# Report 32: Age groups that sustain resurging COVID-19 epidemics in the United States v2

Mélodie Monod*, Alexandra Blenkinsop*, Xiaoyue Xi*, Daniel Hebert*, Sivan Bershan*, Simon Tietze*, Marc Baguelin, Valerie C Bradley, Yu Chen, Helen Coupland, Sarah Filippi, Jonathan Ish-Horowicz, Martin McManus, Thomas Mellan, Axel Gandy, Michael Hutchinson, H Juliette T Unwin, Sabine L van Elsland, Michaela A C Vollmer, Sebastian Weber, Harrison Zhu, Anne Bezancon, Neil M Ferguson, Swapnil Mishra, Seth Flaxman[1], Samir Bhatt[1], and Oliver Ratmann[1,*], on behalf of the Imperial College COVID-19 Response Team

Department of Mathematics, Imperial College London
Foursquare Inc.
Emodo Inc.
Department of Infectious Disease Epidemiology, Imperial College London
WHO Collaborating Centre for Infectious Disease Modelling
MRC Centre for Global Infectious Disease Analytics
Abdul Latif Jameel Institute for Disease and Emergency Analytics, Imperial College London
Novartis Pharma AG, Basel, Switzerland
Department of Statistics, University of Oxford

*Contributed equally.
[1]Corresponding authors: Oliver Ratmann, oliver.ratmann@imperial.ac.uk; Samir Bhatt, s.bhatt@imperial.ac.uk; Seth Flaxman, s.flaxman@imperial.ac.uk

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## One sentence summary

As of October 2020, adults aged 20-49 are the primary age group driving COVID-19 epidemics in the United States, with children and teens contributing disproportionately few infections.


## Summary

Following initial declines, in mid 2020 a resurgence in transmission of novel coronavirus disease (COVID-19) occurred in the US and Europe. As COVID-19 disease control becomes more localised, understanding the age demographics driving transmission and how these affect the loosening of interventions is crucial. We analyse aggregated, age-specific mobility trends from more than 10 million individuals in the US and linked these mechanistically to age-specific COVID-19 mortality data. We estimate that as of October 2020, individuals aged 20-49 are the only age groups sustaining resurgent SARS-CoV-2 transmission with reproduction numbers well above one, and that at least 65 of 100 COVID-19 infections originate from individuals aged 20-49 in the US. Targeting interventions to adults aged 20-49 is an important consideration in halting resurgent epidemics and preventing COVID-19-attributable deaths.


## 1 Introduction

Following worldwide spread of the novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), the implementation of large-scale non-pharmaceutical interventions has led to sustained declines in the number of reported SARS-CoV-2 infections and deaths from coronavirus disease 2019 (COVID-19) [1, 2]. However since mid June, the daily number of reported COVID-19 cases is resurging in Europe and North America, and surpassed in the United States alone 40,000 daily reported cases on June 26, and 100,000 on November 4 [3]. Demographic analyses have shown that the share of individuals aged 20-29 among reported cases increased most, suggesting that young adults may be driving re-surging epidemics [4]. However reported COVID-19 case data may not be a reliable indicator of disease spread due to the large proportion of asymptomatic COVID-19, increased testing, and changing testing behaviour [5]. Here, we use detailed, longitudinal, and age-specific population mobility and COVID-19 mortality data to estimate how non-pharmaceutical interventions, changing contact intensities, age, and other factors have interplayed and led to resurgent disease spread. We test previous claims that resurgent COVID-19 is a result of increased spread from young adults, identify the population age groups driving SARS-CoV-2 spread across the US through October 29, 2020, and quantify changes in transmission dynamics since schools reopened.

Similar to many other respiratory diseases, the spread of SARS-CoV-2 occurs primarily through close human contact, which, at a population level, is highly structured [6]. Prior to the implementation of COVID-19 interventions, contacts concentrated among individuals of similar age, were highest among school-aged children and teens, and also common between children/teens and their parents, and middle-aged adults and the elderly [6]. Since the beginning of the pandemic, these contact patterns have changed substantially [7, 8, 9]. In the US, the Berkeley

Interpersonal Contact Study indicates that in late March 2020 after stay-at-home orders were issued, the average number of daily contacts made by a single individual, also known as contact intensity, dropped to four or fewer contacts per day [9]. Data from China show that infants and school-aged children and teens had almost no contact to similarly aged children and teens in the first weeks after stay-at-home orders, and reduced contact intensities with older individuals [7]. However, detailed human contact and mobility data have remained scarce, especially longitudinally, although such data are essential to better understand the engines of COVID-19 transmission [10].

## 2 Results

### Cell-phone data suggest similar rebounds in mobility across age groups

We compiled a national-level, aggregate mobility data set using cell phone data from >10 million individuals with Foursquare's location technology, Pilgrim [11], which leverages a wide variety of mobile device signals to pinpoint the time, duration, and location of user visits to locations such as shops, parks, or universities. Unlike the population-level mobility trends published by Google from cell phone geolocation data [12], the data are disaggregated by age. User venue visits were aggregated and projected to estimate for each state and two metropolitan areas daily percent changes in venue visits for individuals aged $18-24$, $25-34$, $35-44$, $45-54$, $55-64$, and $65+$ years relative to the the baseline period February 3 - February 9, 2020 (Figs. S1 and S2, and Supplementary materials).

Across the US as a whole, the mobility trends indicate substantial initial declines in venue visits followed by a subsequent rebound for all age groups (Fig. 1A and Fig. S1). During the initial phase of epidemic spread, trends declined most strongly among individuals aged 18-24 years across almost all states and metropolitan areas, and subsequently tended to increase most strongly among individuals aged 18-24 in the majority of states and metropolitan areas (Fig. S3), consistent with re-opening policies for restaurants, night clubs, and other venues [10, 13, 14]. Yet, considering both the initial decline and subsequent rebound until October 29, 2020, our data indicate that mobility levels among individuals aged $<35$ years have not increased above those observed among older individuals (Fig. 1B and Fig. S3).

Mobile phone signals are challenging to analyse, owing e.g. to daily fluctuations in the user panel providing location data, imprecise geolocation measurements, and changing user behaviour [15]. We cross-validated the inferred mobility trends against age-specific mobility data from a second mobile phone intelligence provider, Emodo. This second data set quantified the daily proportions of age-stratified users who spent time outside their home location, and also showed no evidence for faster mobility rebounds among young adults aged $<35$ years as compared to older age groups (see Supplementary materials). While other age-specific behavioural differences in for example consistent social distancing, mask use, duration of visits, or types of venues visited could also explain age-specific differences in transmission risk [10, 13, 14, 16, 17], these observations nonetheless led us to hypothesize that the resurgent epidemics in the US may not be driven by increased transmission from young adults aged 20-34.

## Reconstructing human contact patterns and SARS-CoV-2 transmission

To test this hypothesis and disentangle the various factors, we incorporated the mobility data into a Bayesian contact-and-infection model that describes time-changing contact and transmission dynamics at state and metropolitan area-level across the US. For the time period prior to changes in mobility trends, we used data from pre-COVID-19 contact surveys [6], and each locations's age composition and population density to predict contact intensities between individuals grouped in 5-year age bands (Figs. S4 to S6), similar as in [18]. On weekends, contact intensities between school-aged children and teens are lower than on weekdays, while inter-generational contact intensities are higher. In the model, the observed age-specific mobility trends of Figure 1 are then used to estimate in each location (state or metropolitan area) daily changes in age-specific contact intensities for individuals aged 20 and above. For younger individuals, for who mobility trends are not recorded, contact intensities during school closure periods were set to estimates from two contact surveys conducted post COVID-19 emergence [8, 7]. After school reopening in August 2020, relative changes in disease relevant contacts from and to children and teens aged 0-19 were estimated through the model. Contact intensities between children and teens were modelled and estimated separately, to account for potentially lower or higher disease relevant contacts between children and teens in the context of existing non-pharmaceutical interventions within and outside schools (see Materials and methods). As in [19], the model further incorporates random effects in space, time, and by age to allow for unobserved, potentially age-specific factors that could modulate disease-relevant contact patterns. These random effects enabled us to identify signatures of age-specific, behavioral drivers of SARS-CoV-2 transmission beyond the mobility data in Figure 1, that may underlie the highly heterogeneous epidemic trajectories across the US. Finally, the reconstructed contact intensities are used in the model to estimate the rate of SARS-CoV-2 transmission, and subsequently infections and deaths. Figure 0 in the extended abstract provides a model overview, and full details are in the Supplementary materials.

## Estimated disease dynamics closely reproduce age-specific COVID-19 attributable death counts

The contact-and-infection model was fitted to the Foursquare mobility trends, and age-specific, COVID-19-attributed mortality time series data, which we recorded daily from publicly available sources in 43 US states, the District of Columbia and New York City since March 15, 2020 (Fig. S7, see also Supplementary materials). Our overall rationale was that, reflecting the highly structured nature of human contacts, transmissions from age groups are received by specific other age groups, and mortality accrues in the age groups receiving infections. Thus, working back from the time evolution of reliably documented, age-specific COVID-19 attributable deaths, it is possible to reconstruct age-specific drivers of transmission during particular periods in time. Inference was performed in a Bayesian framework and restricted to 38 US states, the District of Columbia and New York City with at least 300 COVID-19-attributed deaths, giving a total of 8,676 observation days. The estimated disease dynamics closely reproduced the age-specific COVID-19 death counts (Fig. S8).

Figure 2 illustrates the model fits for New York City, Florida, California, and Arizona, showing that the inferred epidemic dynamics differed markedly across locations. For example, in New York City, the epidemic accelerated for at least 4 weeks since the 10th cumulative death and until age-specific reproduction numbers started to decline, resulting in an epidemic of large magnitude as shown through the estimated number of infectious individuals (Fig. 2, mid column). Subsequently, we find that reproduction numbers for all age groups were controlled to well

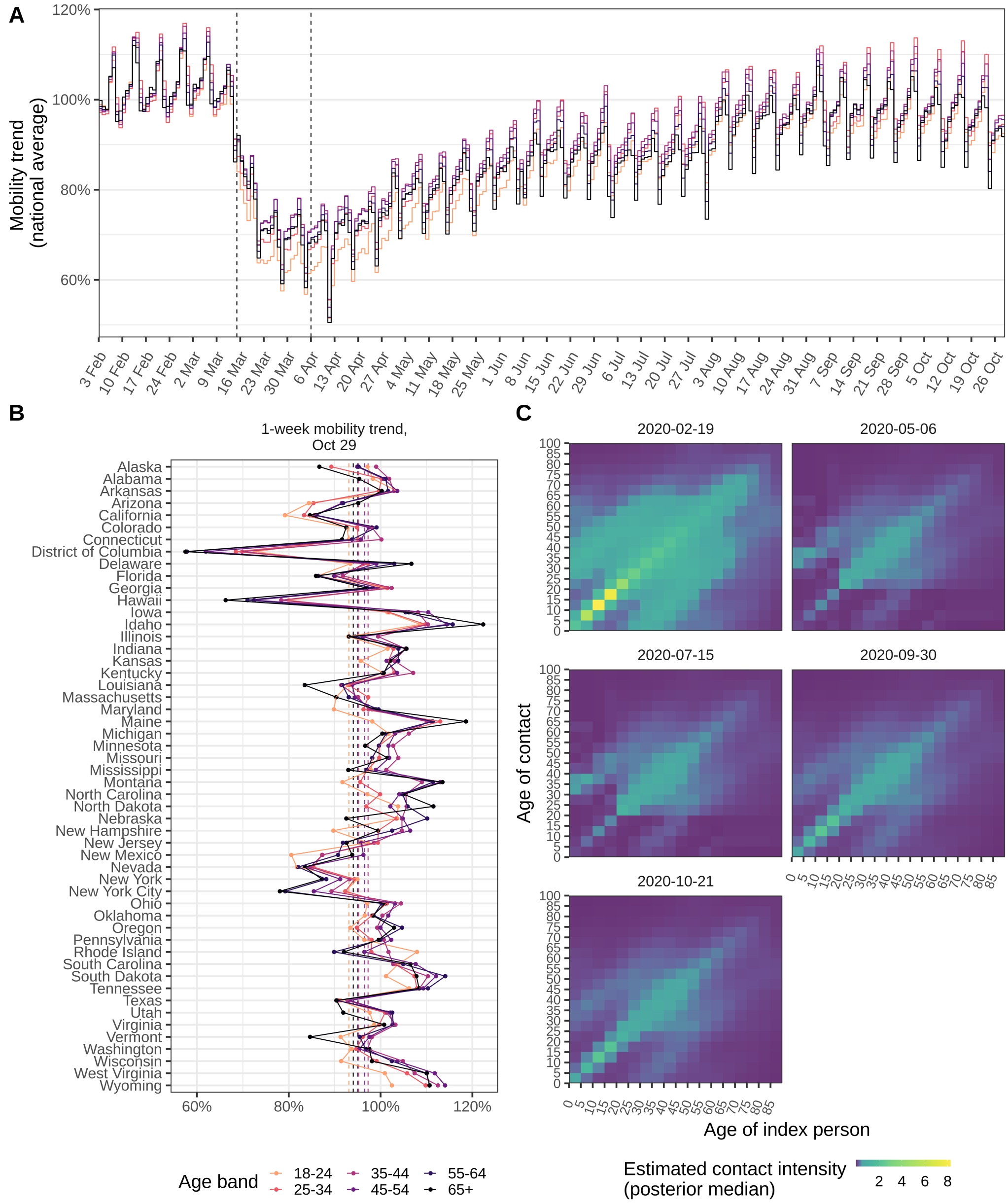


**Figure 1: Mobility trends, and estimated time evolution of contact intensities in the United States.** (**A**) National, longitudinal mobility trends for individuals aged 18-24, 25-34, 35-44, 45-54, 55-64, 65+, relative to the baseline period February 3 to February 9, 2020. Projected per capita visits standardised daily visit volumes by the population size in each location and age group. The vertical dashed lines show the dip and rebound dates since when mobility trends began to decrease and increase, which were estimated from the time series data. (**B**) 1-week average of age-specific mobility trends between October 23, 2020 - October 29, 2020 across the United States. (**C**) Inferred time evolution of contact intensities in California, calculated as per Equation 4

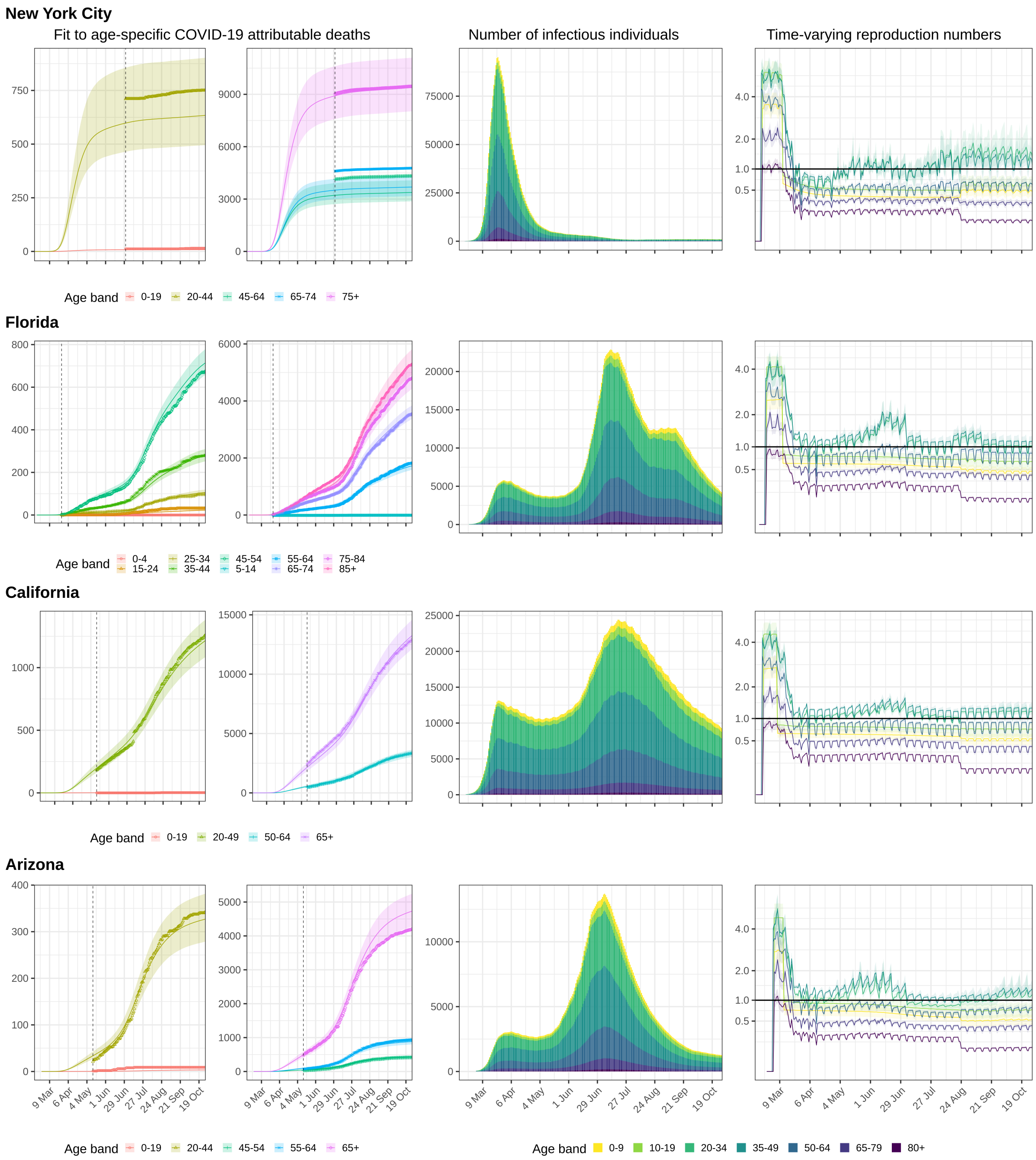


**Figure 2: Model fits and key generated quantities for New York City, California, Florida and Arizona.** (**Left**) Observed cumulative COVID-19 mortality data (dots) versus posterior median estimates (line) and 95% credible intervals (ribbon). The vertical line indicates the collection start date of age-specific death counts. (**Middle**) Estimated number of infectious individuals by age (posterior median). (**Right**) Estimated age-specific effective reproduction number, posterior median (line) and 95% credible intervals (ribbon).

below one except for individuals aged 20-49 (Fig. 2, rightmost column), resulting in a steady decline of infectious individuals. In the model, children and teens returned to their pre-lockdown contact intensities on August 24, 2020 or later, depending on when state administrations no longer mandated state-wide school closures, and relative decreases or increases in their disease relevant contact intensities after school-reopening were estimated. Concomitantly, reproduction numbers from children aged 0-9 and teens aged 10-19 increased, but as of the last observation week in October, 2020 we find no strong evidence that their reproduction numbers have exceeded one at population level in most states and metropolitan areas considered. Detailed situation analyses for all locations are presented in the supplemetary materials.

