.

	Austin	
j	$\hat{\kappa}_j$	$\hat{c}_j$
1	0.0699	0.0000
2	0.7460	0.7460
3	0.5934	0.7460
4	0.7820	0.7820
5	0.7820	0.7820
6	0.7350	0.7820
7	0.7079	0.7460
8	0.6293	0.7820
9	0.7427	0.7427
10	0.7648	0.7648
11	0.5992	0.5992
α_H	0.3113	
α_{ICU}	0.0090	
α_D	4.4665	
δ	0.0032	

Table 4: Fitted transmission reduction parameters, $\hat{\kappa}_j$, and cocooning effectiveness parameters, $\hat{c}_j$, for each time block $\mathcal{T}_j$, along with estimated hospitalization duration adjustment parameters, α_H, α_{ICU}, and α_D and the percent of out-of-hospital death δ.

Stages	Example measures	Transmission reduction	Cocooning
red	shelter-in-place order: mask mandate, no public activities, gatherings, or travel	largest (78.2%)	78.2%
orange	mask mandate, no indoor dining, no medium or large gatherings	moderate (69.2%)	74.6%
yellow	mask mandate, partial limitations on indoor dining and bars, no large gatherings	modest (60.3%)	74.6%
blue	new normal: avoid large gatherings, masks and physical distancing recommended	low (51.3%)	68.25%
green	no restrictions	no reduction (0%)	0%

Table 5: Structure and impact of five-stage COVID-19 alert system. Colors indicate stages. For each stage, the table provides example measures, which may evolve with future data on the impact of mitigation strategies and roll-out of surveillance testing. The model assumes high risk sub-populations are sheltered to a greater degree, described as cocooning. Transmission reduction estimates and cocooning numbers are derived from COVID-19 hospital admissions data from the Austin, Texas MSA during a period that included a stay-home order, a re-opening phase that led to an early summer surge, followed by reduced transmission with the implementation of face-mask requirements and reinstatement of other distancing measures.

Parameters	Values	Source
β: transmission rate	Austin: 0.06901	[6]
P: proportion of pre-symptomatic transmission (%)	44	[8]
ω_A: infectiousness of individuals in compartment IA, relative to IY	$\omega_A \sim$ Triangular (0.29,0.29,1.4)	[16]
τ : symptomatic proportion (%)	57	[17]
ω_P: infectiousness of individuals in pre-symptomatic and pre-asymptomatic compartments, relative to symptomatic and asymptomatic compartments	$\omega_P = \frac{P}{1-P}\frac{\tau(\frac{YHR}{\eta_H}+\frac{1-YHR}{\gamma_Y})+(1-\tau)\frac{\omega_A}{\gamma_A}}{\frac{\tau}{\rho_Y}+(1-\tau)\frac{\omega_A}{\rho_A}}$	
σ : exposed rate	$\frac{1}{\sigma} \sim$ Triangular (1.9, 2.9, 3.9)	Based on incubation [18] and pre-symptomatic periods
γ_A: recovery rate from compartment IA	$\frac{1}{\gamma_A} \sim$ Triangular (3, 4, 5)	[8]
γ_Y: recovery rate from symptomatic compartment IY	$\frac{1}{\gamma_Y} \sim$ Triangular (3, 4, 5)	[8]
ρ_A: rate at which pre-asymptomatic individuals become asymptomatic	Equal to ρ_Y	[8]
ρ_Y: rate at which pre-symptomatic individuals become symptomatic	$\frac{1}{\rho_Y} = 2.3$	[8]
IFR: infected fatality ratio, age specific (%)	Low risk / High risk 0.000917 / 0.00917 0.00218 / 0.0218 0.0339 / 0.339 0.252 / 2.52 0.644 / 6.44	Age adjusted from [19]
YFR: symptomatic fatality ratio, age specific (%)	Low risk / High risk 0.00161 / 0.0161 0.00382 / 0.0382 0.0594 / 0.594 0.442 / 4.42 1.13 / 11.3	$YFR = \frac{IFR}{1-\tau}$

Table 6: Model parameters

Parameters	Value	Source
η_H : rate from symptom onset to hospital admission	0.1695	5.9 day average from symptom onset to hospital admission [20]
YHR: symptomatic case hospitalization rate (%)	Low risk / High risk 0.0279 / 0.2791 0.0215 / 0.2146 1.3215 / 13.2514 2.8563 / 28.5634 3.3873 / 33.8730	Age adjusted from [19]
p_{IH}	Fitted time series, starting at 0.6717	hospital system data
γ_H, γ_{ICU} : recovery rate in compartment IH and ICU	Fitted parameters	hospital system data
π : rate symptomatic individuals go to hospital, age-specific	$\pi = \frac{\gamma_Y \cdot YHR}{\eta_H + (\gamma_Y - \eta_H) YHR}$	
η_{ICU} : rate from hospital admission to ICU	A time series which is constant specific to time blocks	hospital system data
μ : rate from ICU to death	Fitted parameters	hospital system data
$ICUFR$: ICU death ratio, age specific (%)	$ICUFR$ 5.8592 5.8592 5.8592 15.6207 30.8526	hospital system data
$HICUR$: hospitalized ICU ratio	A time series with a decreasing rate specific to time blocks, starting at 0.1574	hospital system data
ν_H : ICU rate on hospitalized individuals, age-specific	$\nu_H = \frac{\gamma_H * HICUR}{\eta_{ICU} + (\gamma_H - \eta_{ICU}) HICUR}$	
ν_{ICU} : death rate on ICU individuals, age-specifc	$\nu_{ICU} = \frac{\gamma_{ICU} * ICUFR}{\mu + (\gamma_{ICU} - \mu) ICUFR}$	
B: Total hospital bed capacity (including ICU)	Austin: 1500	Estimates provided by each of the region's hospital systems and aggregated by regional public health leaders
B_{ICU}: ICU capacity	Austin: 331	Estimates provided by each of the region's hospital systems and aggregated by regional public health leaders
$1_{\{\text{school closure}\}}$: school closure dates	Austin: $3/19/2020 - 9/8/2020$, $5/26/2021 - 8/23/2021$	

Table 7: Hospitalization parameters

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