COVID-19 in Austin, Texas: Relaxing Social Distancing Measures

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Overview

To support planning by the city of Austin and Travis County, we analyzed the Austin-Round Rock module of our *US COVID-19 Pandemic Model* to project the number of hospitalizations under different scenarios for relaxing social distancing measures following the March 24th *Stay Home-Work Safe* order. Note that the results presented herein are based on multiple assumptions about the transmission rate and age-specific severity of COVID-19. There is still much we do not understand about the transmission dynamics of this virus, including the extent of asymptomatic infection and transmission. These results do not represent the full range of uncertainty. Rather, they are meant to serve as plausible scenarios for gauging the likely impacts of social distancing measures in the Austin-Round Rock Metropolitan Area.

We have updated our model inputs based on the daily number of COVID-19 hospitalizations in the Austin-Round Rock MSA between March 13 and April 19, 2020. The data suggest that social distancing following the March 24th Stay Home-Work Safe order has resulted in a 94% reduction in COVID-19 transmission, with our uncertainty in this estimate ranging from 70% and 100%. The data also suggest that approximately 13.6% of symptomatic cases are detected (i.e., reported as confirmed cases).

We are posting these results prior to peer review to provide intuition for both policy makers and the public regarding both the threat of COVID-19 and the extent to which social distancing measures can mitigate that threat. Our projections indicate that the *Stay Home-Work Safe* has likely prevented a COVID-19 healthcare crisis in the region during the first wave of the pandemic. When current measures are relaxed, we may see more COVID-19 transmission in the area leading to a second pandemic wave. Whether or not and how quickly COVID-19 cases and hospitalizations rise in the second wave

will critically depend on the extent to which individuals and communities continue to take steps to reduce the risks of transmission.

COVID-19 projections for the five-county Austin-Round Rock MSA as social distancing measures are lifted

We updated the Austin-Round Rock module of our *US COVID-19 Pandemic Model* to simulate COVID-19 epidemics under various assumptions about the future relaxation of social distancing measures that began with the March 24th *Stay Home-Work Safe* order. We consider all 30 combinations of the following scenarios:

- Lifting date: May 1, June 1 or July 1

- Transmission reduction after lifting date: 50%, 60%, 70%, 80%, or 90% reduction in risk relative to the baseline prior to school closures and social distancing in Austin (~94% reduction achieved under Stay Home-Work Safe)

- Cocooning after lifting date: High risk groups either do or do not maintain a 94% reduction transmission risk

The simulations ran from February 15 through mid-August, 2020 by assuming the following initial conditions and key parameters:

- Starting condition: February 15, 2020 with 1 infected adult

- Time course of interventions

    - February 15 - March 18: No interventions

    - March 15 - Aug 17: Schools closed [1]

    - March 25: *Stay Home - Work Safe* enacted, reducing transmission (beyond school closures) by an additional 94%

    - Relaxation date for social distancing: May 1, June 1, or July 1

    - Transmission reduction following relaxation date: 50%, 60%, 70%, 80%, or 90% (achieved by social distancing and other measures to reduce the likelihood of transmission)

○ Cocooning: In cocooning scenarios, we assume that the 94% reduction in transmission is maintained for all high-risk groups even after measures are relaxed (over 65 and younger individuals with high-risk conditions).

- β = 0.035 (based on fitting our model to daily COVID-19 hospitalizations in Austin-Round Rock MSA for March 13-April 5, 2020). This corresponds to an epidemic doubling time prior to school closures of 2.9 days.

- Average incubation period (assuming 12.1% of transmission happens pre-symptomatically): 6.9 days [2]

- Proportion of cases asymptomatic (assumed 46% as infectious as symptomatic cases): 17.9% [3]

Tables 1-3 and Figures 1-3 summarize results of COVID-19 simulations for the Austin-Round Rock MSA. The model structure and parameters, including age-specific hospitalization and fatality rates, are described in the Appendix below.

The model projects that the relaxation of social distancing measures would be expected to lead to a second pandemic wave, unless the Austin-Round Rock MSA population continues to take precautions that reduce the risk of transmission by over 80%. The CDC provides guidance on such measures [4], including limiting daily contacts with other people, taking precautions to prevent transmission during contacts such as keeping physical distance, wearing protective face coverings, and washing hands, voluntary and rapid self-isolation upon feeling symptoms, receiving a positive COVID-19 test result, or close contact with an infectious case.

Our projections highlight the **importance of cocooning high risk groups**, including older adults and individuals of all ages with underlying high risk conditions. Such measures would be expected to substantially reduce the numbers of COVID-19 hospitalizations and deaths during a second pandemic wave. Residents of long-term care facilities such as nursing homes are at particular risk. Measures to prevent COVID-19 introductions and rapidly contain cases in long-term care facilities are critical and may require substantial increases in staffing, limiting the numbers of residents that each caregiver contacts [5], aggressive testing and isolation, and sufficient PPE supplies. In addition, measures should be taken to protect members of the Austin-Round Rock MSA workforce with high risk conditions from possible exposures in the workplace.

Table 1. Estimated time to key COVID-19 hospitalization thresholds and cumulative COVID-19 hospitalizations for the Austin-Round Rock MSA from February 15 through August 17, 2020, assuming that social distancing measures are relaxed on May 1, 2020. The values are medians (with interquartile range in parentheses) across 150 stochastic simulations based on the parameters given in Appendix 1. Entries with *NE* are not expected to surpass the specified thresholds prior to August 17, 2020.