## SARS-CoV-2 transmission is sustained only from age groups 20-49, and in some locations also from 10-19

Figure 3 summarises the epidemic situation for all states and metropolitan areas evaluated, and the age groups that sustain COVID-19 spread. In the last observation week in October, 2020, the estimated reproduction number across all locations evaluated was highest from individuals aged 35-49 (1.40 [1.35-1.46]) and close to or above one only for individuals aged 20-34 and 10-19 (Tables S1 and S2). The mechanism underlying the high reproduction numbers from the age groups 20-34, 35-49 are estimated, high numbers of COVID-19 relevant contacts from these age bands. This reflected in part the typical large contact intensities from these age groups in comparison to older individuals (Fig. S6), increasing mobility trends since April 2020 for these age groups (Fig. 1), and school closures until fall 2020. In addition, from the death time series data, the model inferred characteristic random effect signatures in time and by age across locations (Fig. S9), which indicate elevated transmission risk per venue visit for individuals aged 20-49 relative to other age groups. Figure S10 visualises the combined, estimated effects of mobility and behaviour on transmission risk, and reveals together with Figure 3 considerable heterogeneity in age-specific transmission dynamics across locations. While the model consistently estimates effective reproduction numbers close to or above one across all locations from adults aged 35-49, disease dynamics are more variable from young adults aged 20-34, with some states (Arizona, Florida, Texas) showing sustained transmission from young adults in May and June, and other states (e.g. Colorado, Illinois, Wisconsin) showing sustained transmission from young adults since August. This suggests that targeted interventions to adults aged 20-49, and foremost adults aged 35-49, could bring resurgent COVID-19 epidemics under control.

## The majority of COVID-19 infections originate from age groups 20-49

To quantify how age groups contribute to resurgent COVID-19, it is not enough to estimate reproduction numbers, because reproduction numbers estimate the number of secondary infections per infectious individual, and the number of infectious individuals varies by age as a result of age-specific susceptibility gradients and age-specific contact exposures. We therefore considered the reconstructed transmission flows, and calculated from the fitted model the contribution of each age group to new infections in each US location over time. Across all locations evaluated, we estimate that until mid August 2020, before schools were considered to re-open in the first locations in the model, the percent contribution to onward spread was 41.0% [40.7%-41.3%] from individuals aged 35-49, compared to 2.5% [1.9%-3.4%] from individuals aged 0-9, 4.3% [3.8%-5.0%] from individuals aged 10-19, 34.2% [33.2%-35.1%] from individuals aged 20-34, 15.1% [14.5%-15.6%] from individuals aged 50-64, 2.6% [2.2%-3.0%]

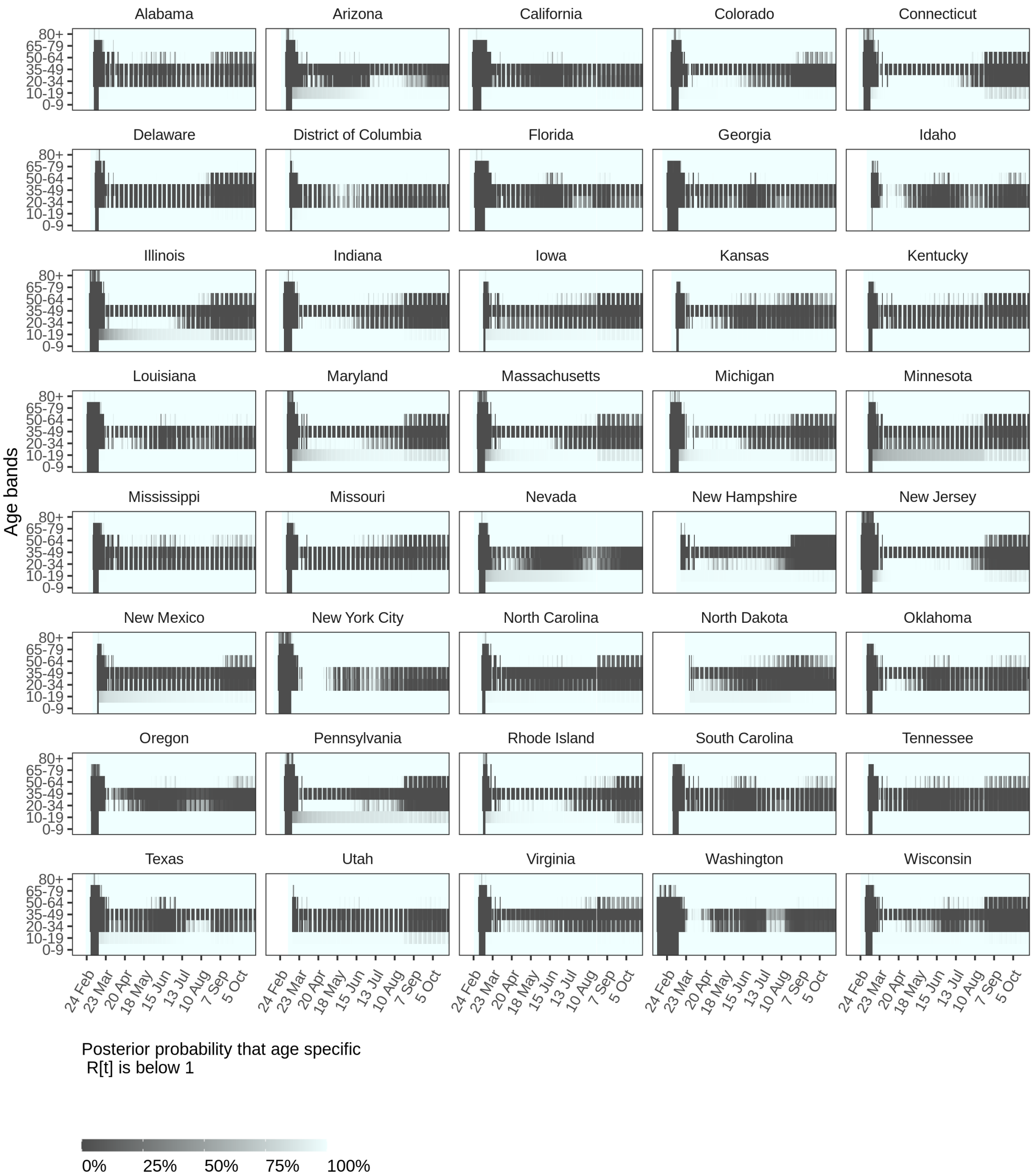


**Figure 3: Time evolution of estimated age-specific SARS-CoV-2 reproduction numbers across the US.** Each panel shows for the corresponding location (state or metropolitan area) the estimated posterior probability that the daily effective reproduction number from individuals stratified in 7 age groups were below. Darker colours indicate low probability that reproduction numbers were below one.

from individuals aged 65-79 age group, and 0.3% [0.3%-0.3%] from individuals aged 80+ (Table S4). Spatially, the contribution of adults aged 35-49 were estimated to be remarkably homogeneous across states, whereas the estimated contributions of young adults aged 20-34 to COVID-19 spread tended to be higher in Southern, South-western, and Western regions of the US (Fig. 4), in line with previous observations [4].

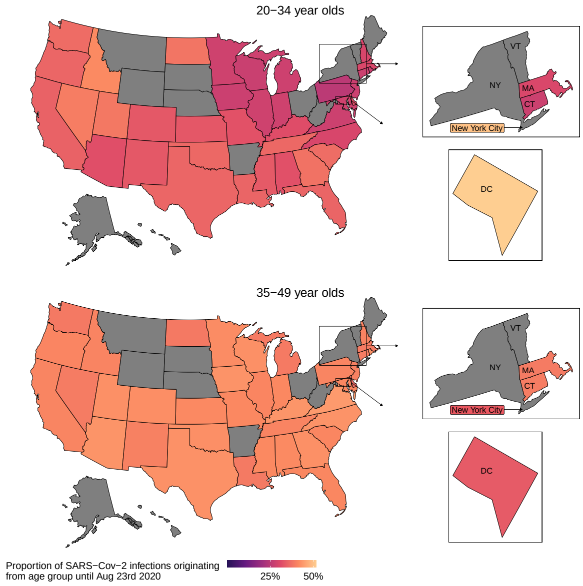


**Figure 4: Estimated spatial variation in the share of young adults aged 20-34 and adults aged 35-49 to COVID-19 spread until mid August, 2020.** Posterior median estimates of the contribution to cumulated SARS-CoV-2 infections until August 17, 2020, prior to school reopening in the first states in the model. State-level COVID-19 epidemics not considered in this study are in grey.

## No substantial shifts in age-specific disease dynamics over time

Over time, we found that the share of age groups among the observed COVID-19 attributable deaths was remarkably constant (Fig. 5A and Fig. S11), which stands in contrast to the large fluctuations in the share of age groups among reported cases [4]. To test for shifts in the share of age groups among COVID-19 infections, we next back-calculated the number of expected, age-specific infections per calendar month of aggregated COVID-19 attributable deaths using meta-analysis estimates of the age-specific COVID-19 infection fatality ratio [20]. This empirical analysis suggested no statistically significant trends in the share of age groups among COVID-19 infections (Fig. 5B and Fig. S12), which is further supported by model estimates (Fig. 5C and Fig. S13). Based on the combined mobility and death data, we find the reconstructed fluctuations in age-specific reproduction numbers had only a relatively modest impact on the contribution of age groups to onward spread over time, and no evidence that young adults aged 20-34 were the primary source of resurgent COVID-19 in the US over summer 2020. These results underscore that, when testing rates are heterogeneous and not population representative, it is challenging to determine the age-specific pattern of transmission based only on reported case data.

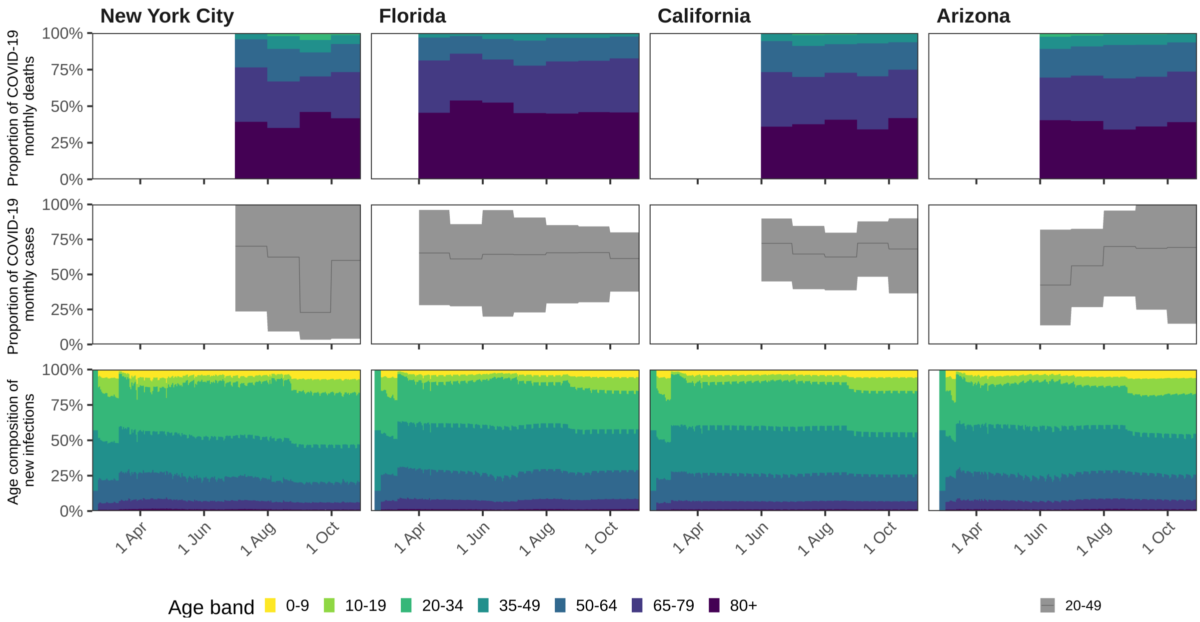


**Figure 5: Share of age groups among COVID-19 attributable deaths and infections in the United States. (Top)** Proportion of monthly observed deaths attributed to COVID-19 by age group. Age-specific COVID-19 attributable deaths were recorded from state or city Departments of Health. Departments of Health used their own age stratification, and the observed data were re-estimated into common age groups across states with a Dirichlet-Multinomial model. More details are given in the Supplementary materials. **(Middle)** Proportion of monthly reported cases among 20-49 year olds. Monthly cases were back calculated the monthly cases by dividing the observed monthly deaths to the infection fatality rate estimated by Levin and colleagues [20]. The figure shows the share of individuals aged 20 to 49 among monthly cases. **(Bottom)** New daily estimated infections by age group for New York City, Florida, California and Arizona (posterior median).

## School reopening has not resulted in significant increases in COVID-19 attributable deaths

Since August 2020, school closure mandates have been lifted in 39 out of 40 of the US locations evaluated in this study, and provided 2,570 observation days to estimate the impact of school reopening on COVID-19 spread. The following analyses are therefore based on fewer data points than those aforementioned, rely on mortality figures accrued until end of October 2020, as well as reported school case data from Florida and Texas, which were used to define lower and upper bounds on cumulative attack rates among children and teens aged 5-18 (see Materials and methods). Reproduction numbers from teens aged 10-19 were estimated at slightly below one (0.75 [0.59-0.89]) after schools were considered to have reopened in the model (Fig. 3 and Table S2). Reproduction numbers from children aged 0-9 were estimated to be lower than from teens, 0.54 [0.44-0.62], because at population-level preschoolers have fewer contacts than school-aged children (Fig. S6). We find that the higher reproduction numbers from children and teens resulted in age shifts in the sources of SARS-CoV-2 infections, for instance in October 2020 an estimated 3.3% [2.2%-4.4%] of infections originated from children aged 0-9, 7.8% [5.1%-11.1%] from teens aged 10-19, 32.7% [30.8%-34.8%] from 20-34, 37.8% [36.3%-39.2%] from 35-49, 15.4% [14.3%-16.4%] from 50-64, 2.7% [2.3%-3.1%] from 65-79, and 0.3% [0.2%-0.3%] from individuals aged 80+ across all locations evaluated (Table S5).

The reconstructed shifts in the age of COVID-19 sources after school reopening are relatively modest compared to the typical age profile of infection sources of pandemic flu [21], and reflect lower age-specific susceptibility to SARS-CoV-2 transmission among children and teens, but also substantially fewer, inferred disease relevant contacts from children and teens than would be expected from their corresponding pre-pandemic contact intensities. The mechanisms behind these beneficial effects remain unclear, but the model suggests they are substantial. In retrospective counterfactual scenarios we explored what COVID-19 death trajectories would have been expected if schools had remained closed, and find a large overlap between the counterfactual and actual case and death trajectories (Fig. 6, Fig. S15). However, since children and teens seed infections in older age groups that are more transmission efficient, we find that as of October 2020, school opening is associated with an estimated 28.3% [16.3%-42.4%] increase of COVID-19 infections and an estimated 6.5% [3.7%-9.5%] increase in COVID-19 attributable deaths (Fig. S16 and Table S7). These findings indicate that adults aged 20-34 and 35-49 continue to be the only age groups that contribute disproportionally to COVID-19 spread relative to their size in the population (Fig. S14), and that the impact of school reopening on resurgent COVID-19 is mitigated most effectively by targeting disease control to adults aged 20-49.

## Caveats

The findings of this study need to be considered in the context of the following limitations. First, Rossen and colleagues [22] observed that US excess deaths between the beginning of the pandemic and October, 2020 were by 38% higher than the reported COVID-19 attributable deaths, suggesting that the death data on which this analysis rests are subject to under-reporting. The scale of the US epidemics may be larger than we infer, and our age-specific analyses may be biased if underreporting of deaths depends on age. However, due to the high proportion of asymptomatic COVID-19 cases [5], underreporting is a substantially larger caveat for reported case data, and in particular the observed shifts in the share of age groups among reported cases [4, 23], which are absent from the share of age groups among reported deaths (Fig. S11). This suggests that the age-specific death data provide a more reliable picture into resurgent COVID-19 epidemics than reported cases. Second, we rely on limited data from two contact surveys performed in the United Kingdom and China to characterise contact patterns from and to younger individuals during school closure periods [7, 8], and this could have biased our findings that children and teens have contributed negligibly to SARS-CoV-2 spread until school reopening. To address this limitation, we explored the impact of higher inter-generational contact intensities involving children during school closure periods, and in these analyses the estimated contribution of children aged 0-9 to onward spread until August 2020 remained below 5% and the contribution of teens aged 10-19 remained below 12.5% (see supplementary materials). Third, epidemiologic models are sensitive to assumptions on the infection fatality ratio (IFR) that enables the estimation of actual cases from observed deaths by age. Our analyses are based on a meta-analysis that consolidates estimates from 27 studies and 34 geographic locations [20]. To test the assumed IFR, we compared the scale of the estimated resurgent epidemics against data from sero-prevalence surveys conducted by the Centers for Disease Control and Prevention (CDC) [24], and found good congruence (Table S6 and supplementary materials). Fourth, the COVID-19 epidemic is more granular than considered in our spatial modelling approach. Substantial heterogeneity in disease transmission exists at county level [25], and our situation analyses by state and metropolitan areas need to be interpreted as averages. Fifth, the model underlying our analyses relies to no exception on simplifying mathematical assumptions on population-level disease spread, which may be shown unsuitable as further evidence on SARS-Cov-2 transmission accumulates [26]. For instance, the model assumes children and teens are as transmissible as adults, which has been challenging to quantify to

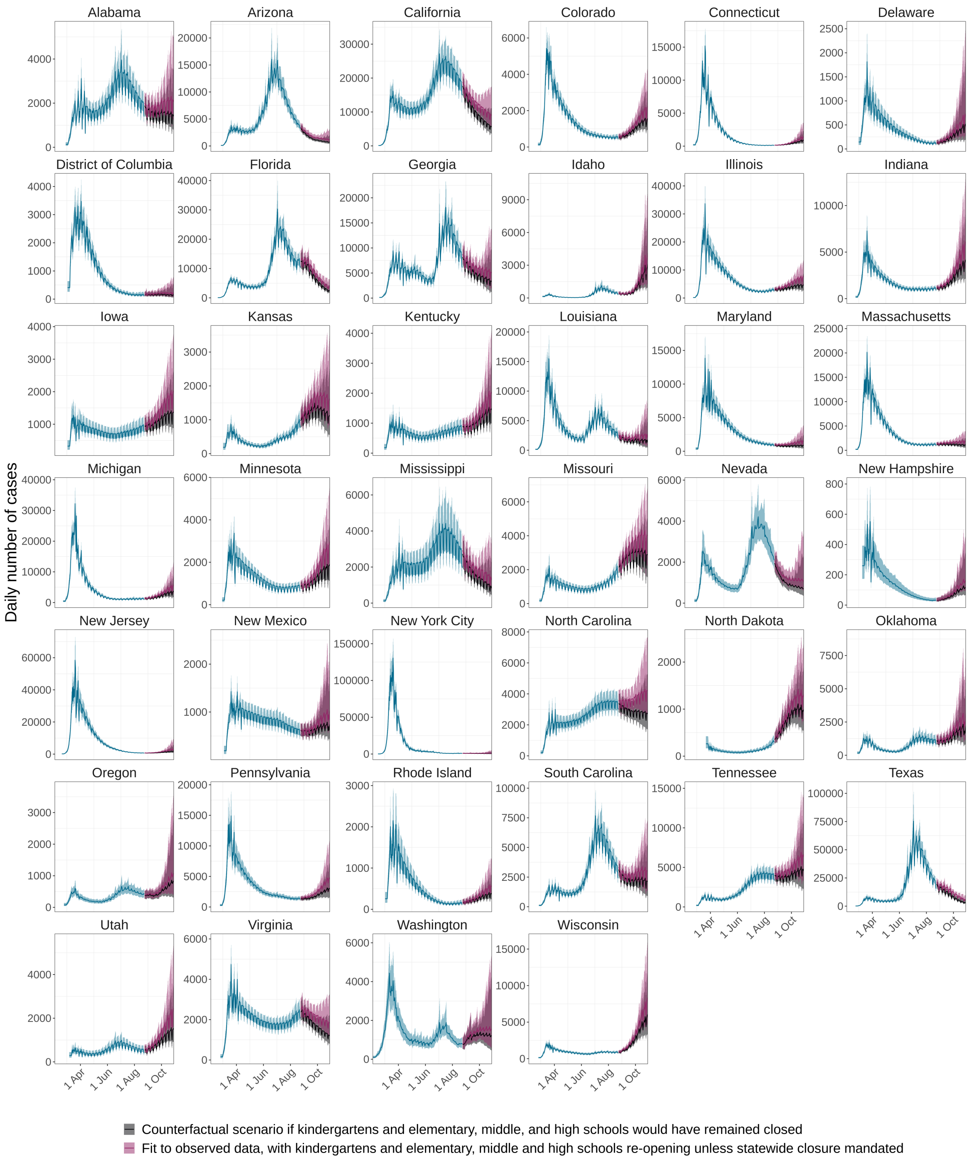


**Figure 6: Retrospective counterfactual modelling scenarios exploring the impact of school reopening on COVID-19-attributable cases.** Shown in blue are estimated, daily COVID-19 cases (posterior median: blue line, 95% credible interval: blue ribbon) under the model until October 29, 2020 for states in which state-wide school closures were no longer mandated since August, 2020. In counterfactual modelling scenarios, the retrospective impact of continued school closures was explored until October 29, 2020, and the predicted case trajectories are shown (posterior median: red line, 95% credible interval: red ribbon), revealing no statistically significant differences.

date [27], and falls short of accounting for population structure other than age, such as household settings, where attack rates have been estimated to be substantially higher than in non-household settings [28]. It is possible that the model under-estimates the impact of school reopening on SARS-Cov-2 transmission within households. However, contact tracing in elementary schools and further data from countries that have re-opened schools have provided no evidence for substantial transmission in schools, nor increased community-level infection rates [29, 30], although most reports stem from locations prior to resurgent COVID-19, and it remains challenging to predict the longer-term impact of school reopening into winter 2020 [26, 31].

# 3 Conclusions

This study provides evidence that the resurgent COVID-19 epidemics in the US are driven by adults aged 20-49, and in particular adults aged 35-49, before and after school reopening. Unlike pandemic flu, these adults accounted after school reopening in October, 2020 for an estimated 70.5% [67.0%-73.9%] of SARS-CoV-2 infections in the US locations considered, whereas less than 5% originated from children aged 0-9 and less than 10% from teens aged 10-19. The population mobility data, and the death data provided by state and city Departments of Health reveal heterogeneous disease spread in the US, with higher transmission risk per venue visit attributed to individuals aged 20-49 and over distinct time periods for many locations, and younger epidemics with a greater share of individuals aged 20-34 among cumulated infections in the South, South-western, and Western regions of the US. Over time, the share of age groups among reported deaths has been remarkably constant, suggesting that young adults are unlikely to have been the primary source of resurgent epidemics since summer 2020, and that instead changes in mobility and behaviour among the broader group of adults aged 20-49 underlie resurgent COVID-19 in the US. This study indicates that targeting interventions at adults aged 20-49, and in particular adults aged 35-49, could bring resurgent COVID-19 epidemics under control and avert deaths.

# 4 Materials and Methods

To characterise the role of age groups in driving resurgent COVID-19, we have taken a systematic approach that involved data collection, mathematical modelling, likelihood-based inference, and validation against external data. The following sections summarise our materials and methods, and full technical details are in the Data Availability Statement and the Supplementary Materials.

## Data and data processing

The analyses presented in this study are based on age-specific COVID-19 attributable mortality counts that were collected daily from US state and city Departments of Health (DoH), all-age COVID-19 death counts, all-age COVID-19 case counts, COVID-19 case counts in school settings K1-K15, human contact data before and during the pandemic, and human mobility data during the pandemic.

Briefly, age-specific COVID-19 cumulative death counts were retrieved for 43 US states, the District of Columbia and New York City from city or state DoH websites, data repositories, or via data requests to DoH (table **??**). Data were checked for consistency and adjusted when necessary. Age-specific COVID-19 death time series were reconstructed from cumulative counts, and the time series were used for model fitting [32].

All-age daily COVID-19 case and death counts from February 01, 2020 until October 30, 2020 regardless of age were obtained from John Hopkins University (JHU) for all U.S. states and the District of Columbia [3], except New York State. For New York State, daily COVID-19 death counts from February 01, 2020 until October 30, 2020 were obtained from the New York Times' (NYT) data [33]. For New York City, daily COVID-19 deaths counts were obtained from the GitHub Repository [34]. The all-age death counts were used for model fitting prior to when age-specific death counts were reported for each location, and all-age case counts were used for model fitting for the entire study period.

COVID-19 case counts in school settings K1-K15 were retrieved for Florida and Texas and matched with student enrolment numbers in each school from the Common Core of Data America's Public Schools database [35]. Cumulative attack rates were obtained by dividing cumulative reported cases among students by student numbers, and used for model fitting.

Human contact data before the pandemic were obtained from the Polymod study [6], and used to predict baseline contact matrices during the early part of the pandemic for each location, similar as in [18]. Given the variation in contact patterns seen across survey settings, baseline contact matrices for each study location in the US were predicted based on each location's population density and age composition with a log linear regression model. Age-specific population counts were obtained from [36]. Area measurements were obtained for every US states and for New York City respectively from [37] and [38]. Contact matrices were predicted by 5-year age bands for weekdays and weekends, and used in the model. Human contact data during the pandemic were retrieved from two surveys [8, 7], and used in the model to specify contact patterns from and to individuals aged 0-19 during periods of school closure.

Age-specific human mobility trends were derived from the Foursquare Labs Inc. US first-party panel that includes >10 million of opt-in, always-on active users. From operated and partner apps, Foursquare collect a variety of device signals against opted-in users including intermittent device GPS coordinate pings, WiFi signals, cell signal strength, device model, and operating system version. A smaller set of labeled explicit check-ins are captured from a portion of the user panel. Check-ins are explicit confirmations that a user was at a given venue at a given point of time, and serve as training labels for a non-linear model that is used to predict visits among users with unlabeled visits in terms of probabilities as to which venue users ultimately visited [11]. Visit probabilities among panelists were processed and aggregated by day, age, and study location, and standardised to daily per capita visits using latest US Census data. Percent changes in daily venue visits by age and study location were obtained relative to the baseline period February 3 to February 9, 2020, and used for analysis and model fitting. For validation purposes, a second mobility data set was obtained from Emodo. The Emodo data set quantifies the proportion of individuals with at least one observed ping outside the user's home location, out of a panel of individuals whose GPS enabled devices emitted at least one ping on the corresponding day. Primary data were similarly aggregated by day, age, and study location, standardised to daily per capita visits using latest US Census data, and mobility trends were calculated relative to the baseline period February 19 to March 3, 2020.

## Statistical analysis of human mobility data and COVID-19 attributable death data

The age-specific human mobility data showed marked time trends, which were characterised in terms of three phases defined by the dip date after which the 15-day moving average fell below 10% compared to the average value in the two prior weeks, and the rebound date that corresponded to the date at which the 15-day moving average was lowest. Differences in the mobility trends relative to the February baseline period, before and after rebound dates, and relative to individuals aged 35-44 were assessed using Gamma regression models using log link and location by age interaction covariates.

To characterise the time evolution of deaths across locations and validate model fits, age-specific COVID-19 attributable deaths among the same age strata across locations were predicted by month with Dirichlet-Multinomial regression models. Trends in the share of age groups among monthly deaths were assessed by testing for differences in the proportions in the first month relative to subsequent months.

To test for potential differences in age-specific transmission dynamics based on the collected death data and without epidemic models, meta-analysis estimates of age-specific infection fatality ratios [20] were used to predict the share of age groups among infections from monthly age-specific deaths. Trends in the share of age groups among monthly infections were assessed by testing for differences in the proportions in the first month relative to subsequent months.

## Contact-and-infection model

To quantify age-specific aspects of COVID-19 spread in heterogeneous populations, we formulated an age-specific, discrete-time renewal model in which disease transmission occurs via contact intensities between population groups stratified by 5-year age bands. The model has four key features described below. First, contact intensities vary in time and are inferred from signatures in the age-specific mortality and mobility data. This feature aims to reflect the substantial changes in human contact patterns during the pandemic [7, 9, 8]. Second, the challenge and value of the model to produce generalizable knowledge is to explain disease spread across multiple locations with distinct demographics simultaneously. To this end, the renewal equations were embedded into a hierarchical model in which information on disease spread is borrowed across locations [39, 1]. Third, the model describes disease spread during the initial and later phase of the pandemic, as mobility patterns become less correlated with transmission risk and schools reopen [40, 41]. This feature allowed us to test for changes in disease dynamics over time. Fourth, the model is fitted in a Bayesian framework to the all-age and age-specific death data, all-age case data, case data from schools, and age-specific human mobility trends [42]. This feature forced us to focus on a model whose parameters are inferable from the data across all locations. The model is described in detail in the Supplementary materials.

Briefly, we consider populations stratified by the 5-year age bands $\mathcal{A}$, such that

$$a \in \mathcal{A} = \Big\{[0-4], [5-9], \dots, [75-79], [80-84], [85+]\Big\}, \tag{1}$$

and denote the number of new infections, $c$, on day $t$, in age band $a$, and location $m$ as $c_{m,t,a}$. In the renewal equation, past infections are weighted by their relative infectiousness on day $t$, and the sum of these individuals has contacts with individuals in other age groups. Contacts are described by the expected number of disease relevant human contacts one person in age $a$ has with other individuals in age band $a'$ on day $t$ in location $m$, $\mathbf{C}_{m,t,a,a'}$. Upon contact, a proportion $s_{m,t,a'}$ of individuals of age $a'$ on day $t$ in location $m$ remains susceptible to SARS-CoV-2 infection, and transmission occurs with probability $\rho_{a'}$. Thus, the age-specific renewal equation with time-changing contact intensities is

$$c_{m,t,a'} = s_{m,t,a'}\rho_{a'} \sum_a \mathbf{C}_{m,t,a,a'} \left( \sum_{s=1}^{t-1} c_{m,s,a}\, g(t-s) \right) \tag{2}$$

where $g$ quantifies the relative infectiousness of individuals $s$ days after infection. An important feature of SARS-CoV-2 transmission is that similarly to other coronaviruses but unlike pandemic influenza [43], susceptibility to SARS-CoV-2 infection increases with age [7, 44, 21]. Here, we used contact tracing data from Hunan province, China [7] to specify lower susceptibility to SARS-CoV-2 infection among children aged 0-9, and higher susceptibility among individuals aged 60+, when compared to the 10-59 age group as part of the transmission probabilities $\rho_{a'}$. Previously infected individuals are assumed to be immune to re-infection within the analysis period, consistent with mounting evidence for sustained antibody responses to SARS-CoV-2 antigens [45, 46], so that

$$s_{m,t,a'} = 1 - \frac{\sum_{s=1}^{t-1} c_{m,t,a'}}{N_{m,a'}}, \tag{3}$$

where $N_{m,a'}$ denotes the population count in age group $a'$ and location $m$.

For adults aged 20+, the time changing contact intensities were described in terms of the pre-pandemic baseline contact intensities in location $m$, which we denote by $\mathbf{C}_{m,a,a'}$, and expected reductions in disease relevant contacts from contacting individuals of age $a$ on day $t$ in location $m$, which we denote by $\eta_{m,t,a}$, and contacted individuals of age $a'$ on day $t$ in location $m$, $\eta_{m,t,a'}$,

$$\mathbf{C}_{m,t,a,a'} = \eta_{m,t,a}\, \mathbf{C}_{m,a,a'}\, \eta_{m,t,a'}, \tag{4}$$

where $a,\ a' \in \{[20-24], \ldots, [85+]\}$. Expected reductions in disease relevant contacts were specified as a random effects model that included the observed, age-specific mobility trends as covariates. In the model, each age-specific mobility trend was decoupled into three separate covariates that reflect the initial pre-pandemic, dip, and rebound phases in human mobility trends, so that previously observed decreases in correlation between mobility trends and transmission risk could be captured [47, 40, 41]. As the same number of venue visits in e.g. Wyoming may translate to different transmission risk than in e.g. New York City, spatial random effects allowed for scaling of mobility trends during the dip and rebound phase in each location. As venue visits do not capture all aspects of transmission risk, the model further incorporates independently for each location autocorrelated biweekly random effects to capture information on elevated, disease relevant contact intensities and transmission risk that is present in the death time series data. To test for age-specific signatures of elevated transmission risk, the model further included for each location age-specific random effects for individuals aged 20-49.

For children and teens aged 0-20, mobility data are not available, and during periods of school closure the contact intensities from and to children and teens were set to the average contact intensities reported in [7]. This implied that relative to pre-pandemic contact patterns, peer-based contacts were substantially reduced, whereas contacts from an adult to children and teens increased slightly. In the model, schools were set to re-open on or after August 24, 2020 when state administrations no longer mandated state-wide school closures by that date [48, 49]. Thereafter, Equation (4) was extended to include children and teens, and expected mobility reductions where estimated from the case and death data. In the absence of further data, a common average effect could be estimated across locations and children and teen age groups for the last two observation months, $\eta_{m,t,a} = \eta^{\text{children}}$ for $a \in [0-20]$. A further compound effect $\gamma$ was added to modulate the number of disease relevant child/teen-child/teen contacts, which we interpreted as reduced infectiousness from children and teens and/or a positive impact of non-pharmaceutical interventions among school-aged children and teens.

## Bayesian inference

Past age-specific disease dynamics across all locations were inferred from age-specific death data available across locations, and age-specific mobility data. To do this, in the model, a proportion $\pi_{m,a}$ of new infections in location $m$ of age $a$ die, and the day of death is determined by the infection-to-death distribution, which was assumed to be constant across age groups. The proportions $\pi_{m,a}$ were associated with a strongly informative prior derived from the meta-analysis of [20], but were allowed to deviate from the baseline infection fatality ratio through location-specific random effects. The expected number of deaths in location $m$ on day $t$ in age band $a$, $d_{m,t,a}$, were aggregated to the reporting strata in each location, and fitted to the observed data using a Negative Binomial likelihood model. When age-specific death data were not available, the model was fitted to all-age death data with a Negative Binomial likelihood model. All-age case data were smoothed, and used to specify a lower bound on the overall number of infections $c_{m,t} = \sum_a c_{m,t,a}$ through a student-t cumulative density likelihood model. Case data from schools were used to calculate empirical attack rates in school settings during specified observation windows. In turn, the empirical attack rates were used to describe a lower bound on the actual attack rate among 5-18 year old children and teens in the same observation periods in the model, using a normal cumulative density likelihood model. An upper bound on the actual attack rates was also specified by assuming that actual cases in school settings were under-reported at most 10-fold, using a normal complementary cumulative density likelihood model. The contact-and-infection model was fit with CmdStan release 2.23.0 (22 April 2020), using an adaptive Hamiltonian Monte Carlo (HMC) sampler [42]. 8 HMC chains were run in parallel for $1,000$ iterations, of which the first 400 iterations were specified as warm-up. There were no divergent transitions.

## Generated quantities

Results were reported in the age bands $d \in \mathcal{D} = \{[0-9], [10-19], [20-34], [35-49], [50-64], [65-79], [80+]\}$. The primary model outputs were aggregated correspondingly, e.g. the number of new infections in location $m$ on day $t$ in reporting age band $d$ was $c_{m,t,d} = \sum_{a\in d} c_{m,t,a}$. The effective number of infectious individuals $c^*$ in location $m$ and age band $d$ on day $t$ was calculated based on the renewal model (2), $c^*_{m,t,d} = \sum_{s=1}^{t-1} c_{m,s,d}\, g(t-s)$, and is shown in Figure 2. Following (2), the time-varying reproduction number on day $t$ from one infectious person in $a$ in location $m$ is $R_{m,t,a} = \sum_{a'} s_{m,t,a'}\, \rho_{a'}\, \mathbf{C}_{m,t,a,a'}$, and the reproduction numbers were aggregated to the reporting strata based on the identity $R_{m,t,d} = \sum_{a\in d}(c^*_{m,t,a})/(\sum_{k\in d} c^*_{m,t,k})R_{m,t,a}$, and are shown in Figure 2 and Tables S1-S2. The transmission flows from age group $a$ to age group $a'$ at time $t$ in location $m$ are given by $F_{m,t,a,a'} = s_{m,t,a'}\, \rho_{a'}\, \mathbf{C}_{m,t,a,a'}\, (\sum_{s=1}^{t-1} c_{m,s,a}\, g(t-s))$, and are aggregated using $F_{m,t,d,d'} = \sum_{a\in d, a'\in d'} F_{m,t,a,a'}$. In turn, the contributions of age groups to COVID-19 spread are $S_{m,t,d} = (\sum_{d'} F_{m,t,d,d'})/(\sum_d \sum_{d'} F_{m,t,d,d'})$, and are reported in Tables S4. Cumulated COVID-19 attack rates were calculated through $A_{m,t,d} = (\sum_{s=1}^{t} c_{m,s,d})/(N_{m,d})$, where $N_{m,d}$ is the number of individuals in location $m$ and age band $d$, and are reported in Table S6.