Transmission reduction after lifting on May 1st	With cocooning			Without Cocooning		
	Days to exceed 500 beds	**Days to exceed max capacity**	**Cumulative**	**Days to exceed 500 beds**	**Days to exceed max capacity**	**Cumulative**
50%	50 (46 - 61)	82 (78 - 93)	19,360 (14,863 - 21,258)	29 (24 - 36)	50 (44 - 57)	66,998 (61,862 - 70,691)
60%	61 (48 - 74)	104 (92 - NE)	11,643 (6,941 - 16,146)	36 (30 - 44)	62 (55 - 70)	49,248 (42,322 - 55,738)
70%	81 (68 - 96)	NE	4,457 (2,533 - 6,827)	49 (37 - 60)	87 (76 - 100)	20,665 (13,083 - 29,142)
80%	NE	NE	1,235 (471 - 2,272)	88 (65 - NE)	NE	3,342 (1,749 - 6,016)
90%	NE	NE	548 (288 - 1,006)	NE	NE	617 (323 - 1,199)

Table 2. Estimated time to key COVID-19 hospitalization thresholds and cumulative COVID-19 hospitalizations for the Austin-Round Rock MSA from February 15 through August 17, 2020, assuming that social distancing measures are relaxed on June 1, 2020. The values are medians (with interquartile range in parentheses) across 150 stochastic simulations based on the parameters given in Appendix 1. Entries with *NE* are not expected to surpass the specified thresholds prior to August 17, 2020.

Transmission reduction after lifting on June 1st	With cocooning			Without Cocooning		
	Days to exceed 500 beds	Days to exceed max capacity	Cumulative	Days to exceed 500 beds	Days to exceed max capacity	Cumulative
50%	56 (48 - 65)	NE	5,101 (2,921 - 7,953)	36 (31 - 45)	56 (51 - 66)	27,469 (17,078 - 35,736)
60%	68 (58 - 76)	NE	2,595 (1,560 - 4,420)	43 (35 - 52)	70 (61 - NE)	12,516 (7,149 - 20,154)
70%	NE	NE	1,012 (474 - 1,711)	60 (50 - 73)	NE	3,420 (1,767 - 5,662)
80%	NE	NE	655 (355 - 1,137)	NE	NE	968 (396 - 1,807)
90%	NE	NE	697 (322 - 1,160)	NE	NE	688 (329 - 1,038)

Table 3. Estimated time to key COVID-19 hospitalization thresholds and cumulative COVID-19 hospitalizations for the Austin-Round Rock MSA from February 15 through August 17, 2020, assuming that social distancing measures are relaxed on July 1, 2020. The values are medians (with interquartile range in parentheses) across 150 stochastic simulations based on the parameters given in Appendix 1. Entries with *NE* are not expected to surpass the specified thresholds prior to August 17, 2020.

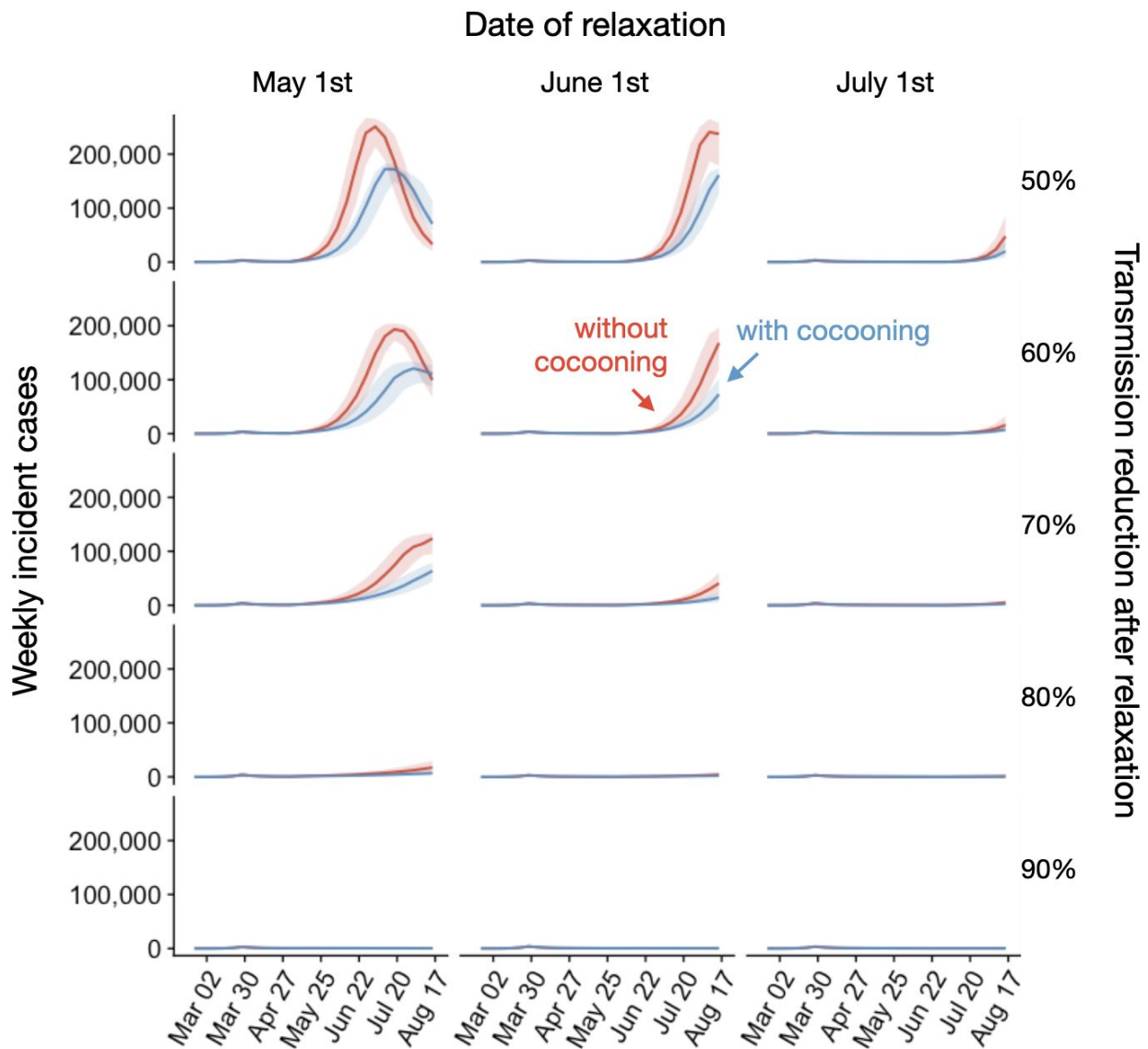| Transmission reduction after lifting on July 1st	With cocooning			Without Cocooning		
	Days to exceed 500 beds	Days to exceed max capacity	Cumulative	Days to exceed 500 beds	Days to exceed max capacity	Cumulative
50%	NE	NE	879 (384 - 1,760)	42 (35 - NE)	NE	2,079 (1,122 - 3,937)
60%	NE	NE	775 (326 - 1,356)	NE (42 - NE)	NE	1,252 (652 - 2,443)
70%	NE	NE	583 (270 - 1,108)	NE	NE	891 (402 - 1,493)
80%	NE	NE	506 (283 - 1,002)	NE	NE	598 (329 - 1,164)
90%	NE	NE	602 (352 - 967)	NE	NE	582 (290 - 943)