### Validation and sensitivity analyses

Reconstructed past transmission dynamics were assessed against external data on the scale of the epidemic from seroprevalence surveys conducted across the US by the CDC [24]. Validation results are reported in the Supplementary materials, suggesting larger discrepancies between model fit and seroprevalence data for Connecticut and New York City, with larger epidemics reconstructed in the model than the data suggest. The contact-and-infection model does not account for sustained spatial importation of SARS-CoV-2 infections such as from New York City to Connecticut, and may have over-estimated the magnitude of self-sustaining epidemic in locations receiving sustained SARS-Cov-2 importations. However, we also note that the Connecticut seroprevalence estimates predict an infection to observed case ratio that is substantially below those of the other CDC seroprevalence studies. The inferred contact patterns were assessed against external data from the BICS study that quantified human contact patterns during the pandemic [9]. Validation results are reported in the Supplementary materials, suggesting similarly strong reductions in human contact intensities as in the survey data. Disaggregated by age, the model reproduces highest contact intensities among 35-44 year old individuals, comparatively lower contact intensities from individuals aged $45+$, and largest reductions in contact intensities from individuals aged 25-34. The survey data suggest that contact intensities from individuals aged 18-24 could be higher than reconstructed through the contact-and-infection model, but we also note large confidence intervals around the survey estimates.

Sensitivity analyses were conducted to assess central modelling assumptions on the infection fatality ratio, contact intensities among children and teens during periods of school closure, relative susceptibility of children and teens to SARS-CoV-2 infection, and are reported in the Supplementary materials. Our findings on the age groups that drive SARS-CoV-2 transmission were found to be robust to these assumptions.

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**claimer**: ”The views expressed are those of the authors and not necessarily those of the United Kingdom (UK) Department of Health and Social Care, the National Health Service, the National Institute for Health Research (NIHR), or Public Health England (PHE) **Author contributions**: OR conceived the study. AG, SM, SF, SB, NF, OR oversaw the study. MM, DH, SBe, ST, YC, McM, MH, HZ, ABe, OR oversaw and performed data collection. MM, ABl, XX, OR lead the analysis. VCB, HC, SF, JIH, TM, AG, HJTU, MV, SW, SM contributed to the analysis. All authors discussed the results and contributed to the revision of the final manuscript. **Competing interests**: SB acknowledges the National Institute for Health Research (NIHR) BRC Imperial College NHS Trust Infection and COVID themes, the Academy of Medical Sciences Springboard award and the Bill and Melinda Gates Foundation. OR reports grants from the Bill & Melinda Gates Foundation during the conduct of the study. **Data and materials availability**: The COVID-19 mortality data used in this study are available on GitHub, https://github.com/ImperialCollegeLondon/US-covid19-agespecific-mortality-data, under the Creative Commons Attribution 4.0 International Public License. The Foursquare population mobility data are available on Github, https://github.com/ImperialCollegeLondon/covid19model, under the Creative Commons Attribution-NonCommercial-NoDerivs 4.0 International Public License. The Emodo population mobility data are available on Github, https://github.com/ImperialCollegeLondon/covid19model, under the Creative Commons Attribution-NonCommercial 4.0 International Public License. Code are available on Github, https://github.com/ImperialCollegeLondon/covid19model, under the MIT License. 

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# 6 Supplementary Tables and Figures

**Table S1: Estimated probability that age-specific reproduction numbers were below one for the week October 19, 2020 - October 25, 2020.** Posterior mean estimates are shown in percent.

| | | Age of infectious individuals (years) | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Location | Overall | [0 – 9] | [10 – 19] | [20 – 34] | [35 – 49] | [50 – 64] | [65 – 79] | 80+ |
| All locations | 0.0% | 100.0% | 100.0% | 0.0% | 0.0% | 100.0% | 100.0% | 100.0% |
| Alabama | 22.9% | 100.0% | 100.0% | 0.5% | 0.0% | 89.4% | 100.0% | 100.0% |
| Alaska | - | - | - | - | - | - | - | - |
| Arizona | 57.5% | 100.0% | 99.7% | 4.5% | 0.0% | 100.0% | 100.0% | 100.0% |
| Arkansas | - | - | - | - | - | - | - | - |
| California | 66.7% | 100.0% | 100.0% | 0.1% | 0.0% | 100.0% | 100.0% | 100.0% |
| Colorado | 0.1% | 100.0% | 99.9% | 0.0% | 0.0% | 96.9% | 100.0% | 100.0% |
| Connecticut | 0.0% | 100.0% | 89.0% | 0.0% | 0.0% | 5.7% | 100.0% | 100.0% |
| Delaware | 0.7% | 100.0% | 99.7% | 0.0% | 0.0% | 2.3% | 100.0% | 100.0% |
| District of Columbia | 64.7% | 100.0% | 100.0% | 11.0% | 16.4% | 100.0% | 100.0% | 100.0% |
| Florida | 99.3% | 100.0% | 100.0% | 65.8% | 7.0% | 100.0% | 100.0% | 100.0% |
| Georgia | 50.3% | 100.0% | 100.0% | 13.2% | 1.5% | 100.0% | 100.0% | 100.0% |
| Hawaii | - | - | - | - | - | - | - | - |
| Idaho | 0.2% | 100.0% | 100.0% | 0.0% | 0.0% | 99.9% | 100.0% | 100.0% |
| Illinois | 1.2% | 100.0% | 90.6% | 0.0% | 0.0% | 61.6% | 100.0% | 100.0% |
| Indiana | 0.0% | 100.0% | 99.0% | 0.0% | 0.0% | 2.4% | 100.0% | 100.0% |
| Iowa | 1.2% | 100.0% | 98.2% | 0.1% | 0.0% | 17.2% | 100.0% | 100.0% |
| Kansas | 43.4% | 100.0% | 100.0% | 6.7% | 0.1% | 94.6% | 100.0% | 100.0% |
| Kentucky | 0.0% | 100.0% | 100.0% | 0.0% | 0.0% | 36.9% | 100.0% | 100.0% |
| Louisiana | 26.4% | 100.0% | 100.0% | 2.6% | 1.4% | 100.0% | 100.0% | 100.0% |
| Maine | - | - | - | - | - | - | - | - |
| Maryland | 4.0% | 100.0% | 90.8% | 0.1% | 0.0% | 44.8% | 100.0% | 100.0% |
| Massachusetts | 14.5% | 100.0% | 94.1% | 0.5% | 0.0% | 70.6% | 100.0% | 100.0% |
| Michigan | 2.3% | 100.0% | 96.6% | 0.1% | 0.0% | 52.3% | 100.0% | 100.0% |
| Minnesota | 0.1% | 100.0% | 93.3% | 0.0% | 0.0% | 22.4% | 100.0% | 100.0% |
| Mississippi | 68.8% | 100.0% | 100.0% | 9.1% | 0.0% | 99.7% | 100.0% | 100.0% |
| Missouri | 21.5% | 100.0% | 100.0% | 0.6% | 0.0% | 77.2% | 100.0% | 100.0% |
| Montana | - | - | - | - | - | - | - | - |
| Nebraska | - | - | - | - | - | - | - | - |
| Nevada | 35.6% | 100.0% | 100.0% | 0.1% | 0.1% | 100.0% | 100.0% | 100.0% |
| New Hampshire | 0.1% | 100.0% | 98.6% | 0.0% | 0.0% | 0.2% | 100.0% | 100.0% |
| New Jersey | 0.0% | 100.0% | 94.0% | 0.0% | 0.0% | 11.4% | 100.0% | 100.0% |
| New Mexico | 1.3% | 100.0% | 98.7% | 0.0% | 0.0% | 72.4% | 100.0% | 100.0% |
| New York | - | - | - | - | - | - | - | - |
| New York City | 31.5% | 100.0% | 100.0% | 0.1% | 2.9% | 100.0% | 100.0% | 100.0% |
| North Carolina | 7.0% | 100.0% | 99.0% | 0.1% | 0.0% | 59.7% | 100.0% | 100.0% |
| North Dakota | 15.5% | 100.0% | 100.0% | 0.0% | 0.0% | 98.2% | 100.0% | 100.0% |
| Ohio | - | - | - | - | - | - | - | - |
| Oklahoma | 7.9% | 100.0% | 100.0% | 0.1% | 0.0% | 99.7% | 100.0% | 100.0% |
| Oregon | 2.6% | 100.0% | 100.0% | 0.0% | 0.0% | 87.7% | 100.0% | 100.0% |
| Pennsylvania | 0.2% | 100.0% | 87.3% | 0.0% | 0.0% | 1.5% | 100.0% | 100.0% |
| Rhode Island | 0.0% | 100.0% | 89.8% | 0.0% | 0.0% | 19.0% | 100.0% | 100.0% |
| South Carolina | 33.4% | 100.0% | 100.0% | 2.4% | 0.1% | 99.5% | 100.0% | 100.0% |
| South Dakota | - | - | - | - | - | - | - | - |
| Tennessee | 8.6% | 100.0% | 100.0% | 0.0% | 0.0% | 80.7% | 100.0% | 100.0% |
| Texas | 98.9% | 100.0% | 100.0% | 56.2% | 3.1% | 100.0% | 100.0% | 100.0% |
| Utah | 0.1% | 100.0% | 95.6% | 0.0% | 0.0% | 100.0% | 100.0% | 100.0% |
| Vermont | - | - | - | - | - | - | - | - |
| Virginia | 48.8% | 100.0% | 99.9% | 13.5% | 0.0% | 92.9% | 100.0% | 100.0% |
| Washington | 32.3% | 100.0% | 100.0% | 2.3% | 0.6% | 100.0% | 100.0% | 100.0% |
| West Virginia | - | - | - | - | - | - | - | - |
| Wisconsin | 0.0% | 100.0% | 99.6% | 0.0% | 0.0% | 1.2% | 100.0% | 100.0% |
| Wyoming | - | - | - | - | - | - | - | - |

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**Table S2: Estimated age-specific reproduction numbers for the week October 19, 2020 to October 25, 2020.** Posterior median estimates and 95% credible intervals are reported.

| | Age of infectious individuals (years) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Location | Overall | [0 − 9] | [10 − 19] | [20 − 34] | [35 − 49] | [50 − 64] | [65 − 79] | 80+ |
| All locations | 1.10 [1.07-1.15] | 0.54 [0.44-0.62] | 0.75 [0.59-0.89] | 1.29 [1.23-1.36] | 1.40 [1.35-1.46] | 0.93 [0.89-0.97] | 0.43 [0.40-0.45] | 0.12 [0.11-0.12] |
| Alabama | 1.05 [0.93-1.24] | 0.50 [0.39-0.60] | 0.70 [0.54-0.87] | 1.20 [1.04-1.45] | 1.34 [1.19-1.58] | 0.94 [0.85-1.04] | 0.45 [0.40-0.50] | 0.12 [0.11-0.13] |
| Alaska | - | - | - | - | - | - | - | - |
| Arizona | 0.98 [0.87-1.22] | 0.53 [0.42-0.64] | 0.74 [0.58-0.93] | 1.16 [0.98-1.50] | 1.28 [1.12-1.58] | 0.77 [0.70-0.85] | 0.39 [0.36-0.43] | 0.11 [0.10-0.12] |
| Arkansas | - | - | - | - | - | - | - | - |
| California | 0.98 [0.91-1.11] | 0.53 [0.42-0.63] | 0.73 [0.56-0.89] | 1.15 [1.05-1.34] | 1.21 [1.13-1.38] | 0.83 [0.78-0.89] | 0.37 [0.35-0.41] | 0.11 [0.10-0.11] |
| Colorado | 1.18 [1.07-1.33] | 0.54 [0.44-0.65] | 0.73 [0.57-0.90] | 1.38 [1.24-1.58] | 1.50 [1.36-1.68] | 0.89 [0.79-1.00] | 0.38 [0.33-0.44] | 0.10 [0.09-0.12] |
| Connecticut | 1.32 [1.16-1.58] | 0.58 [0.46-0.69] | 0.87 [0.68-1.08] | 1.53 [1.30-1.87] | 1.70 [1.49-2.03] | 1.11 [0.98-1.29] | 0.44 [0.38-0.52] | 0.12 [0.11-0.14] |
| Delaware | 1.23 [1.05-1.50] | 0.52 [0.41-0.64] | 0.73 [0.57-0.93] | 1.48 [1.24-1.85] | 1.49 [1.26-1.82] | 1.15 [1.00-1.31] | 0.63 [0.55-0.74] | 0.15 [0.13-0.18] |
| District of Columbia | 0.96 [0.79-1.20] | 0.41 [0.31-0.52] | 0.54 [0.42-0.70] | 1.14 [0.93-1.43] | 1.10 [0.91-1.34] | 0.59 [0.49-0.74] | 0.28 [0.22-0.37] | 0.15 [0.12-0.20] |
| Florida | 0.85 [0.79-0.96] | 0.46 [0.38-0.54] | 0.64 [0.50-0.78] | 0.98 [0.89-1.13] | 1.07 [0.98-1.22] | 0.78 [0.73-0.84] | 0.39 [0.36-0.42] | 0.10 [0.10-0.11] |
| Georgia | 1.00 [0.78-1.27] | 0.45 [0.36-0.53] | 0.63 [0.49-0.77] | 1.19 [0.90-1.56] | 1.29 [1.02-1.60] | 0.73 [0.65-0.82] | 0.29 [0.25-0.33] | 0.08 [0.07-0.09] |
| Hawaii | - | - | - | - | - | - | - | - |
| Idaho | 1.38 [1.10-1.64] | 0.48 [0.38-0.58] | 0.63 [0.49-0.79] | 1.68 [1.34-1.99] | 1.69 [1.35-2.00] | 0.83 [0.73-0.94] | 0.42 [0.37-0.48] | 0.11 [0.09-0.12] |
| Illinois | 1.11 [1.01-1.23] | 0.62 [0.50-0.74] | 0.87 [0.67-1.07] | 1.25 [1.12-1.41] | 1.43 [1.29-1.58] | 0.98 [0.88-1.09] | 0.45 [0.39-0.51] | 0.12 [0.11-0.14] |
| Indiana | 1.22 [1.10-1.39] | 0.58 [0.47-0.69] | 0.79 [0.61-0.97] | 1.37 [1.20-1.61] | 1.56 [1.40-1.78] | 1.11 [1.00-1.23] | 0.51 [0.45-0.58] | 0.14 [0.12-0.16] |
| Iowa | 1.09 [1.01-1.20] | 0.56 [0.44-0.69] | 0.78 [0.59-0.98] | 1.17 [1.06-1.32] | 1.41 [1.31-1.57] | 1.04 [0.96-1.13] | 0.55 [0.51-0.60] | 0.15 [0.14-0.17] |
| Kansas | 1.01 [0.87-1.16] | 0.51 [0.40-0.62] | 0.70 [0.54-0.88] | 1.15 [0.96-1.35] | 1.28 [1.09-1.47] | 0.90 [0.81-1.03] | 0.43 [0.38-0.50] | 0.12 [0.10-0.14] |
| Kentucky | 1.14 [1.05-1.29] | 0.50 [0.40-0.61] | 0.66 [0.51-0.82] | 1.26 [1.15-1.46] | 1.46 [1.35-1.67] | 1.01 [0.94-1.10] | 0.45 [0.40-0.50] | 0.12 [0.11-0.13] |
| Louisiana | 1.09 [0.83-1.42] | 0.50 [0.40-0.61] | 0.68 [0.53-0.84] | 1.37 [1.00-1.82] | 1.37 [1.04-1.76] | 0.77 [0.67-0.87] | 0.33 [0.29-0.37] | 0.09 [0.08-0.10] |
| Maine | - | - | - | - | - | - | - | - |
| Maryland | 1.10 [0.99-1.31] | 0.63 [0.50-0.76] | 0.86 [0.65-1.08] | 1.22 [1.07-1.51] | 1.41 [1.26-1.69] | 1.01 [0.91-1.12] | 0.43 [0.38-0.49] | 0.12 [0.10-0.13] |
| Massachusetts | 1.07 [0.94-1.25] | 0.57 [0.45-0.68] | 0.84 [0.65-1.04] | 1.25 [1.07-1.50] | 1.33 [1.16-1.55] | 0.96 [0.85-1.09] | 0.41 [0.36-0.47] | 0.11 [0.10-0.13] |
| Michigan | 1.17 [1.00-1.37] | 0.59 [0.47-0.70] | 0.82 [0.64-1.01] | 1.33 [1.11-1.61] | 1.50 [1.29-1.75] | 1.00 [0.84-1.18] | 0.49 [0.42-0.59] | 0.13 [0.11-0.16] |
| Minnesota | 1.15 [1.06-1.28] | 0.64 [0.51-0.78] | 0.84 [0.65-1.05] | 1.27 [1.15-1.45] | 1.46 [1.34-1.63] | 1.04 [0.94-1.14] | 0.47 [0.42-0.51] | 0.13 [0.11-0.14] |
| Mississippi | 0.96 [0.85-1.16] | 0.46 [0.37-0.56] | 0.67 [0.52-0.84] | 1.11 [0.96-1.40] | 1.25 [1.10-1.51] | 0.85 [0.76-0.95] | 0.38 [0.33-0.43] | 0.10 [0.09-0.12] |
| Missouri | 1.05 [0.93-1.15] | 0.50 [0.40-0.60] | 0.67 [0.52-0.83] | 1.18 [1.04-1.32] | 1.32 [1.17-1.46] | 0.96 [0.87-1.06] | 0.46 [0.41-0.51] | 0.12 [0.11-0.14] |
| Montana | - | - | - | - | - | - | - | - |
| Nebraska | - | - | - | - | - | - | - | - |
| Nevada | 1.04 [0.89-1.32] | 0.52 [0.41-0.63] | 0.69 [0.54-0.87] | 1.29 [1.09-1.64] | 1.29 [1.10-1.64] | 0.73 [0.63-0.85] | 0.33 [0.27-0.39] | 0.08 [0.07-0.10] |
| New Hampshire | 1.22 [1.08-1.42] | 0.50 [0.39-0.63] | 0.75 [0.56-0.97] | 1.33 [1.17-1.60] | 1.49 [1.31-1.78] | 1.23 [1.07-1.40] | 0.50 [0.42-0.58] | 0.12 [0.10-0.14] |
| New Jersey | 1.28 [1.10-1.59] | 0.61 [0.49-0.73] | 0.85 [0.66-1.04] | 1.51 [1.26-1.94] | 1.67 [1.44-2.05] | 1.09 [0.95-1.26] | 0.47 [0.41-0.55] | 0.13 [0.11-0.16] |
| New Mexico | 1.10 [1.01-1.28] | 0.53 [0.42-0.65] | 0.78 [0.60-0.97] | 1.27 [1.16-1.50] | 1.38 [1.26-1.64] | 0.97 [0.89-1.07] | 0.47 [0.41-0.54] | 0.12 [0.11-0.14] |
| New York | - | - | - | - | - | - | - | - |
| New York City | 1.09 [0.83-1.59] | 0.48 [0.38-0.59] | 0.63 [0.48-0.80] | 1.52 [1.12-2.22] | 1.28 [0.99-1.75] | 0.61 [0.52-0.71] | 0.28 [0.24-0.32] | 0.08 [0.07-0.09] |
| North Carolina | 1.07 [0.98-1.20] | 0.54 [0.43-0.66] | 0.76 [0.59-0.96] | 1.16 [1.06-1.34] | 1.37 [1.26-1.56] | 0.99 [0.92-1.08] | 0.45 [0.41-0.50] | 0.12 [0.11-0.13] |
| North Dakota | 1.07 [0.94-1.19] | 0.51 [0.39-0.65] | 0.62 [0.46-0.81] | 1.33 [1.17-1.50] | 1.25 [1.11-1.39] | 0.87 [0.75-0.99] | 0.40 [0.33-0.48] | 0.12 [0.09-0.14] |
| Ohio | - | - | - | - | - | - | - | - |
| Oklahoma | 1.15 [0.95-1.40] | 0.49 [0.39-0.60] | 0.66 [0.51-0.81] | 1.38 [1.11-1.71] | 1.45 [1.20-1.74] | 0.85 [0.76-0.95] | 0.40 [0.35-0.45] | 0.11 [0.10-0.12] |
| Oregon | 1.21 [1.00-1.53] | 0.43 [0.34-0.53] | 0.58 [0.45-0.72] | 1.43 [1.16-1.82] | 1.52 [1.26-1.91] | 0.93 [0.82-1.05] | 0.52 [0.47-0.59] | 0.13 [0.12-0.15] |
| Pennsylvania | 1.21 [1.07-1.41] | 0.62 [0.50-0.75] | 0.88 [0.68-1.09] | 1.31 [1.13-1.61] | 1.54 [1.35-1.82] | 1.15 [1.01-1.29] | 0.54 [0.47-0.61] | 0.15 [0.13-0.17] |
| Rhode Island | 1.18 [1.07-1.37] | 0.56 [0.44-0.69] | 0.85 [0.64-1.08] | 1.36 [1.20-1.63] | 1.50 [1.36-1.74] | 1.06 [0.94-1.19] | 0.53 [0.48-0.60] | 0.15 [0.13-0.17] |
| South Carolina | 1.03 [0.87-1.23] | 0.43 [0.35-0.52] | 0.61 [0.47-0.75] | 1.22 [1.00-1.48] | 1.31 [1.10-1.56] | 0.87 [0.78-0.97] | 0.44 [0.39-0.49] | 0.11 [0.10-0.12] |
| South Dakota | - | - | - | - | - | - | - | - |
| Tennessee | 1.11 [0.95-1.33] | 0.47 [0.38-0.57] | 0.64 [0.49-0.79] | 1.32 [1.11-1.60] | 1.39 [1.19-1.66] | 0.95 [0.86-1.06] | 0.42 [0.37-0.48] | 0.11 [0.10-0.13] |
| Texas | 0.86 [0.79-0.97] | 0.54 [0.45-0.62] | 0.75 [0.60-0.89] | 0.99 [0.88-1.16] | 1.09 [1.00-1.25] | 0.68 [0.64-0.74] | 0.31 [0.28-0.33] | 0.09 [0.08-0.09] |
| Utah | 1.20 [1.07-1.38] | 0.63 [0.49-0.77] | 0.81 [0.62-1.03] | 1.45 [1.28-1.69] | 1.47 [1.33-1.68] | 0.76 [0.68-0.86] | 0.32 [0.27-0.36] | 0.09 [0.08-0.11] |
| Vermont | - | - | - | - | - | - | - | - |
| Virginia | 1.00 [0.93-1.12] | 0.53 [0.42-0.63] | 0.72 [0.56-0.89] | 1.06 [0.96-1.21] | 1.30 [1.21-1.46] | 0.94 [0.88-1.02] | 0.41 [0.38-0.45] | 0.11 [0.10-0.12] |
| Washington | 1.06 [0.84-1.38] | 0.38 [0.31-0.45] | 0.49 [0.38-0.59] | 1.29 [1.00-1.70] | 1.30 [1.04-1.66] | 0.79 [0.69-0.91] | 0.39 [0.34-0.45] | 0.10 [0.09-0.11] |
| West Virginia | - | - | - | - | - | - | - | - |
| Wisconsin | 1.23 [1.10-1.38] | 0.54 [0.43-0.66] | 0.75 [0.58-0.93] | 1.34 [1.17-1.54] | 1.59 [1.41-1.79] | 1.13 [1.01-1.26] | 0.49 [0.44-0.56] | 0.13 [0.12-0.15] |
| Wyoming | - | - | - | - | - | - | - | - |