Figure 1. Projected weekly incident COVID-19 cases in the Austin-Round Rock MSA from February 15 to August 17, 2020 coupled with different degrees of transmission reduction after the relaxation of *Stay Home-Work Safe* order on either May 1 (left), June 1 (middle) or July 1 (right). From top to bottom, the graphs reflect increasing efforts to reduce transmission. For example, a 90% reduction means that following relaxation people continue to social distance and take other precautions to prevent the spread of COVID-19 to the extent that the transmission rate is reduced by 90% relative to COVID-19 transmission that occurred prior to school closures and the *Stay Home-Work Safe* order in mid-March. The blue lines assume that high risk individuals *cocoon*: everyone over 65 or with a known high-risk condition continues to social distance and take precautions that reduce their risk of infection by 94%. The red lines project COVID-19 cases assuming that older and high risk groups do not cocoon and instead have the same transmission reduction as the rest of the population. Lines and shading indicate the median and interquartile range across 150 stochastic simulations.
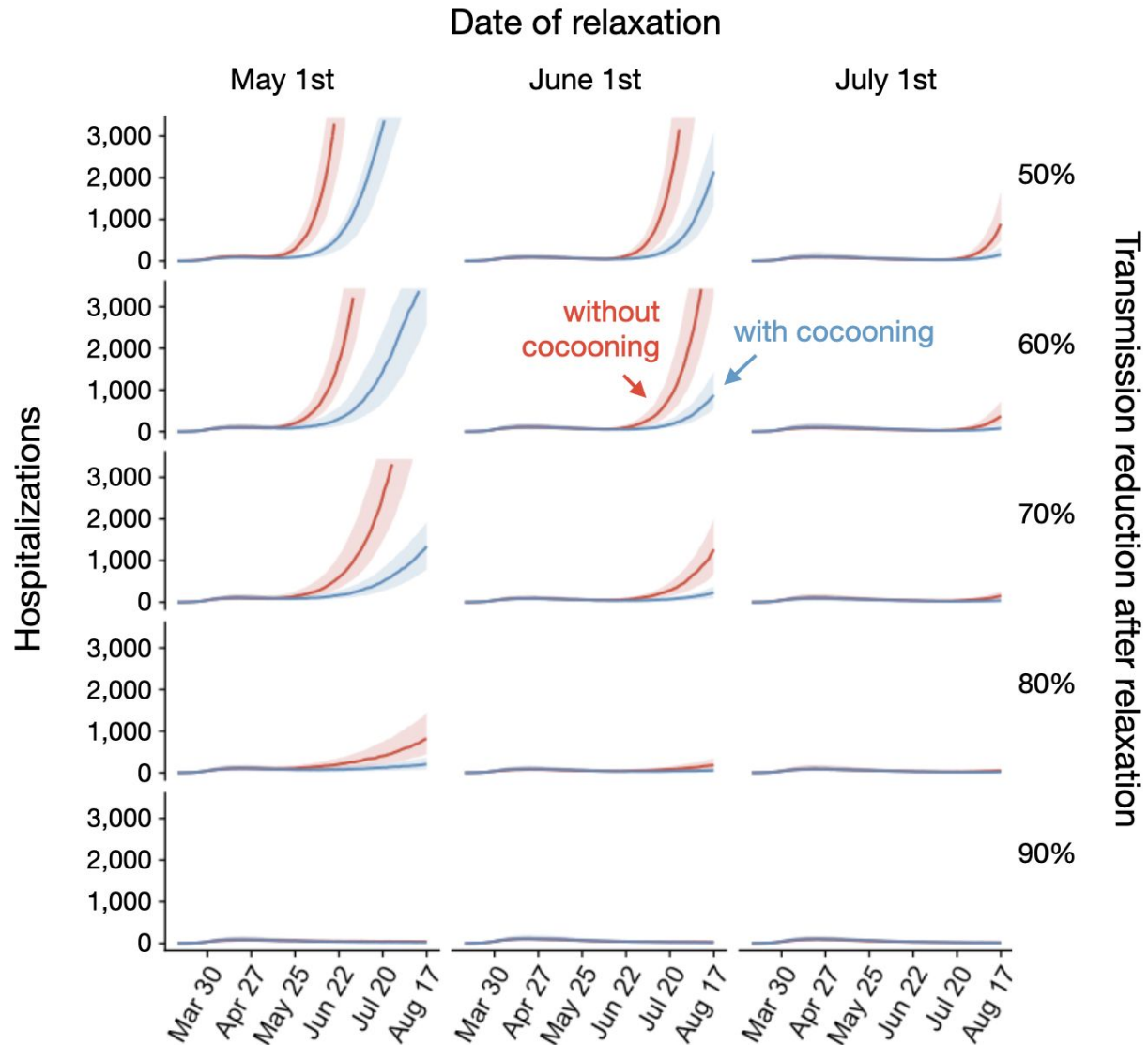
Figure 2. Projected daily COVID-19 hospitalizations in the Austin-Round Rock MSA from February 15 to August 17, 2020 coupled with different degrees of transmission reduction after the relaxation of *Stay Home-Work Safe* order on either May 1 (left), June 1 (middle) or July 1 (right). Graphs are truncated at the estimated COVID-19 hospital surge capacity of 3,440 beds for the metropolitan area. From top to bottom, the graphs reflect increasing efforts to reduce transmission. For example, a 90% reduction means that following relaxation people continue to social distance and take other precautions to prevent the spread of COVID-19 to the extent that the transmission rate is reduced by 90% relative to COVID-19 transmission that occurred prior to school closures and the *Stay Home-Work Safe* order in mid-March. The blue lines assume that high risk individuals *cocoon*: everyone over 65 or with a known high-risk condition continues to social distance and take precautions that reduce their risk of infection by 94%. The red lines project COVID-19 cases assuming that older and high risk groups do not cocoon and instead have the same transmission reduction as the rest of the population. Lines and shading indicate the median and interquartile range across 150 stochastic simulations.
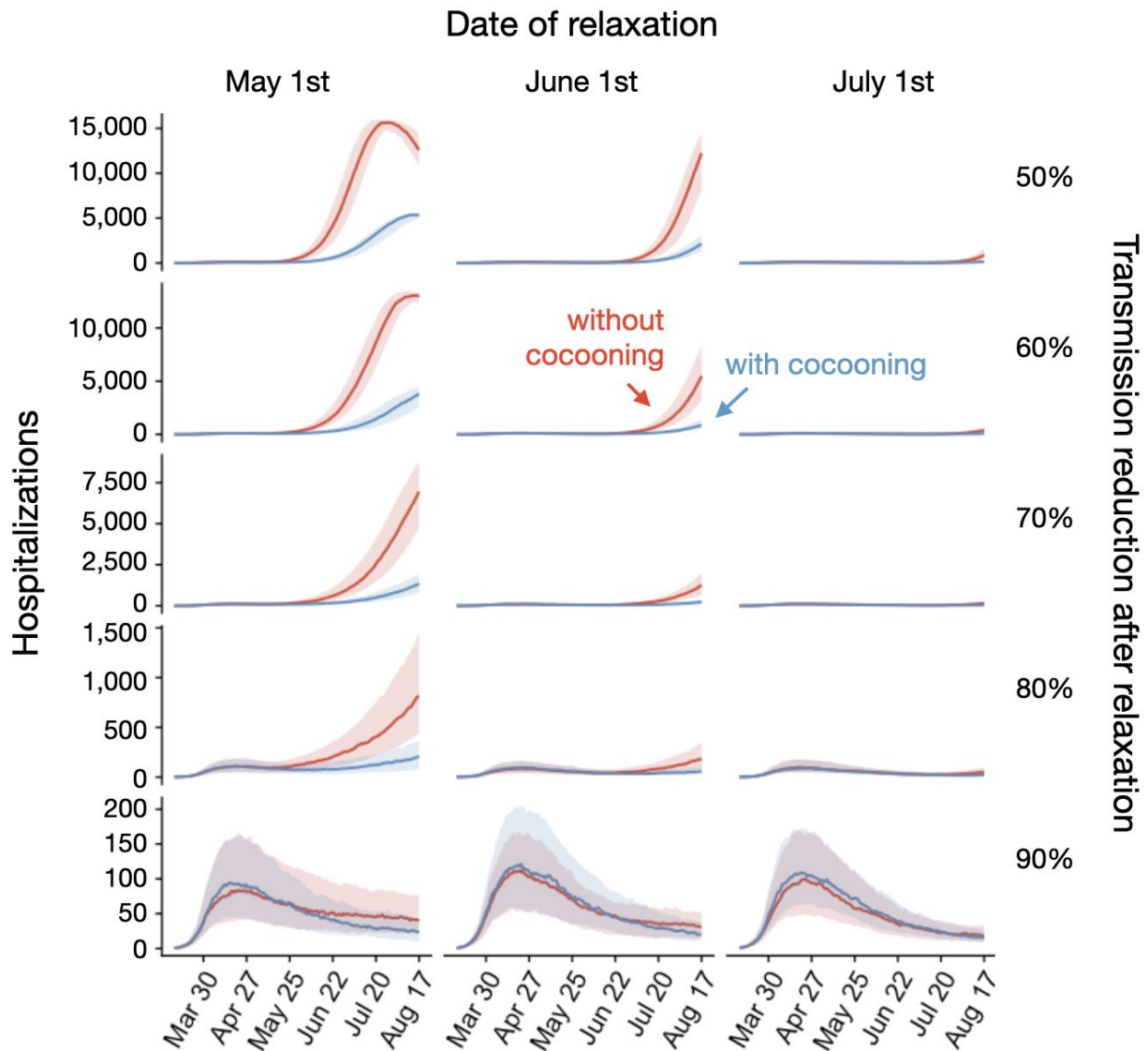
Figure 3. Projected daily COVID-19 hospitalizations in the Austin-Round Rock MSA from February 15 to August 17, 2020 coupled with different degrees of transmission reduction after the relaxation of *Stay Home-Work Safe* order on either May 1 (left), June 1 (middle) or July 1 (right). This is identical to Figure 2, except that it shows the full range of hospitalization values. Note that the y-axes scale differs between the rows. From top to bottom, the graphs reflect increasing efforts to reduce transmission. For example, a 90% reduction means that following relaxation people continue to social distance and take other precautions to prevent the spread of COVID-19 to the extent that the transmission rate is reduced by 90% relative to COVID-19 transmission that occurred prior to school closures and the *Stay Home-Work Safe* order in mid-March. The blue lines assume that high risk individuals *cocoon*: everyone over 65 or with a known high-risk condition continues to social distance and take precautions that reduce their risk of infection by 94%. The red lines project COVID-19 cases assuming that older and high risk groups do not cocoon and instead have the same transmission reduction as the rest of the population. Lines and shading indicate the median and interquartile range across 150 stochastic simulations.