**Table S3: Estimated age-specific reproduction numbers in the week August 17, 2020 to August 23, 2020.** Posterior median estimates and 95% credible intervals are reported. Estimates correspond to the last week before schools were set to reopen in the first US locations in the model.

| | Age of infectious individuals (years) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Location | Overall | [0 − 9] | [10 − 19] | [20 − 34] | [35 − 49] | [50 − 64] | [65 − 79] | 80+ |
| All locations | 0.92 [0.89-0.95] | 0.57 [0.54-0.60] | 0.73 [0.69-0.77] | 1.01 [0.97-1.06] | 1.14 [1.10-1.18] | 0.73 [0.71-0.75] | 0.43 [0.41-0.44] | 0.23 [0.22-0.24] |
| Alabama | 0.92 [0.83-1.02] | 0.54 [0.45-0.64] | 0.69 [0.58-0.82] | 1.00 [0.88-1.15] | 1.15 [1.05-1.29] | 0.77 [0.70-0.83] | 0.47 [0.43-0.51] | 0.25 [0.23-0.27] |
| Alaska | - | - | - | - | - | - | - | - |
| Arizona | 0.82 [0.76-0.91] | 0.58 [0.48-0.68] | 0.75 [0.63-0.88] | 0.87 [0.78-1.01] | 1.05 [0.97-1.18] | 0.65 [0.61-0.70] | 0.40 [0.37-0.43] | 0.22 [0.20-0.23] |
| Arkansas | - | - | - | - | - | - | - | - |
| California | 0.91 [0.87-0.97] | 0.58 [0.51-0.67] | 0.74 [0.65-0.85] | 0.99 [0.93-1.07] | 1.12 [1.07-1.20] | 0.76 [0.72-0.79] | 0.44 [0.42-0.47] | 0.24 [0.22-0.25] |
| Colorado | 1.03 [0.92-1.13] | 0.62 [0.52-0.73] | 0.78 [0.66-0.91] | 1.10 [0.98-1.24] | 1.29 [1.16-1.42] | 0.78 [0.70-0.86] | 0.42 [0.38-0.47] | 0.22 [0.20-0.25] |
| Connecticut | 1.07 [0.97-1.19] | 0.58 [0.50-0.66] | 0.76 [0.65-0.87] | 1.18 [1.04-1.37] | 1.38 [1.23-1.56] | 0.83 [0.74-0.93] | 0.46 [0.41-0.52] | 0.25 [0.22-0.28] |
| Delaware | 1.02 [0.91-1.15] | 0.52 [0.42-0.64] | 0.67 [0.54-0.82] | 1.18 [1.04-1.36] | 1.26 [1.11-1.44] | 0.88 [0.79-0.98] | 0.58 [0.53-0.65] | 0.31 [0.28-0.34] |
| District of Columbia | 1.01 [0.88-1.17] | 0.42 [0.32-0.53] | 0.56 [0.43-0.71] | 1.20 [1.04-1.40] | 1.16 [1.01-1.33] | 0.61 [0.53-0.70] | 0.27 [0.22-0.32] | 0.14 [0.12-0.17] |
| Florida | 0.99 [0.87-1.14] | 0.55 [0.48-0.62] | 0.70 [0.61-0.79] | 1.15 [0.97-1.38] | 1.25 [1.08-1.46] | 0.75 [0.70-0.81] | 0.44 [0.41-0.48] | 0.24 [0.22-0.25] |
| Georgia | 0.86 [0.75-1.01] | 0.43 [0.38-0.49] | 0.56 [0.50-0.64] | 0.97 [0.81-1.20] | 1.07 [0.92-1.27] | 0.65 [0.59-0.71] | 0.34 [0.30-0.37] | 0.18 [0.16-0.20] |
| Hawaii | - | - | - | - | - | - | - | - |
| Idaho | 0.85 [0.71-1.04] | 0.44 [0.35-0.54] | 0.55 [0.45-0.68] | 0.98 [0.80-1.25] | 1.02 [0.83-1.28] | 0.64 [0.56-0.72] | 0.39 [0.35-0.44] | 0.21 [0.18-0.23] |
| Illinois | 1.08 [1.00-1.16] | 0.69 [0.60-0.79] | 0.88 [0.76-1.01] | 1.17 [1.06-1.29] | 1.36 [1.25-1.47] | 0.88 [0.78-0.96] | 0.52 [0.46-0.57] | 0.28 [0.25-0.30] |
| Indiana | 1.04 [0.94-1.13] | 0.58 [0.49-0.68] | 0.73 [0.63-0.86] | 1.10 [0.97-1.23] | 1.31 [1.18-1.42] | 0.90 [0.82-0.98] | 0.53 [0.47-0.58] | 0.28 [0.25-0.31] |
| Iowa | 1.05 [0.95-1.13] | 0.63 [0.50-0.78] | 0.79 [0.63-0.98] | 1.09 [0.96-1.20] | 1.33 [1.21-1.45] | 0.91 [0.82-0.98] | 0.60 [0.55-0.66] | 0.32 [0.29-0.35] |
| Kansas | 1.17 [1.05-1.34] | 0.57 [0.46-0.71] | 0.72 [0.58-0.89] | 1.30 [1.12-1.54] | 1.46 [1.29-1.68] | 0.91 [0.82-1.01] | 0.53 [0.47-0.59] | 0.28 [0.25-0.31] |
| Kentucky | 1.02 [0.92-1.09] | 0.51 [0.42-0.61] | 0.64 [0.53-0.77] | 1.08 [0.96-1.19] | 1.28 [1.16-1.38] | 0.84 [0.77-0.91] | 0.47 [0.42-0.52] | 0.25 [0.23-0.27] |
| Louisiana | 0.87 [0.73-1.04] | 0.49 [0.43-0.56] | 0.63 [0.56-0.73] | 1.02 [0.81-1.30] | 1.08 [0.89-1.30] | 0.65 [0.58-0.72] | 0.35 [0.32-0.39] | 0.19 [0.17-0.21] |
| Maine | - | - | - | - | - | - | - | - |
| Maryland | 0.96 [0.87-1.03] | 0.66 [0.56-0.78] | 0.85 [0.71-1.00] | 1.01 [0.90-1.12] | 1.20 [1.09-1.30] | 0.80 [0.72-0.87] | 0.45 [0.41-0.50] | 0.25 [0.22-0.27] |
| Massachusetts | 1.02 [0.93-1.12] | 0.63 [0.54-0.73] | 0.82 [0.70-0.95] | 1.11 [0.99-1.25] | 1.29 [1.16-1.42] | 0.83 [0.74-0.93] | 0.47 [0.41-0.53] | 0.25 [0.22-0.28] |
| Michigan | 1.03 [0.88-1.16] | 0.64 [0.54-0.76] | 0.82 [0.69-0.96] | 1.09 [0.90-1.28] | 1.33 [1.14-1.52] | 0.81 [0.68-0.95] | 0.52 [0.44-0.61] | 0.27 [0.24-0.32] |
| Minnesota | 1.03 [0.95-1.12] | 0.74 [0.61-0.89] | 0.93 [0.77-1.11] | 1.08 [0.97-1.19] | 1.30 [1.19-1.41] | 0.85 [0.77-0.92] | 0.50 [0.45-0.54] | 0.27 [0.25-0.29] |
| Mississippi | 0.90 [0.81-1.00] | 0.48 [0.39-0.57] | 0.62 [0.52-0.74] | 1.00 [0.87-1.14] | 1.13 [1.01-1.26] | 0.75 [0.67-0.83] | 0.42 [0.37-0.47] | 0.23 [0.20-0.25] |
| Missouri | 1.15 [1.07-1.25] | 0.56 [0.46-0.67] | 0.70 [0.58-0.84] | 1.27 [1.16-1.41] | 1.44 [1.33-1.58] | 0.93 [0.86-1.01] | 0.55 [0.51-0.60] | 0.29 [0.27-0.32] |
| Montana | - | - | - | - | - | - | - | - |
| Nebraska | - | - | - | - | - | - | - | - |
| Nevada | 0.83 [0.75-0.95] | 0.62 [0.51-0.75] | 0.79 [0.65-0.96] | 0.95 [0.84-1.12] | 0.99 [0.88-1.14] | 0.59 [0.52-0.66] | 0.33 [0.29-0.38] | 0.18 [0.16-0.20] |
| New Hampshire | 1.01 [0.89-1.14] | 0.59 [0.45-0.75] | 0.75 [0.57-0.96] | 1.12 [0.97-1.30] | 1.24 [1.09-1.43] | 0.87 [0.77-0.97] | 0.48 [0.42-0.54] | 0.25 [0.23-0.28] |
| New Jersey | 0.94 [0.84-1.06] | 0.53 [0.47-0.61] | 0.70 [0.61-0.80] | 1.06 [0.92-1.24] | 1.21 [1.08-1.37] | 0.77 [0.69-0.86] | 0.47 [0.42-0.52] | 0.25 [0.23-0.28] |
| New Mexico | 0.97 [0.91-1.03] | 0.65 [0.53-0.79] | 0.82 [0.67-1.00] | 1.06 [0.97-1.14] | 1.20 [1.12-1.27] | 0.79 [0.73-0.85] | 0.44 [0.40-0.49] | 0.24 [0.22-0.26] |
| New York | - | - | - | - | - | - | - | - |
| New York City | 0.99 [0.70-1.33] | 0.37 [0.32-0.42] | 0.50 [0.43-0.57] | 1.22 [0.79-1.75] | 1.17 [0.83-1.56] | 0.57 [0.46-0.67] | 0.33 [0.28-0.38] | 0.18 [0.15-0.20] |
| North Carolina | 0.99 [0.94-1.05] | 0.60 [0.49-0.73] | 0.76 [0.62-0.93] | 1.05 [0.98-1.12] | 1.24 [1.18-1.32] | 0.85 [0.80-0.89] | 0.49 [0.45-0.52] | 0.26 [0.24-0.28] |
| North Dakota | 1.28 [1.15-1.46] | 0.62 [0.46-0.82] | 0.77 [0.57-1.01] | 1.45 [1.28-1.71] | 1.55 [1.38-1.77] | 0.99 [0.86-1.12] | 0.55 [0.46-0.66] | 0.29 [0.24-0.34] |
| Ohio | - | - | - | - | - | - | - | - |
| Oklahoma | 0.96 [0.83-1.12] | 0.49 [0.41-0.59] | 0.62 [0.52-0.75] | 1.08 [0.88-1.31] | 1.19 [1.02-1.39] | 0.73 [0.66-0.81] | 0.42 [0.38-0.46] | 0.22 [0.20-0.24] |
| Oregon | 0.93 [0.82-1.08] | 0.46 [0.38-0.56] | 0.58 [0.47-0.70] | 1.03 [0.89-1.23] | 1.14 [0.99-1.36] | 0.76 [0.69-0.85] | 0.50 [0.46-0.56] | 0.26 [0.24-0.28] |
| Pennsylvania | 1.02 [0.93-1.12] | 0.71 [0.60-0.83] | 0.91 [0.77-1.06] | 1.05 [0.93-1.20] | 1.30 [1.18-1.45] | 0.87 [0.79-0.95] | 0.53 [0.48-0.58] | 0.28 [0.26-0.31] |
| Rhode Island | 1.06 [0.95-1.18] | 0.59 [0.47-0.73] | 0.76 [0.61-0.94] | 1.10 [0.98-1.26] | 1.39 [1.24-1.58] | 0.86 [0.76-0.96] | 0.58 [0.52-0.65] | 0.31 [0.27-0.34] |
| South Carolina | 0.86 [0.80-0.96] | 0.43 [0.37-0.50] | 0.55 [0.47-0.65] | 0.97 [0.88-1.11] | 1.08 [0.99-1.20] | 0.71 [0.66-0.76] | 0.43 [0.40-0.46] | 0.23 [0.21-0.24] |
| South Dakota | - | - | - | - | - | - | - | - |
| Tennessee | 0.99 [0.90-1.09] | 0.48 [0.40-0.59] | 0.62 [0.50-0.75] | 1.11 [0.99-1.26] | 1.21 [1.09-1.34] | 0.82 [0.76-0.88] | 0.45 [0.41-0.49] | 0.24 [0.22-0.26] |
| Texas | 0.82 [0.75-0.91] | 0.59 [0.51-0.68] | 0.75 [0.65-0.87] | 0.87 [0.78-1.02] | 1.01 [0.92-1.14] | 0.65 [0.60-0.69] | 0.38 [0.35-0.40] | 0.21 [0.19-0.22] |
| Utah | 0.96 [0.88-1.08] | 0.58 [0.45-0.73] | 0.73 [0.57-0.92] | 1.05 [0.93-1.21] | 1.17 [1.06-1.32] | 0.73 [0.67-0.79] | 0.37 [0.33-0.41] | 0.20 [0.18-0.22] |
| Vermont | - | - | - | - | - | - | - | - |
| Virginia | 1.06 [0.98-1.14] | 0.59 [0.50-0.69] | 0.74 [0.63-0.88] | 1.09 [1.00-1.21] | 1.34 [1.24-1.46] | 0.90 [0.83-0.96] | 0.50 [0.46-0.54] | 0.27 [0.25-0.29] |
| Washington | 0.97 [0.80-1.19] | 0.36 [0.32-0.40] | 0.45 [0.41-0.50] | 1.12 [0.89-1.42] | 1.19 [0.97-1.48] | 0.73 [0.65-0.81] | 0.44 [0.39-0.49] | 0.23 [0.20-0.25] |
| West Virginia | - | - | - | - | - | - | - | - |
| Wisconsin | 1.02 [0.92-1.13] | 0.59 [0.48-0.72] | 0.75 [0.61-0.90] | 1.05 [0.92-1.20] | 1.31 [1.16-1.47] | 0.87 [0.80-0.96] | 0.50 [0.46-0.56] | 0.27 [0.24-0.29] |
| Wyoming | - | - | - | - | - | - | - | - |