Appendix

COVID-19 Epidemic Model Structure and Parameters

The model structure is diagrammed in Figure A1 and described in the equations below.
For each age and risk group, we build a separate set of compartments to model the transitions between the states: susceptible (S), exposed (E), symptomatic infectious (I^Y), asymptomatic infectious (I^A), symptomatic infectious that are hospitalized (I^H), recovered (R), and deceased (D). The symbols S, E, I^Y, I^A, I^H, R, and D denote the number of people in that state in the given age/risk group and the total size of the age/risk group is $N = S + E + I^Y + I^A + I^H + R + D$.
The model for individuals in age group a and risk group r is given by:

$$\frac{dS_{a,r}}{dt} = -\sum_{i \in A}\sum_{j \in K}(I_{i,j}^Y \omega^Y + I_{i,j}^A \omega^A + E_{i,j}\omega^E)\beta\phi_{a,i}/N_i$$

$$\frac{dE_{a,r}}{dt} = \sum_{i \in A}\sum_{j \in K}(I_{i,j}^Y \omega^Y + I_{i,j}^A \omega^A + E_{i,j}\omega^E)\beta\phi_{a,i}/N_i - \sigma E_{a,r}$$

$$\frac{dI_{a,r}^A}{dt} = (1-\tau)\sigma E_{a,r} - \gamma^A I_{a,r}^A$$

$$\frac{dI_{a,r}^Y}{dt} = \tau\sigma E_{a,r} - (1-\pi)\gamma^Y I_{a,r}^Y - \pi\eta I_{a,r}^Y$$

$$\frac{dI_{a,r}^H}{dt} = \pi\eta I_{a,r}^Y - (1-\nu)\gamma^H I_{a,r}^H - \nu\mu I_{a,r}^H$$

$$\frac{dR_{a,r}}{dt} = \gamma^A I_{a,r}^A + (1-\pi)\gamma^Y I_{a,r}^Y + (1-\nu)\gamma^H I_{a,r}^H$$

$$\frac{dD_{a,r}}{dt} = \nu\mu I_{a,r}^H$$

where A and K are all possible age and risk groups, ^{A}, ^{Y}, ^{H} are relative infectiousness of the I^A, I^Y, E compartments, respectively, β is transmission rate, $_{a,i}$ is the mixing rate between age group a, $i \in A$, ^{A}, ^{Y}, ^{H} are the recovery rates for the I^A, I^Y, I^H compartments, respectively, σ is the exposed rate, τ is the symptomatic ratio, π is the proportion of symptomatic individuals requiring hospitalization, η is rate at which hospitalized cases enter the hospital following symptom onset, ν is mortality rate for hospitalized cases, and μ is rate at which terminal patients die.

We model stochastic transitions between compartments using the τ-leap method[6,7] with key parameters given in Table S1. Assuming that the events at each time-step are independent and

do not impact the underlying transition rates, the numbers of each type of event should follow Poisson distributions with means equal to the rate parameters. We thus simulate the model according to the following equations:

$$S_{a,r}(t+1) - S_{a,r}(t) = -P_1$$

$$E_{a,r}(t+1) - E_{a,r}(t) = P_1 - P_2$$

$$I_{a,r}^A(t+1) - I_{a,r}^A(t) = (1-\tau)P_2 - P_3$$

$$I_{a,r}^Y(t+1) - I_{a,r}^Y(t) = \tau P_2 - P_4 - P_5$$

$$I_{a,r}^H(t+1) - I_{a,r}^H(t) = P_5 - P_6 - P_7$$

$$R_{a,r}(t+1) - R_{a,r}(t) = P_3 + P_4 + P_6$$

$$D_{a,r}(t+1) - D_{a,r}(t) = P_7 \, ,$$

with

$$P_1 \sim \mathrm{Pois}(S_{a,r}(t)F_{a,r}(t))$$

$$P_2 \sim \mathrm{Pois}(\sigma E_{a,r}(t))$$

$$P_3 \sim \mathrm{Pois}(\gamma^A I_{a,r}^A(t))$$

$$P_4 \sim \mathrm{Pois}((1-\pi)\gamma^Y I_{a,r}^Y(t))$$

$$P_5 \sim \mathrm{Pois}(\pi\eta I_{a,r}^Y(t))$$

$$P_6 \sim \mathrm{Pois}((1-\nu)\gamma^H I_a^H)$$

$$P_7 \sim \mathrm{Pois}(\nu\mu I_{a,r}^H(t))$$

and where $F_{a,r}$ denotes the force of infection for individuals in age group a and risk group r and is given by:

$$F_{a,r}(t) = \sum_{i \in A} \sum_{j \in K} (I_{i,r}^Y(t)\omega^Y + I_{i,r}^A(t)\omega^A + E_{i,j}(t)\omega^E)\beta_{a,i}\phi_{a,i}/N_i$$
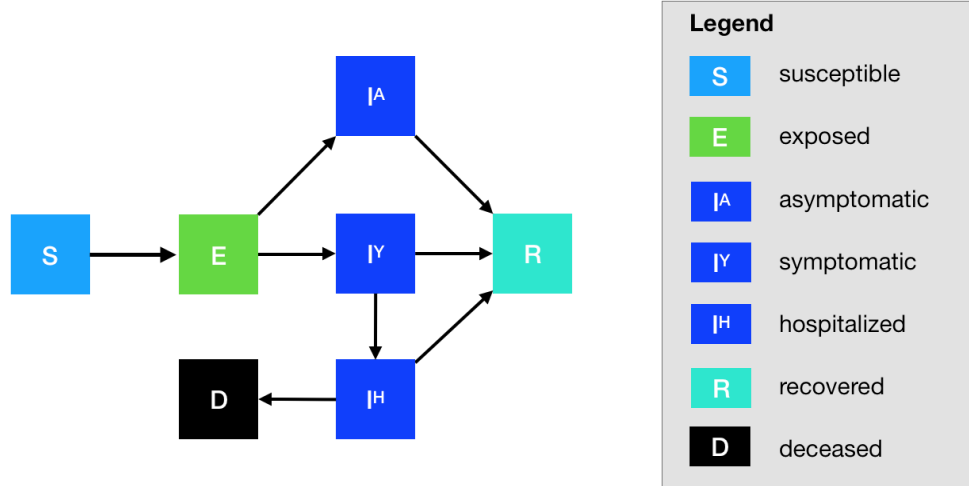
Figure A1. Compartmental model of COVID-19 transmission in a US city. Each subgroup (defined by age and risk) is modeled with a separate set of compartments. Upon infection, susceptible individuals (S) progress to exposed (E) and then to either symptomatic infectious (I^Y) or asymptomatic infectious (I^A). All asymptomatic cases eventually progress to a recovered class where they remain protected from future infection (R); symptomatic cases are either hospitalized (I^H) or recover. Mortality (D) varies by age group and risk group and is assumed to be preceded by hospitalization.