**Table S4: Estimated cumulated contribution of age groups to SARS-CoV-2 transmission as of August 17, 2020.** Posterior median estimates and 95% credible intervals are reported. Estimates are up to the last week before schools were set to reopen in the first US locations in the model.

| | Age of infected individuals (years) | | | | | | |
|---|---|---|---|---|---|---|---|
| Location | [0 − 9] | [10 − 19] | [20 − 34] | [35 − 49] | [50 − 64] | [65 − 79] | 80+ |
| Alabama | 1.9% [1.2%-2.9%] | 3.1% [2.1%-4.4%] | 31.8% [29.7%-33.8%] | 41.5% [40.2%-42.7%] | 17.9% [16.3%-19.4%] | 3.4% [2.9%-4.0%] | 0.4% [0.3%-0.4%] |
| Alaska | - | - | - | - | - | - | - |
| Arizona | 2.9% [1.9%-4.5%] | 4.8% [3.3%-6.9%] | 31.6% [29.0%-34.0%] | 42.8% [41.8%-43.6%] | 14.6% [13.2%-15.6%] | 3.0% [2.5%-3.5%] | 0.3% [0.3%-0.4%] |
| Arkansas | - | - | - | - | - | - | - |
| California | 2.2% [1.5%-3.2%] | 3.5% [2.6%-4.6%] | 34.6% [32.9%-36.2%] | 40.6% [39.9%-41.2%] | 16.0% [15.1%-16.8%] | 2.7% [2.4%-3.2%] | 0.3% [0.3%-0.4%] |
| Colorado | 2.8% [1.9%-4.1%] | 4.7% [3.6%-6.3%] | 33.1% [31.0%-34.9%] | 42.1% [41.3%-42.7%] | 14.7% [13.8%-15.5%] | 2.3% [2.0%-2.6%] | 0.2% [0.2%-0.3%] |
| Connecticut | 3.0% [2.1%-4.2%] | 6.3% [5.2%-7.7%] | 27.6% [26.2%-29.1%] | 39.2% [38.7%-39.7%] | 20.0% [19.0%-20.8%] | 3.4% [3.0%-4.0%] | 0.4% [0.3%-0.4%] |
| Delaware | 2.0% [1.2%-3.1%] | 3.1% [2.1%-4.7%] | 31.6% [30.1%-33.1%] | 36.5% [36.1%-36.9%] | 21.1% [20.0%-21.7%] | 5.1% [4.4%-5.9%] | 0.5% [0.4%-0.6%] |
| District of Columbia | 2.1% [1.2%-3.6%] | 2.8% [1.6%-4.6%] | 51.4% [49.1%-52.8%] | 33.5% [33.3%-33.7%] | 9.3% [8.5%-10.1%] | 0.8% [0.6%-1.0%] | 0.1% [0.1%-0.1%] |
| Florida | 2.0% [1.4%-2.8%] | 3.2% [2.5%-4.2%] | 35.2% [34.0%-36.3%] | 40.9% [40.3%-41.5%] | 15.4% [14.4%-16.4%] | 2.9% [2.5%-3.4%] | 0.3% [0.3%-0.4%] |
| Georgia | 1.5% [1.0%-2.1%] | 2.7% [2.2%-3.4%] | 37.4% [36.1%-38.5%] | 42.3% [41.4%-43.1%] | 14.1% [12.9%-15.0%] | 1.9% [1.6%-2.3%] | 0.2% [0.2%-0.2%] |
| Hawaii | - | - | - | - | - | - | - |
| Idaho | 1.2% [0.7%-1.8%] | 1.8% [1.2%-2.6%] | 41.4% [39.8%-42.8%] | 40.5% [39.6%-41.3%] | 12.4% [11.0%-13.8%] | 2.5% [2.1%-3.0%] | 0.2% [0.2%-0.3%] |
| Illinois | 3.7% [2.6%-5.3%] | 6.8% [5.3%-8.8%] | 28.1% [26.1%-30.0%] | 40.7% [40.2%-41.1%] | 17.2% [16.0%-18.1%] | 3.1% [2.7%-3.6%] | 0.4% [0.3%-0.4%] |
| Indiana | 2.4% [1.6%-3.4%] | 4.6% [3.6%-5.9%] | 28.1% [26.1%-30.1%] | 41.2% [40.4%-41.9%] | 19.8% [19.0%-20.5%] | 3.5% [3.0%-4.0%] | 0.4% [0.3%-0.4%] |
| Iowa | 2.3% [1.4%-3.8%] | 3.8% [2.5%-5.9%] | 27.5% [24.5%-30.6%] | 42.7% [41.4%-43.8%] | 19.0% [17.7%-19.7%] | 4.1% [3.6%-4.8%] | 0.5% [0.4%-0.5%] |
| Kansas | 1.9% [1.1%-3.1%] | 3.1% [2.0%-4.7%] | 33.0% [30.0%-35.7%] | 41.3% [40.0%-42.5%] | 17.4% [16.1%-18.8%] | 2.9% [2.5%-3.4%] | 0.3% [0.3%-0.4%] |
| Kentucky | 1.5% [1.0%-2.3%] | 2.5% [1.8%-3.6%] | 31.4% [28.9%-33.8%] | 43.0% [41.3%-44.5%] | 18.4% [17.4%-19.2%] | 2.9% [2.4%-3.3%] | 0.3% [0.3%-0.3%] |
| Louisiana | 2.5% [1.8%-3.7%] | 4.9% [4.0%-6.1%] | 35.2% [33.7%-36.4%] | 38.7% [38.2%-39.2%] | 16.0% [15.1%-16.7%] | 2.4% [2.0%-2.7%] | 0.3% [0.2%-0.3%] |
| Maine | - | - | - | - | - | - | - |
| Maryland | 3.2% [2.1%-4.7%] | 5.5% [4.0%-7.6%] | 28.3% [26.1%-30.2%] | 40.8% [40.4%-41.2%] | 18.7% [17.4%-19.6%] | 3.1% [2.7%-3.6%] | 0.4% [0.3%-0.4%] |
| Massachusetts | 3.2% [2.2%-4.5%] | 5.9% [4.6%-7.7%] | 30.0% [28.0%-31.7%] | 38.8% [38.4%-39.2%] | 18.6% [17.6%-19.4%] | 3.1% [2.7%-3.6%] | 0.4% [0.3%-0.4%] |
| Michigan | 3.2% [2.2%-4.8%] | 6.8% [5.5%-8.8%] | 27.9% [25.8%-29.9%] | 38.8% [38.2%-39.3%] | 18.8% [17.6%-19.8%] | 3.9% [3.4%-4.5%] | 0.4% [0.4%-0.5%] |
| Minnesota | 3.4% [2.2%-5.2%] | 5.6% [3.9%-7.9%] | 28.1% [25.5%-30.6%] | 41.8% [41.1%-42.3%] | 17.6% [16.2%-18.7%] | 3.0% [2.6%-3.5%] | 0.3% [0.3%-0.4%] |
| Mississippi | 1.7% [1.1%-2.6%] | 2.8% [2.0%-4.0%] | 33.4% [31.4%-35.2%] | 41.3% [39.9%-42.6%] | 17.6% [15.9%-19.0%] | 2.9% [2.4%-3.5%] | 0.3% [0.3%-0.4%] |
| Missouri | 1.9% [1.2%-2.8%] | 3.1% [2.2%-4.4%] | 32.1% [29.8%-34.3%] | 41.1% [39.9%-42.2%] | 18.1% [17.1%-19.0%] | 3.3% [2.8%-3.8%] | 0.4% [0.3%-0.4%] |
| Montana | - | - | - | - | - | - | - |
| Nebraska | - | - | - | - | - | - | - |
| Nevada | 3.0% [1.9%-4.9%] | 4.8% [3.3%-7.0%] | 39.3% [37.1%-40.8%] | 39.0% [38.5%-39.4%] | 11.7% [10.0%-13.3%] | 1.9% [1.5%-2.3%] | 0.2% [0.2%-0.2%] |
| New Hampshire | 2.3% [1.2%-3.9%] | 3.6% [2.0%-6.1%] | 29.6% [27.4%-31.7%] | 40.3% [39.6%-40.9%] | 20.9% [19.2%-22.0%] | 2.9% [2.4%-3.4%] | 0.3% [0.3%-0.4%] |
| New Jersey | 3.1% [2.2%-4.4%] | 6.3% [5.2%-7.9%] | 27.6% [26.2%-28.9%] | 39.9% [39.4%-40.3%] | 19.2% [18.1%-20.0%] | 3.5% [3.0%-4.0%] | 0.4% [0.4%-0.5%] |
| New Mexico | 2.8% [1.7%-4.4%] | 4.3% [2.8%-6.5%] | 33.1% [30.5%-35.4%] | 39.9% [39.0%-40.5%] | 16.8% [15.4%-17.7%] | 2.8% [2.4%-3.4%] | 0.3% [0.3%-0.3%] |
| New York | - | - | - | - | - | - | - |
| New York City | 2.8% [1.9%-3.9%] | 5.6% [4.7%-6.7%] | 38.3% [37.1%-39.3%] | 35.3% [34.8%-35.7%] | 15.0% [14.2%-15.6%] | 2.7% [2.4%-3.1%] | 0.3% [0.3%-0.4%] |
| North Carolina | 2.1% [1.3%-3.3%] | 3.5% [2.3%-5.2%] | 29.8% [27.3%-32.1%] | 42.7% [41.7%-43.6%] | 18.4% [17.3%-19.2%] | 3.1% [2.7%-3.7%] | 0.3% [0.3%-0.4%] |
| North Dakota | 2.2% [1.1%-4.0%] | 3.2% [1.7%-5.7%] | 37.9% [33.1%-42.2%] | 38.6% [36.7%-40.1%] | 15.7% [13.8%-17.0%] | 2.1% [1.7%-2.7%] | 0.3% [0.2%-0.3%] |
| Ohio | - | - | - | - | - | - | - |
| Oklahoma | 1.6% [1.0%-2.5%] | 2.7% [2.0%-3.8%] | 35.7% [33.3%-37.9%] | 42.2% [40.8%-43.6%] | 14.9% [13.8%-16.0%] | 2.5% [2.2%-3.0%] | 0.3% [0.2%-0.3%] |
| Oregon | 1.5% [1.0%-2.4%] | 2.6% [1.9%-3.7%] | 35.4% [33.3%-37.3%] | 40.6% [39.5%-41.8%] | 15.8% [14.4%-17.3%] | 3.6% [3.0%-4.3%] | 0.3% [0.3%-0.4%] |
| Pennsylvania | 3.6% [2.4%-5.2%] | 6.8% [5.1%-9.0%] | 24.8% [22.8%-26.9%] | 40.6% [40.0%-41.1%] | 20.0% [18.6%-21.1%] | 3.7% [3.1%-4.3%] | 0.4% [0.4%-0.5%] |
| Rhode Island | 2.6% [1.6%-4.2%] | 4.6% [3.0%-7.2%] | 27.4% [24.2%-30.4%] | 42.7% [41.5%-43.7%] | 18.0% [16.4%-19.0%] | 4.1% [3.6%-4.7%] | 0.5% [0.4%-0.5%] |
| South Carolina | 1.2% [0.8%-1.8%] | 2.0% [1.5%-2.8%] | 36.5% [35.0%-37.8%] | 40.8% [39.7%-41.9%] | 16.0% [14.8%-17.2%] | 3.1% [2.7%-3.7%] | 0.3% [0.3%-0.4%] |
| South Dakota | - | - | - | - | - | - | - |
| Tennessee | 1.4% [0.9%-2.2%] | 2.2% [1.5%-3.3%] | 35.6% [33.8%-37.4%] | 40.4% [39.4%-41.4%] | 17.4% [16.1%-18.6%] | 2.6% [2.2%-3.1%] | 0.3% [0.2%-0.3%] |
| Texas | 2.6% [1.8%-3.7%] | 4.2% [3.1%-5.6%] | 35.3% [33.5%-37.0%] | 42.4% [41.8%-43.0%] | 13.1% [12.0%-13.9%] | 2.2% [1.9%-2.5%] | 0.2% [0.2%-0.3%] |
| Utah | 2.0% [1.2%-3.4%] | 3.1% [1.9%-5.1%] | 38.3% [34.8%-41.3%] | 42.3% [40.7%-43.6%] | 12.4% [11.3%-13.3%] | 1.7% [1.4%-2.0%] | 0.2% [0.2%-0.2%] |
| Vermont | - | - | - | - | - | - | - |
| Virginia | 2.3% [1.5%-3.5%] | 4.0% [2.9%-5.5%] | 27.8% [25.6%-29.9%] | 43.7% [42.7%-44.5%] | 18.9% [17.9%-19.6%] | 3.0% [2.6%-3.5%] | 0.3% [0.3%-0.4%] |
| Washington | 1.8% [1.3%-2.7%] | 4.8% [4.0%-5.8%] | 36.4% [35.3%-37.5%] | 38.5% [37.7%-39.3%] | 15.3% [14.2%-16.2%] | 2.9% [2.5%-3.4%] | 0.3% [0.2%-0.3%] |
| West Virginia | - | - | - | - | - | - | - |
| Wisconsin | 2.3% [1.4%-3.6%] | 4.1% [2.9%-5.8%] | 27.3% [24.7%-29.9%] | 42.2% [41.0%-43.3%] | 20.3% [19.1%-21.3%] | 3.3% [2.9%-3.9%] | 0.4% [0.3%-0.4%] |
| Wyoming | - | - | - | - | - | - | - |
| All locations | 2.5% [1.9%-3.4%] | 4.3% [3.8%-5.0%] | 34.2% [33.2%-35.1%] | 41.0% [40.7%-41.3%] | 15.1% [14.5%-15.6%] | 2.6% [2.2%-3.0%] | 0.3% [0.3%-0.3%] |
| | Percent of population | | | | | | |
| All locations | 12.1% | 13.1% | 20.6% | 19.2 % | 19.2% | 12.1% | 3.7% |

**Table S5: Estimated contribution of age groups to SARS-CoV-2 transmission between October 05, 2020 and October 26, 2020.** Posterior median estimates and 95% credible intervals are reported.