Estimating the effect of the Stay Home-Work Safe order

We estimated the transmission rate of COVID-19 in the Austin-Round Rock MSA before and after the March 24th *Stay Home-Work Safe* order using least-squares fitting, which compares the predicted and observed numbers of daily hospitalizations (i.e., heads in beds) for the Austin-Round Rock MSA. We assume that: (i) the epidemic starts with a single case on February 15, 2020 with an initial transmission rate of β, (ii) the transmission rate decreases when school closures are enacted on March 14, 2020 (by an amount determined by our pre-set contact matrices), (iii) the transmission rate decreases further by an amount d on March 25th following the *Stay Home-Work Safe* order.

We estimate β and d simultaneously using a nonlinear least squares fitting procedure in the SciPy/Python package [8]. For a given pair of β and d, we run a deterministic simulation of our model assuming central values for each parameter. Using a trust region method, the algorithm finds values of β and d that minimize the sum of squared daily differences between the simulated ($\hat{H}_t$) and actual (H_t) daily hospitalizations from March 13, 2020 through April 19, 2020:

$$S(\beta, d) = \sum_t (H_t - \hat{H}_t)^2$$

We calculated 95% confidence intervals for the social distancing parameter d indirectly by running 500 stochastic simulations for each of the following possible values of d': 0.0, 0.05, ...,

0.95, 1.0. For each value of d', we conducted the following analysis to determine if d' lies inside the 95% confidence interval for d.

- For all simulations, we calculate the day-to-day difference in hospitalizations (i.e., heads in beds) during the period following the *Stay Home-Work Safe* order: $\hat{z}_t = \hat{H}_t - \hat{H}_{t-1}$. We do the same for the actual data: $z_t = H_t - H_{t-1}$.

- We compute the 95% prediction interval for $\hat{z}_t$ across all 500 stochastic simulations for d' for each day t.

- We then conduct a test of the null hypothesis $H_0 : d' = d$. Under this null hypothesis, we would expect roughly 95% of the observed data (z_t) to fall within the 95% prediction band for $\hat{z}_t$ that we constructed from our simulations. By analyzing the day-to-day difference in hospitalizations rather than daily hospitalizations, we can assume that the data are independent from one day to the next. Then the expected number of observed values contained in the 95% prediction band is given by the binomial expression:

$$N_{\text{contained}} \sim B\left(N_{\text{points}}, 0.95\right)$$

  where $N_{\text{contained}}$ is the number of data points contained within the 95% prediction band and N_{points} is the total number of data points (i.e., days).

- If the binomial probability of $N_{\text{contained}}$ is less than 0.05, we reject the null hypothesis $H_0 : d' = d$

To construct a 95% confidence interval for d we take the minimum and maximum d' for which we did not reject the null hypothesis $H_0 : d' = d$.

Table A1. Initial conditions, school closures and social distancing policies

Variable	Settings
Initial day of simulation	2/15/2020
Initial infection number in locations	1 symptomatic case in 18-49y age group
School closure	3/15/2020 - 8/17/2020
Social distancing reduction in contacts	0.94
Relaxation date	Three scenarios: May 1, Jun 1, July 1
Transmission reduction following relaxation date	Five scenarios: [0.5, 0.6, 0.7, 0.8, 0.9]
Age-specific and day-specific contact rates	Home, work, other and school matrices provided in Tables S4.1-S4.4 ● From 2020-02-15 to 2020-03-14 Weekday = home + school + work + other Weekend = home + other Weekday holiday = home + other ● From 2020-03-15 to 2020-03-24 Weekday = home + work + other Weekend = home + other Weekday holiday = home + other ● Since 2020-03-25 Weekday = (1-a)*(home + work + other) Weekend = (1-a)*(home + other) Weekday holiday = (1-a)*(home + other)

Table A2. Model parameters[a]

Parameters	Best guess values (doubling time = 4 days)	Source
R_0: reproduction number	2.8	Derived from fitted model
δ: doubling time	2.9 days	Derived from fitted model

β: transmission rate	0.035	Fitted to daily COVID-19 hospitalizations in Austin-Round Rock MSA
γ^A: recovery rate on asymptomatic compartment	Equal to γ^Y	
γ^Y: recovery rate on symptomatic non-treated compartment	$\frac{1}{\gamma^Y} \sim \mathrm{Triangular}(21.2, 22.6, 24.4)$	Verity et al. [9]
τ: symptomatic proportion (%)	82.1	Mizumoto et al.[3]
σ: exposed rate	$\frac{1}{\sigma} \sim \mathrm{Triangular}(5.6, 7, 8.2)$	Lauer et al.[2]
P: proportion of pre-symptomatic transmission (%)	12.6	Du et al.[10]
ω^E: relative infectiousness of infectious individuals in compartment E	$\omega^E = \frac{(\frac{YHR}{\eta} + \frac{1-YHR}{\gamma^Y})\omega^Y \sigma P}{1 - P}$	
ω^A: relative infectiousness of infectious individuals in compartment I^A	0.4653	Set to mean of ω^E
IFR: infected fatality ratio, age specific (%)	Low risk: [0.0009, 0.0022, 0.0339, 0.2520, 0.6440] High risk: [0.0092, 0.0218, 0.3388, 2.5197, 6.4402]	Age adjusted from Verity et al. [9]
YFR: symptomatic fatality ratio, age specific (%)	Low risk: [0.0011165, 0.0027 , 0.0412, 0.3069, 0.7844] High risk: [0.0112, 0.0265, 0.4126, 3.0690, 7.8443]	$YFR = \frac{IFR}{1 - \tau}$

		Estimated using 2015-2016 Behavioral Risk Factor Surveillance System (BRFSS) data with multilevel regression and poststratification using CDC's list of conditions that may increase the risk of serious complications from influenza[11–13]
h : high-risk proportion, age specific (%)	[8.2825, 14.1121, 16.5298, 32.9912, 47.0568]	
rr : relative risk for high risk people compared to low risk in their age group	10	Assumption

[a]Values given as five-element vectors are age-stratified with values corresponding to 0-4, 5-17, 18-49, 50-64, 65+ year age groups, respectively.