| | Age of infected individuals (years) | | | | | | |
|---|---|---|---|---|---|---|---|
| Location | [0 − 9] | [10 − 19] | [20 − 34] | [35 − 49] | [50 − 64] | [65 − 79] | 80+ |
| Alabama | 2.4% [1.5%-3.7%] | 5.7% [3.5%-9.3%] | 32.7% [29.3%-36.7%] | 38.6% [36.9%-40.5%] | 16.8% [13.7%-19.3%] | 3.2% [2.4%-4.0%] | 0.3% [0.2%-0.4%] |
| Alaska | - | - | - | - | - | - | - |
| Arizona | 3.6% [2.2%-5.4%] | 9.0% [5.2%-15.9%] | 32.0% [27.1%-36.8%] | 37.7% [34.6%-39.7%] | 14.1% [11.5%-15.9%] | 3.1% [2.4%-3.8%] | 0.3% [0.2%-0.4%] |
| Arkansas | - | - | - | - | - | - | - |
| California | 3.3% [2.1%-4.8%] | 7.7% [4.8%-11.9%] | 32.8% [30.0%-35.7%] | 36.8% [35.1%-38.2%] | 16.1% [14.4%-17.3%] | 2.8% [2.4%-3.3%] | 0.3% [0.2%-0.3%] |
| Colorado | 2.6% [1.7%-3.9%] | 5.4% [3.3%-8.2%] | 33.8% [31.0%-36.7%] | 41.8% [40.1%-43.5%] | 14.0% [11.6%-16.4%] | 2.1% [1.6%-2.7%] | 0.2% [0.1%-0.3%] |
| Connecticut | 2.4% [1.6%-3.6%] | 6.3% [3.9%-10.0%] | 33.0% [29.4%-37.0%] | 40.4% [38.1%-42.4%] | 14.9% [11.7%-18.9%] | 2.4% [1.7%-3.3%] | 0.2% [0.2%-0.3%] |
| Delaware | 2.2% [1.3%-3.3%] | 4.7% [2.8%-7.4%] | 34.2% [30.8%-39.0%] | 34.7% [32.5%-36.7%] | 18.9% [14.7%-22.5%] | 4.7% [3.4%-6.1%] | 0.4% [0.3%-0.5%] |
| District of Columbia | 1.7% [0.9%-3.2%] | 2.2% [1.1%-4.0%] | 54.0% [51.2%-57.2%] | 32.4% [31.7%-33.0%] | 8.3% [6.5%-9.8%] | 1.0% [0.7%-1.5%] | 0.1% [0.1%-0.2%] |
| Florida | 3.3% [2.2%-4.5%] | 7.8% [4.8%-11.5%] | 31.7% [29.4%-34.3%] | 36.1% [34.3%-38.0%] | 17.3% [15.5%-18.5%] | 3.4% [2.9%-4.0%] | 0.3% [0.3%-0.4%] |
| Georgia | 2.5% [1.6%-3.8%] | 6.0% [3.6%-10.0%] | 36.7% [32.0%-41.5%] | 39.7% [37.7%-40.9%] | 13.0% [10.1%-15.8%] | 1.8% [1.3%-2.4%] | 0.2% [0.1%-0.2%] |
| Hawaii | - | - | - | - | - | - | - |
| Idaho | 1.4% [0.9%-2.1%] | 2.9% [1.8%-4.6%] | 42.9% [40.6%-44.7%] | 41.3% [39.4%-42.9%] | 9.4% [7.3%-11.8%] | 1.9% [1.4%-2.5%] | 0.2% [0.1%-0.2%] |
| Illinois | 3.5% [2.3%-5.0%] | 8.4% [5.0%-13.6%] | 30.7% [27.6%-34.1%] | 37.4% [35.2%-39.5%] | 16.6% [13.7%-18.8%] | 2.9% [2.3%-3.5%] | 0.3% [0.2%-0.4%] |
| Indiana | 2.4% [1.5%-3.6%] | 5.3% [3.3%-8.1%] | 30.8% [27.3%-35.0%] | 40.0% [38.1%-42.0%] | 17.8% [14.5%-20.9%] | 3.1% [2.4%-4.0%] | 0.3% [0.2%-0.4%] |
| Iowa | 2.6% [1.6%-4.1%] | 6.1% [3.6%-10.1%] | 27.5% [23.9%-31.1%] | 39.8% [38.2%-42.2%] | 19.0% [16.3%-20.7%] | 4.3% [3.5%-5.1%] | 0.4% [0.4%-0.5%] |
| Kansas | 2.6% [1.6%-4.0%] | 5.9% [3.5%-9.5%] | 31.9% [28.2%-35.6%] | 38.7% [37.1%-40.6%] | 17.4% [15.0%-19.3%] | 3.0% [2.4%-3.6%] | 0.3% [0.2%-0.4%] |
| Kentucky | 2.0% [1.3%-3.1%] | 4.3% [2.6%-6.6%] | 32.0% [29.0%-35.5%] | 41.5% [39.7%-43.6%] | 17.2% [14.3%-19.0%] | 2.7% [2.1%-3.3%] | 0.3% [0.2%-0.3%] |
| Louisiana | 2.8% [1.7%-4.4%] | 6.2% [3.6%-10.5%] | 39.6% [34.2%-44.4%] | 36.8% [34.3%-38.3%] | 12.5% [9.4%-15.5%] | 1.8% [1.3%-2.5%] | 0.2% [0.1%-0.2%] |
| Maine | - | - | - | - | - | - | - |
| Maryland | 3.7% [2.4%-5.6%] | 8.6% [4.9%-14.6%] | 29.1% [25.5%-33.6%] | 37.6% [34.9%-40.5%] | 17.4% [13.8%-19.9%] | 2.9% [2.2%-3.6%] | 0.3% [0.2%-0.4%] |
| Massachusetts | 3.4% [2.2%-4.9%] | 8.8% [5.1%-15.1%] | 32.3% [28.4%-36.5%] | 35.5% [33.1%-37.3%] | 16.9% [13.9%-19.5%] | 2.7% [2.1%-3.3%] | 0.3% [0.2%-0.3%] |
| Michigan | 2.7% [1.7%-4.1%] | 6.4% [3.9%-10.5%] | 32.1% [28.0%-36.7%] | 39.8% [37.1%-42.3%] | 15.0% [11.1%-20.0%] | 3.1% [2.2%-4.4%] | 0.3% [0.2%-0.4%] |
| Minnesota | 3.1% [1.9%-4.7%] | 6.6% [3.9%-10.8%] | 30.1% [27.1%-33.6%] | 39.4% [37.7%-41.5%] | 17.3% [14.2%-19.1%] | 3.0% [2.3%-3.6%] | 0.3% [0.2%-0.4%] |
| Mississippi | 2.6% [1.6%-3.9%] | 6.8% [4.0%-11.0%] | 32.8% [29.5%-37.3%] | 37.0% [35.1%-39.1%] | 17.3% [13.6%-19.5%] | 3.0% [2.2%-3.8%] | 0.3% [0.2%-0.4%] |
| Missouri | 2.4% [1.5%-3.6%] | 5.1% [3.2%-7.9%] | 31.8% [29.1%-34.4%] | 39.0% [37.7%-40.4%] | 17.9% [16.1%-19.2%] | 3.3% [2.8%-3.9%] | 0.3% [0.3%-0.4%] |
| Montana | - | - | - | - | - | - | - |
| Nebraska | - | - | - | - | - | - | - |
| Nevada | 3.2% [1.9%-5.1%] | 6.9% [3.9%-12.0%] | 38.8% [35.5%-42.5%] | 37.1% [34.6%-39.4%] | 11.5% [8.8%-14.0%] | 1.9% [1.4%-2.5%] | 0.2% [0.1%-0.2%] |
| New Hampshire | 2.0% [1.2%-3.2%] | 4.8% [2.7%-8.2%] | 30.4% [27.6%-33.8%] | 38.8% [36.6%-42.2%] | 20.5% [16.0%-23.7%] | 3.0% [2.1%-3.8%] | 0.3% [0.2%-0.4%] |
| New Jersey | 3.2% [2.0%-4.6%] | 7.3% [4.3%-11.6%] | 33.6% [29.1%-39.5%] | 36.8% [34.4%-38.7%] | 15.5% [11.6%-19.7%] | 2.8% [2.0%-3.8%] | 0.3% [0.2%-0.4%] |
| New Mexico | 2.6% [1.6%-3.9%] | 6.5% [3.8%-10.5%] | 34.0% [31.1%-37.1%] | 36.8% [35.1%-39.4%] | 16.6% [13.6%-18.8%] | 3.0% [2.2%-3.7%] | 0.3% [0.2%-0.4%] |
| New York | - | - | - | - | - | - | - |
| New York City | 3.9% [2.3%-6.1%] | 7.2% [4.0%-12.4%] | 45.9% [39.4%-53.7%] | 31.4% [29.6%-32.7%] | 9.1% [6.3%-11.4%] | 1.8% [1.2%-2.4%] | 0.2% [0.1%-0.3%] |
| North Carolina | 2.8% [1.7%-4.2%] | 6.8% [4.0%-11.1%] | 28.9% [26.0%-31.7%] | 39.5% [38.0%-41.6%] | 18.3% [16.3%-19.5%] | 3.2% [2.6%-3.7%] | 0.3% [0.3%-0.4%] |
| North Dakota | 2.5% [1.4%-4.0%] | 4.6% [2.7%-7.8%] | 38.7% [34.6%-42.6%] | 35.5% [33.9%-37.4%] | 15.8% [12.8%-18.1%] | 2.5% [1.8%-3.2%] | 0.3% [0.2%-0.4%] |
| Ohio | - | - | - | - | - | - | - |
| Oklahoma | 2.1% [1.3%-3.2%] | 4.4% [2.7%-6.9%] | 37.2% [33.4%-41.1%] | 40.7% [39.2%-42.3%] | 13.0% [10.5%-15.3%] | 2.2% [1.7%-2.8%] | 0.2% [0.2%-0.3%] |
| Oregon | 1.6% [1.0%-2.5%] | 3.3% [2.0%-5.2%] | 36.6% [33.3%-40.2%] | 40.5% [38.3%-43.1%] | 14.1% [10.6%-17.2%] | 3.3% [2.3%-4.4%] | 0.3% [0.2%-0.4%] |
| Pennsylvania | 3.0% [1.9%-4.5%] | 7.3% [4.2%-12.1%] | 27.5% [23.8%-32.0%] | 39.4% [37.0%-42.0%] | 18.7% [14.8%-21.9%] | 3.4% [2.5%-4.3%] | 0.3% [0.3%-0.4%] |
| Rhode Island | 2.7% [1.7%-4.0%] | 7.0% [4.1%-11.5%] | 32.5% [28.6%-37.3%] | 37.9% [36.3%-39.9%] | 15.6% [12.5%-18.0%] | 3.6% [2.7%-4.4%] | 0.4% [0.3%-0.5%] |
| South Carolina | 2.0% [1.3%-3.0%] | 4.7% [2.9%-7.3%] | 35.7% [32.6%-39.1%] | 38.3% [36.9%-39.8%] | 15.6% [12.9%-17.7%] | 3.2% [2.5%-4.0%] | 0.3% [0.2%-0.4%] |
| South Dakota | - | - | - | - | - | - | - |
| Tennessee | 2.1% [1.3%-3.2%] | 4.5% [2.8%-7.2%] | 35.4% [32.5%-38.8%] | 38.2% [36.8%-40.0%] | 16.7% [13.6%-18.8%] | 2.6% [2.0%-3.3%] | 0.3% [0.2%-0.3%] |
| Texas | 4.4% [3.0%-5.9%] | 11.0% [6.9%-16.0%] | 31.3% [28.1%-34.7%] | 36.4% [34.0%-38.6%] | 14.0% [12.6%-15.3%] | 2.5% [2.1%-2.9%] | 0.3% [0.2%-0.3%] |
| Utah | 2.8% [1.7%-4.3%] | 6.0% [3.4%-10.2%] | 38.8% [34.6%-42.5%] | 39.7% [38.0%-41.4%] | 10.8% [9.0%-12.8%] | 1.5% [1.2%-1.9%] | 0.2% [0.1%-0.2%] |
| Vermont | - | - | - | - | - | - | - |
| Virginia | 3.1% [2.0%-4.5%] | 7.0% [4.3%-10.9%] | 26.4% [23.6%-29.3%] | 41.2% [39.7%-42.8%] | 19.0% [17.3%-20.1%] | 3.0% [2.5%-3.5%] | 0.3% [0.3%-0.4%] |
| Washington | 1.7% [1.0%-2.5%] | 3.0% [1.8%-4.7%] | 39.6% [36.0%-43.9%] | 39.3% [37.9%-40.7%] | 13.6% [10.1%-16.3%] | 2.5% [1.8%-3.3%] | 0.2% [0.2%-0.3%] |
| West Virginia | - | - | - | - | - | - | - |
| Wisconsin | 2.1% [1.3%-3.2%] | 4.6% [2.8%-7.3%] | 29.7% [26.4%-33.3%] | 42.4% [39.9%-44.8%] | 17.7% [14.6%-21.4%] | 2.8% [2.2%-3.7%] | 0.3% [0.2%-0.4%] |
| Wyoming | - | - | - | - | - | - | - |
| All locations | 3.3% [2.2%-4.4%] | 7.8% [5.1%-11.1%] | 32.7% [30.8%-34.8%] | 37.8% [36.3%-39.2%] | 15.4% [14.3%-16.4%] | 2.7% [2.3%-3.1%] | 0.3% [0.2%-0.3%] |
| | Percent of population | | | | | | |
| All locations | 12.1% | 13.1% | 20.6% | 19.2 % | 19.2% | 12.1% | 3.7% |

**Table S6: Estimated cumulative age-specific attack rates as of October 29, 2020.** Posterior median estimates and 95% credible intervals are reported in percent.

| | Age of infectious individuals (years) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Location | Overall | [0 − 9] | [10 − 19] | [20 − 34] | [35 − 49] | [50 − 64] | [65 − 79] | 80+ |
| Alabama | 10.0% [8.7%-11.5%] | 3.3% [2.3%-4.7%] | 4.2% [3.2%-5.5%] | 15.0% [12.9%-17.5%] | 17.5% [15.1%-20.3%] | 10.5% [9.2%-12.0%] | 5.2% [4.4%-6.1%] | 3.4% [2.9%-4.0%] |
| Alaska | - | - | - | - | - | - | - | - |
| Arizona | 16.2% [14.3%-18.3%] | 6.1% [4.3%-8.7%] | 7.4% [5.8%-9.8%] | 24.0% [21.1%-27.1%] | 29.2% [25.6%-33.0%] | 16.5% [14.5%-18.5%] | 7.7% [6.7%-8.8%] | 5.0% [4.4%-5.8%] |
| Arkansas | - | - | - | - | - | - | - | - |
| California | 9.0% [7.9%-10.0%] | 3.1% [2.3%-4.2%] | 4.0% [3.2%-5.0%] | 12.8% [11.3%-14.4%] | 14.6% [12.8%-16.4%] | 9.3% [8.2%-10.4%] | 4.8% [4.2%-5.5%] | 3.0% [2.6%-3.4%] |
| Colorado | 6.3% [5.5%-7.2%] | 2.4% [1.7%-3.3%] | 3.0% [2.4%-3.8%] | 8.7% [7.6%-10.0%] | 10.5% [9.2%-12.0%] | 6.2% [5.5%-7.0%] | 3.0% [2.6%-3.5%] | 2.1% [1.8%-2.5%] |
| Connecticut | 12.4% [10.9%-14.2%] | 5.1% [3.7%-6.9%] | 5.9% [4.8%-7.3%] | 17.4% [15.1%-20.0%] | 21.2% [18.6%-24.3%] | 13.1% [11.4%-15.0%] | 6.6% [5.6%-7.8%] | 4.0% [3.3%-4.7%] |
| Delaware | 10.5% [8.2%-13.7%] | 3.7% [2.4%-5.5%] | 4.3% [3.0%-6.2%] | 15.4% [11.9%-20.6%] | 17.8% [13.8%-23.2%] | 11.5% [9.0%-14.6%] | 6.0% [4.6%-7.8%] | 4.2% [3.2%-5.4%] |
| District of Columbia | 26.8% [22.5%-30.5%] | 10.2% [6.8%-15.0%] | 11.3% [7.9%-15.9%] | 38.9% [32.8%-43.9%] | 37.8% [31.8%-42.8%] | 24.3% [20.2%-27.6%] | 9.6% [7.7%-11.4%] | 6.5% [5.2%-7.6%] |
| Florida | 10.5% [9.5%-11.5%] | 4.0% [3.0%-5.2%] | 5.2% [4.2%-6.1%] | 17.2% [15.5%-18.9%] | 18.3% [16.4%-20.1%] | 10.3% [9.3%-11.3%] | 4.6% [4.0%-5.2%] | 2.6% [2.2%-2.9%] |
| Georgia | 16.0% [14.3%-17.9%] | 4.7% [3.4%-6.3%] | 6.1% [5.0%-7.5%] | 25.6% [22.8%-29.0%] | 26.8% [23.9%-30.1%] | 15.5% [14.0%-17.1%] | 7.3% [6.3%-8.3%] | 5.4% [4.7%-6.2%] |
| Hawaii | - | - | - | - | - | - | - | - |
| Idaho | 7.9% [5.7%-12.2%] | 2.1% [1.3%-3.4%] | 2.8% [1.8%-4.6%] | 14.4% [10.2%-22.9%] | 14.3% [10.1%-22.3%] | 6.9% [5.2%-10.0%] | 3.3% [2.5%-4.9%] | 2.3% [1.7%-3.3%] |
| Illinois | 13.2% [11.5%-15.2%] | 5.7% [4.1%-7.9%] | 7.6% [6.0%-9.7%] | 17.8% [15.5%-20.4%] | 22.0% [19.2%-25.2%] | 13.6% [11.9%-15.5%] | 7.1% [6.1%-8.4%] | 4.5% [3.8%-5.3%] |
| Indiana | 7.9% [6.7%-9.4%] | 2.7% [1.9%-3.7%] | 3.7% [2.9%-4.8%] | 10.9% [9.1%-13.4%] | 13.6% [11.6%-16.4%] | 8.7% [7.5%-10.2%] | 4.4% [3.7%-5.3%] | 2.8% [2.4%-3.4%] |
| Iowa | 7.4% [6.3%-9.0%] | 2.6% [1.8%-3.7%] | 3.5% [2.6%-4.8%] | 10.1% [8.4%-12.4%] | 13.2% [11.2%-16.1%] | 8.1% [6.9%-9.8%] | 4.5% [3.7%-5.6%] | 2.5% [2.0%-3.1%] |
| Kansas | 6.0% [5.0%-7.3%] | 2.0% [1.4%-2.8%] | 2.8% [2.1%-3.8%] | 8.9% [7.5%-11.2%] | 10.4% [8.8%-12.9%] | 6.3% [5.4%-7.7%] | 3.1% [2.6%-3.9%] | 1.8% [1.5%-2.2%] |
| Kentucky | 4.6% [4.0%-5.5%] | 1.4% [1.0%-1.9%] | 1.9% [1.5%-2.6%] | 6.8% [5.9%-8.3%] | 8.2% [7.0%-9.8%] | 4.8% [4.2%-5.7%] | 2.3% [1.9%-2.7%] | 1.4% [1.2%-1.7%] |
| Louisiana | 20.8% [17.9%-24.0%] | 7.2% [5.2%-10.0%] | 9.7% [7.7%-12.2%] | 32.5% [27.8%-37.7%] | 34.9% [30.1%-40.1%] | 20.8% [17.9%-23.8%] | 9.7% [8.1%-11.5%] | 6.7% [5.6%-8.0%] |
| Maine | - | - | - | - | - | - | - | - |
| Maryland | 11.7% [10.0%-13.5%] | 4.7% [3.3%-6.7%] | 6.1% [4.6%-8.1%] | 15.8% [13.5%-18.3%] | 19.5% [16.7%-22.6%] | 12.1% [10.4%-14.0%] | 6.2% [5.2%-7.3%] | 4.2% [3.5%-5.0%] |
| Massachusetts | 13.0% [11.3%-14.7%] | 5.8% [4.1%-7.9%] | 7.1% [5.6%-8.9%] | 17.0% [14.8%-19.3%] | 21.7% [18.8%-24.5%] | 13.5% [11.7%-15.3%] | 6.8% [5.7%-7.9%] | 4.2% [3.5%-4.9%] |
| Michigan | 10.9% [9.4%-12.5%] | 4.4% [3.1%-6.3%] | 6.2% [4.9%-7.9%] | 14.8% [12.7%-17.3%] | 18.8% [16.2%-21.8%] | 11.1% [9.6%-12.5%] | 5.9% [5.0%-6.9%] | 3.8% [3.2%-4.4%] |
| Minnesota | 5.9% [5.2%-6.9%] | 2.4% [1.7%-3.3%] | 3.3% [2.5%-4.3%] | 8.1% [7.1%-9.6%] | 10.2% [8.9%-12.0%] | 6.1% [5.3%-7.1%] | 3.1% [2.6%-3.7%] | 1.9% [1.6%-2.2%] |
| Mississippi | 19.1% [14.7%-23.0%] | 6.1% [4.0%-8.8%] | 7.4% [5.2%-10.2%] | 29.1% [22.2%-35.3%] | 32.5% [25.1%-39.4%] | 20.9% [16.1%-24.8%] | 9.8% [7.4%-12.0%] | 7.0% [5.2%-8.5%] |
| Missouri | 6.8% [5.9%-7.9%] | 2.3% [1.6%-3.2%] | 3.2% [2.5%-4.2%] | 10.0% [8.7%-11.7%] | 11.9% [10.3%-13.7%] | 7.1% [6.2%-8.2%] | 3.6% [3.0%-4.2%] | 2.2% [1.8%-2.6%] |
| Montana | - | - | - | - | - | - | - | - |
| Nebraska | - | - | - | - | - | - | - | - |
| Nevada | 13.8% [12.0%-16.1%] | 5.5% [3.8%-7.9%] | 7.1% [5.3%-9.6%] | 22.6% [19.6%-26.3%] | 22.2% [19.2%-25.9%] | 12.3% [10.8%-13.9%] | 5.7% [4.8%-6.5%] | 4.1% [3.5%-4.8%] |
| New Hampshire | 2.3% [1.7%-3.1%] | 0.9% [0.5%-1.4%] | 0.9% [0.6%-1.4%] | 3.4% [2.6%-4.6%] | 4.1% [3.1%-5.5%] | 2.4% [1.8%-3.2%] | 1.0% [0.8%-1.4%] | 0.7% [0.5%-0.9%] |
| New Jersey | 22.7% [19.3%-26.4%] | 9.1% [6.4%-12.7%] | 12.1% [9.5%-15.2%] | 31.4% [26.9%-36.6%] | 36.8% [31.6%-42.3%] | 23.9% [20.3%-27.8%] | 13.2% [10.9%-15.7%] | 8.2% [6.7%-9.8%] |
| New Mexico | 9.3% [8.0%-10.9%] | 3.5% [2.4%-5.1%] | 4.0% [2.9%-5.6%] | 14.0% [12.1%-16.6%] | 16.4% [14.1%-19.4%] | 9.9% [8.6%-11.4%] | 4.4% [3.8%-5.1%] | 2.8% [2.4%-3.3%] |
| New York | - | - | - | - | - | - | - | - |
| New York City | 34.9% [29.7%-40.1%] | 13.3% [9.5%-18.2%] | 18.3% [14.7%-22.5%] | 49.1% [41.9%-56.2%] | 51.4% [44.2%-58.5%] | 35.6% [30.0%-41.3%] | 19.6% [16.1%-23.7%] | 12.3% [10.1%-15.1%] |
| North Carolina | 6.6% [5.7%-7.6%] | 2.3% [1.6%-3.3%] | 3.1% [2.4%-4.2%] | 9.3% [8.0%-10.8%] | 11.2% [9.6%-13.0%] | 7.1% [6.1%-8.1%] | 3.4% [2.8%-4.0%] | 2.3% [1.9%-2.7%] |
| North Dakota | 11.0% [8.8%-14.4%] | 3.7% [2.5%-5.6%] | 5.7% [3.9%-8.4%] | 16.4% [12.9%-21.6%] | 18.7% [14.9%-24.2%] | 11.2% [9.0%-14.5%] | 5.4% [4.2%-7.4%] | 2.8% [2.2%-3.8%] |
| Ohio | - | - | - | - | - | - | - | - |
| Oklahoma | 6.5% [5.3%-8.5%] | 1.9% [1.3%-2.9%] | 2.7% [2.0%-3.8%] | 10.3% [8.3%-14.0%] | 11.6% [9.5%-15.4%] | 6.4% [5.3%-8.1%] | 3.1% [2.5%-4.0%] | 1.9% [1.5%-2.4%] |
| Oregon | 2.5% [2.0%-3.4%] | 0.8% [0.5%-1.1%] | 1.0% [0.7%-1.4%] | 3.9% [3.1%-5.4%] | 4.2% [3.3%-5.7%] | 2.5% [2.0%-3.2%] | 1.3% [1.0%-1.6%] | 0.8% [0.6%-1.0%] |
| Pennsylvania | 6.6% [5.5%-7.9%] | 2.9% [2.0%-4.1%] | 3.8% [2.9%-5.1%] | 8.6% [7.1%-10.4%] | 11.8% [9.8%-14.1%] | 7.0% [5.9%-8.3%] | 3.5% [2.9%-4.3%] | 2.0% [1.7%-2.5%] |
| Rhode Island | 11.3% [8.9%-14.3%] | 4.4% [2.9%-6.8%] | 5.5% [3.9%-7.9%] | 14.9% [11.8%-18.9%] | 20.1% [15.9%-25.4%] | 11.4% [9.0%-14.4%] | 6.6% [5.1%-8.6%] | 3.8% [2.9%-4.9%] |
| South Carolina | 13.1% [11.5%-15.2%] | 3.8% [2.7%-5.2%] | 4.9% [3.8%-6.3%] | 21.5% [18.7%-25.0%] | 22.9% [19.9%-26.5%] | 13.3% [11.7%-15.1%] | 6.3% [5.3%-7.5%] | 4.4% [3.7%-5.2%] |
| South Dakota | - | - | - | - | - | - | - | - |
| Tennessee | 10.6% [9.1%-12.6%] | 3.3% [2.3%-4.6%] | 4.5% [3.4%-5.9%] | 16.5% [14.2%-20.1%] | 17.6% [15.1%-21.2%] | 11.0% [9.5%-12.8%] | 5.0% [4.2%-6.0%] | 3.4% [2.8%-4.0%] |
| Texas | 14.7% [13.3%-16.2%] | 5.0% [3.8%-6.6%] | 6.7% [5.6%-7.9%] | 21.9% [19.6%-24.3%] | 24.5% [22.0%-27.1%] | 14.4% [12.9%-15.9%] | 7.7% [6.8%-8.7%] | 5.5% [4.9%-6.2%] |
| Utah | 5.7% [4.9%-7.2%] | 1.7% [1.1%-2.5%] | 2.4% [1.7%-3.4%] | 8.7% [7.4%-11.2%] | 9.9% [8.5%-12.4%] | 6.2% [5.3%-7.5%] | 2.8% [2.3%-3.5%] | 2.0% [1.6%-2.4%] |
| Vermont | - | - | - | - | - | - | - | - |
| Virginia | 6.1% [5.3%-6.8%] | 2.1% [1.5%-2.9%] | 2.9% [2.3%-3.7%] | 8.0% [6.9%-9.1%] | 10.5% [9.1%-11.8%] | 6.6% [5.8%-7.4%] | 3.2% [2.7%-3.7%] | 2.1% [1.8%-2.5%] |
| Washington | 4.8% [3.8%-6.1%] | 1.3% [0.9%-1.9%] | 2.1% [1.5%-2.7%] | 7.5% [5.9%-9.5%] | 7.9% [6.2%-10.0%] | 4.7% [3.8%-5.9%] | 2.4% [1.8%-3.0%] | 1.6% [1.2%-2.0%] |
| West Virginia | - | - | - | - | - | - | - | - |
| Wisconsin | 6.9% [5.8%-8.7%] | 2.5% [1.7%-3.5%] | 3.4% [2.6%-4.7%] | 9.7% [8.0%-12.7%] | 12.3% [10.3%-15.8%] | 7.1% [6.1%-8.7%] | 3.5% [2.9%-4.3%] | 2.1% [1.7%-2.5%] |
| Wyoming | - | - | - | - | - | - | - | - |