Table A3 Hospitalization parameters

Parameters	Value	Source
γ^H : recovery rate in hospitalized compartment	1/14	14 day-average from admission to discharge (UT Austin Dell Med)
YHR: symptomatic case hospitalization rate (%)	Low risk: [0.0279, 0.0215, 1.3215, 2.8563, 3.3873] High risk: [0.2791, 0.2146, 13.2154, 28.5634, 33.8733]	Age adjusted from Verity et al. [9]
π : rate of symptomatic individuals go to hospital, age-specific	$$\pi = \frac{\gamma^Y * YHR}{\eta + (\gamma^Y - \eta)YHR}$$	
η : rate from symptom onset to hospitalized	0.1695	5.9 day average from symptom onset to hospital admission Tindale et al.[14]
μ : rate from hospitalized to death	1/14	14 day-average from admission to death (UT Austin Dell Med)
HFR: hospitalized fatality ratio, age specific (%)	[4, 12.365, 3.122, 10.745, 23.158]	$$HFR = \frac{IFR}{YHR(1 - \tau)}$$

ν: death rate on hospitalized individuals, age specific	[0.0390, 0.1208, 0.0304, 0.1049, 0.2269]	$\nu = \dfrac{\gamma^H HFR}{\mu + (\gamma^H - \mu)HFR}$
ICU: proportion hospitalized people in ICU	[0.15, 0.20, 0.15, 0.20, 0.15]	CDC planning scenarios (based on US seasonal flu data)
Vent: proportion of individuals in ICU needing ventilation	$[\frac{2}{3}, \frac{2}{3}, \frac{2}{3}, \frac{2}{3}, \frac{2}{3}]$	Assumption
d_{ICU}: duration of stay in ICU	10 days	Assumption, set equal to duration of ventilation
d_V: duration of ventilation	10 days	Assumption
Healthcare capacity	Hospital bed: 4299 (assume 80% available for COVID-19) ICU bed: 755 (90% available) Ventilator: 755 (90% available)	Estimates provided by each of the region's hospital systems and aggregated by regional public health leaders

Table A4.1 Home contact matrix. Daily number contacts by age group at home.

	0-4y	5-17y	18-49y	50-64y	65y+
0-4y	0.5	0.9	2.0	0.1	0.0
5-17y	0.2	1.7	1.9	0.2	0.0
18-49y	0.2	0.9	1.7	0.2	0.0
50-64y	0.2	0.7	1.2	1.0	0.1
65y+	0.1	0.7	1.0	0.3	0.6

Table A4.2 School contact matrix. Daily number contacts by age group at school.

	0-4y	5-17y	18-49y	50-64y	65y+
0-4y	1.0	0.5	0.4	0.1	0.0
5-17y	0.2	3.7	0.9	0.1	0.0
18-49y	0.0	0.7	0.8	0.0	0.0
50-64y	0.1	0.8	0.5	0.1	0.0
65y+	0.0	0.0	0.1	0.0	0.0

Table A4.3 Work contact matrix. Daily number contacts by age group at work.

	0-4y	5-17y	18-49y	50-64y	65y+
0-4y	0.0	0.0	0.0	0.0	0.0
5-17y	0.0	0.1	0.4	0.0	0.0
18-49y	0.0	0.2	4.5	0.8	0.0
50-64y	0.0	0.1	2.8	0.9	0.0
65y+	0.0	0.0	0.1	0.0	0.0

Table A4.4 Others contact matrix. Daily number contacts by age group at other locations.

	0-4y	5-17y	18-49y	50-64y	65y+
0-4y	0.7	0.7	1.8	0.6	0.3
5-17y	0.2	2.6	2.1	0.4	0.2
18-49y	0.1	0.7	3.3	0.6	0.2
50-64y	0.1	0.3	2.2	1.1	0.4
65y+	0.0	0.2	1.3	0.8	0.6

Estimation of age-stratified proportion of population at high-risk for COVID-10 complications

We estimate age-specific proportions of the population at high risk of complications from COVID-19 based on data for Austin, TX and Round-Rock, TX from the CDC's 500 cities project (Figure A2).[15] We assume that high risk conditions for COVID-19 are the same as those

specified for influenza by the CDC.[11] The CDC's 500 cities project provides city-specific estimates of prevalence for several of these conditions among adults.[16] The estimates were obtained from the 2015-2016 Behavioral Risk Factor Surveillance System (BRFSS) data using a small-area estimation methodology called multi-level regression and poststratification.[12,13] It links geocoded health surveys to high spatial resolution population demographic and socioeconomic data.[13]

Estimating high-risk proportions for adults. To estimate the proportion of adults at high risk for complications, we use the CDC's 500 cities data, as well as data on the prevalence of HIV/AIDS, obesity and pregnancy among adults (Table A6).

The CDC 500 cities dataset includes the prevalence of each condition on its own, rather than the prevalence of multiple conditions (e.g., dyads or triads). Thus, we use separate co-morbidity estimates to determine overlap. Reference about chronic conditions[17] gives US estimates for the proportion of the adult population with 0, 1 or 2+ chronic conditions, per age group. Using this and the 500 cities data we can estimate the proportion of the population p_{HR} in each age group in each city with at least one chronic condition listed in the CDC 500 cities data (Table A6) putting them at high-risk for flu complications.

HIV: We use the data from table 20a in CDC HIV surveillance report[18] to estimate the population in each risk group living with HIV in the US (last column, 2015 data). Assuming independence between HIV and other chronic conditions, we increase the proportion of the population at high-risk for influenza to account for individuals with HIV but no other underlying conditions.
Morbid obesity: A BMI over 40kg/m^2 indicates morbid obesity, and is considered high risk for influenza. The 500 Cities Project reports the prevalence of obese people in each city with BMI over 30kg/m^2 (not necessarily morbid obesity). We use the data from table 1 in Sturm and Hattori[19] to estimate the proportion of people with BMI>30 that actually have BMI>40 (across the US); we then apply this to the 500 Cities obesity data to estimate the proportion of people who are morbidly obese in each city. Table 1 of Morgan et al.[20] suggests that 51.2% of morbidly obese adults have at least one other high risk chronic condition, and update our high-risk population estimates accordingly to account for overlap.
Pregnancy: We separately estimate the number of pregnant women in each age group and each city, following the methodology in CDC reproductive health report.[21] We assume independence between any of the high-risk factors and pregnancy, and further assume that half the population are women.

Estimating high-risk proportions for children. Since the 500 Cities Project only reports data for adults 18 years and older, we take a different approach to estimating the proportion of children at high risk for severe influenza. The two most prevalent risk factors for children are asthma and obesity; we also account for childhood diabetes, HIV and cancer.
From Miller et al.[22], we obtain national estimates of chronic conditions in children. For asthma, we assume that variation among cities will be similar for children and adults. Thus, we use the

relative prevalences of asthma in adults to scale our estimates for children in each city. The prevalence of HIV and cancer in children are taken from CDC HIV surveillance report[18] and cancer research report,[23] respectively.

We first estimate the proportion of children having either asthma, diabetes, cancer or HIV (assuming no overlap in these conditions). We estimate city-level morbid obesity in children using the estimated morbid obesity in adults multiplied by a national constant ratio for each age group estimated from Hales et al.,[24] this ratio represents the prevalence in morbid obesity in children given the one observed in adults. From Morgan et al.,[20] we estimate that 25% of morbidly obese children have another high-risk condition and adjust our final estimates accordingly.

Resulting estimates. We compare our estimates for the Austin-Round Rock Metropolitan Area to published national-level estimates[25] of the proportion of each age group with underlying high risk conditions (Table A6). The biggest difference is observed in older adults, with Austin having a lower proportion at risk for complications for COVID-19 than the national average; for 25-39 year olds the high risk proportion is slightly higher than the national average.
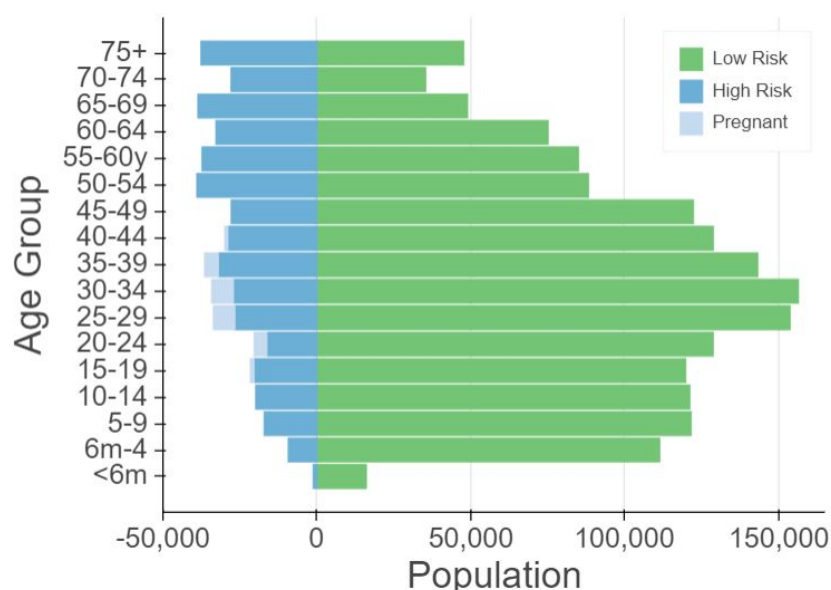

Figure A2. Demographic and risk composition of the Austin-Round Rock MSA. Bars indicate age-specific population sizes, separated by low risk, high risk, and pregnant. High risk is defined as individuals with cancer, chronic kidney disease, COPD, heart disease, stroke, asthma, diabetes, HIV/AIDS, and morbid obesity, as estimated from the CDC 500 Cities Project,[15] reported HIV prevalence[18] and reported morbid obesity prevalence,[19,20] corrected for multiple conditions. The population of pregnant women is derived using the CDC's method combining fertility, abortion and fetal loss rates.[26–28]

Table A6. High-risk conditions for influenza and data sources for prevalence estimation

Condition	Data source
Cancer (except skin), chronic kidney disease, COPD, coronary heart disease, stroke, asthma, diabetes	CDC 500 cities [15]
HIV/AIDS	CDC HIV Surveillance report [18]
Obesity	CDC 500 cities [15], Sturm and Hattori [19], Morgan et al.[20]
Pregnancy	National Vital Statistics Reports [26] and abortion data [27]

Table A7: Comparison between published national estimates and Austin-Round Rock MSA estimates of the percent of the population at high-risk of influenza/COVID-19 complications.

Age Group	National estimates [24]	Austin (excluding pregnancy)	Pregnant women (proportion of age group)
0 to 6 months	NA	6.8	-
6 months to 4 years	6.8	7.4	-
5 to 9 years	11.7	11.6	-
10 to 14 years	11.7	13.0	-
15 to 19 years	11.8	13.3	1.7
20 to 24 years	12.4	10.3	5.1
25 to 34 years	15.7	13.5	7.8
35 to 39 years	15.7	17.0	5.1
40 to 44 years	15.7	17.4	1.2
45 to 49 years	15.7	17.7	-
50 to 54 years	30.6	29.6	-
55 to 60 years	30.6	29.5	-
60 to 64 years	30.6	29.3	-
65 to 69 years	47.0	42.2	-
70 to 74 years	47.0	42.2	-
75 years and older	47.0	42.2	-

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