DOI: https://doi.org/10.25561/82551

**Table S7: Estimated excess SARS-CoV-2 infections and excess COVID-19 attributable deaths in the school re-opening scenario, when compared to continued school closure scenarios.** Posterior median estimates for each location (state or metropolitan area), along with 95% credible intervals for the period August 24, 2020 to October 29, 2020. Transmission are reduced by a factor of $\eta^{\text{school}}$ from and to children and teens aged 0-18 due to face mask use and other non-pharmaceutical interventions (see Supplementary materials).

| Location | Excess SARS-CoV-2 infections (percent increase) | Excess COVID-19 attributable deaths (percent increase) |
|---|---|---|
| All locations | 28.3% [16.3%-42.4%] | 6.5% [3.7%-9.5%] |
| Alabama | 25.4% [14.2%-40.5%] | 5.8% [3.2%-9.1%] |
| Alaska | - | - |
| Arizona | 29.5% [16.4%-47.5%] | 4.2% [2.4%-6.7%] |
| Arkansas | - | - |
| California | 27.1% [15.2%-42.7%] | 5.7% [3.2%-8.7%] |
| Colorado | 26.3% [14.6%-42.4%] | 8.3% [4.7%-13.3%] |
| Connecticut | 39.6% [21.5%-65.2%] | 13.2% [7.2%-21.1%] |
| Delaware | 27.2% [15.0%-44.5%] | 8.7% [4.6%-14.4%] |
| District of Columbia | 24.8% [8.7%-45.1%] | 4.4% [-1.5%-11.0%] |
| Florida | 21.5% [12.7%-32.1%] | 5.0% [2.9%-7.4%] |
| Georgia | 25.8% [14.8%-40.0%] | 4.9% [2.8%-7.4%] |
| Hawaii | - | - |
| Idaho | 24.6% [14.0%-39.1%] | 6.2% [3.4%-9.9%] |
| Illinois | 37.9% [20.6%-61.5%] | 11.2% [6.3%-17.4%] |
| Indiana | 31.3% [17.2%-50.4%] | 9.7% [5.3%-15.3%] |
| Iowa | 27.9% [15.3%-46.1%] | 8.0% [4.3%-12.9%] |
| Kansas | 23.9% [13.6%-38.1%] | 7.7% [4.3%-12.3%] |
| Kentucky | 23.6% [13.3%-38.2%] | 6.5% [3.6%-10.5%] |
| Louisiana | 30.1% [17.2%-47.7%] | 5.5% [3.1%-8.5%] |
| Maine | - | - |
| Maryland | 38.8% [20.4%-65.9%] | 9.4% [5.2%-14.9%] |
| Massachusetts | 35.0% [19.0%-57.6%] | 9.4% [5.3%-14.8%] |
| Michigan | 34.7% [18.8%-56.5%] | 10.6% [5.9%-16.7%] |
| Minnesota | 33.8% [18.3%-57.1%] | 10.1% [5.5%-16.4%] |
| Mississippi | 26.2% [14.8%-41.9%] | 5.1% [2.9%-8.0%] |
| Missouri | 22.9% [12.9%-36.3%] | 7.3% [4.1%-11.8%] |
| Montana | - | - |
| Nebraska | - | - |
| Nevada | 26.0% [14.6%-43.1%] | 4.6% [2.6%-7.2%] |
| New Hampshire | 24.6% [13.2%-41.7%] | 7.6% [4.1%-12.7%] |
| New Jersey | 45.0% [24.3%-73.0%] | 11.4% [6.4%-17.7%] |
| New Mexico | 16.5% [2.5%-33.1%] | 1.4% [-4.0%-6.2%] |
| New York | - | - |
| New York City | 37.1% [21.4%-58.7%] | 9.2% [5.3%-14.2%] |
| North Carolina | 28.0% [15.5%-45.9%] | 7.1% [4.0%-11.4%] |
| North Dakota | 21.0% [11.9%-34.2%] | 8.3% [4.5%-13.7%] |
| Ohio | - | - |
| Oklahoma | 24.8% [13.9%-39.4%] | 6.6% [3.7%-10.5%] |
| Oregon | 18.3% [10.3%-29.6%] | 4.6% [2.5%-7.4%] |
| Pennsylvania | 34.8% [18.6%-58.1%] | 9.8% [5.4%-15.5%] |
| Rhode Island | 27.3% [9.4%-50.8%] | 5.7% [-1.3%-12.8%] |
| South Carolina | 23.0% [13.3%-35.8%] | 4.6% [2.6%-7.2%] |
| South Dakota | - | - |
| Tennessee | 22.8% [12.9%-36.0%] | 6.0% [3.3%-9.4%] |
| Texas | 32.0% [18.7%-46.8%] | 5.6% [3.4%-7.9%] |
| Utah | 37.5% [20.5%-63.8%] | 10.8% [5.9%-17.7%] |
| Vermont | - | - |
| Virginia | 24.5% [13.7%-39.2%] | 6.3% [3.6%-10.0%] |
| Washington | 16.6% [9.6%-26.0%] | 4.6% [2.6%-7.3%] |
| West Virginia | - | - |
| Wisconsin | 27.2% [14.9%-44.0%] | 9.6% [5.2%-15.3%] |
| Wyoming | - | - |

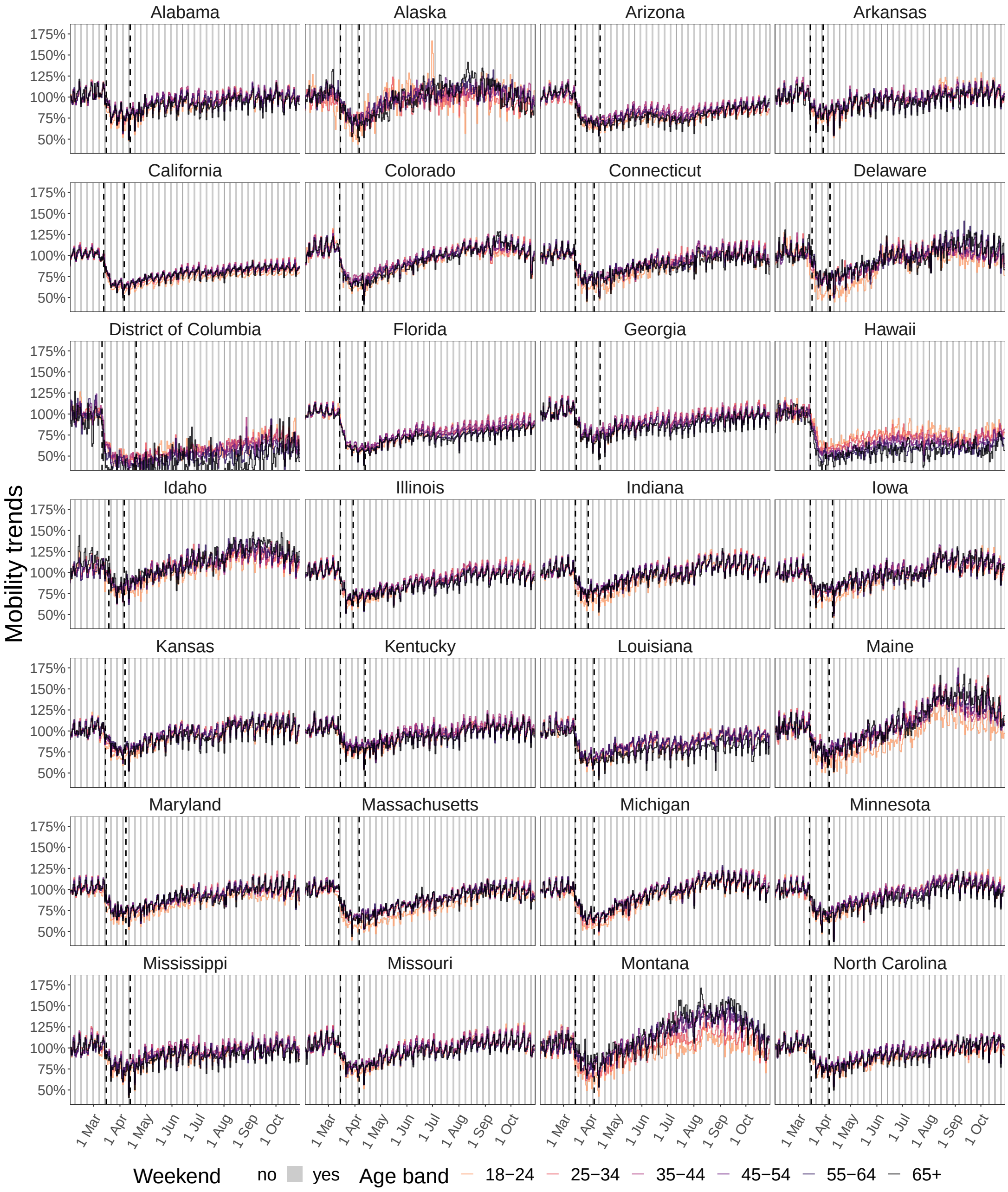


**Figure S1: Daily per person mobility trends for the 50 US states, District of Columbia and New York City (part 1).** Mobility trends quantify change in daily per person venue visits relative to the baseline week February 3 to February 9, 2020. The two dashed lines indicate the dip and rebound time (see Materials and methods).

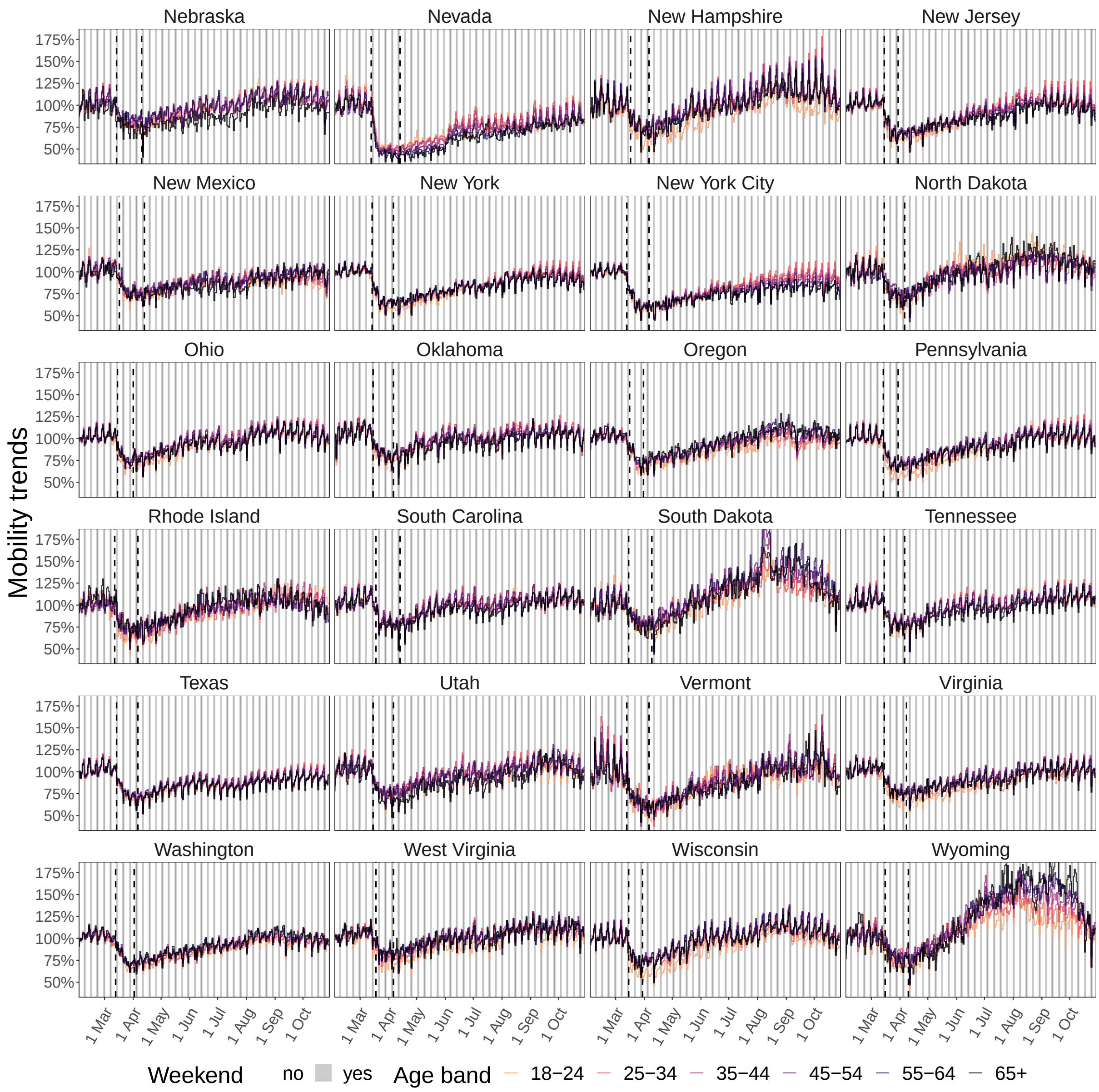


**Figure S2: Daily per person mobility trends for the 50 US states, District of Columbia and New York City (part 2).** Mobility trends quantify change in daily per person venue visits relative to the baseline week February 3 to February 9, 2020. The two dashed lines indicate the dip and rebound time (see Materials and methods).

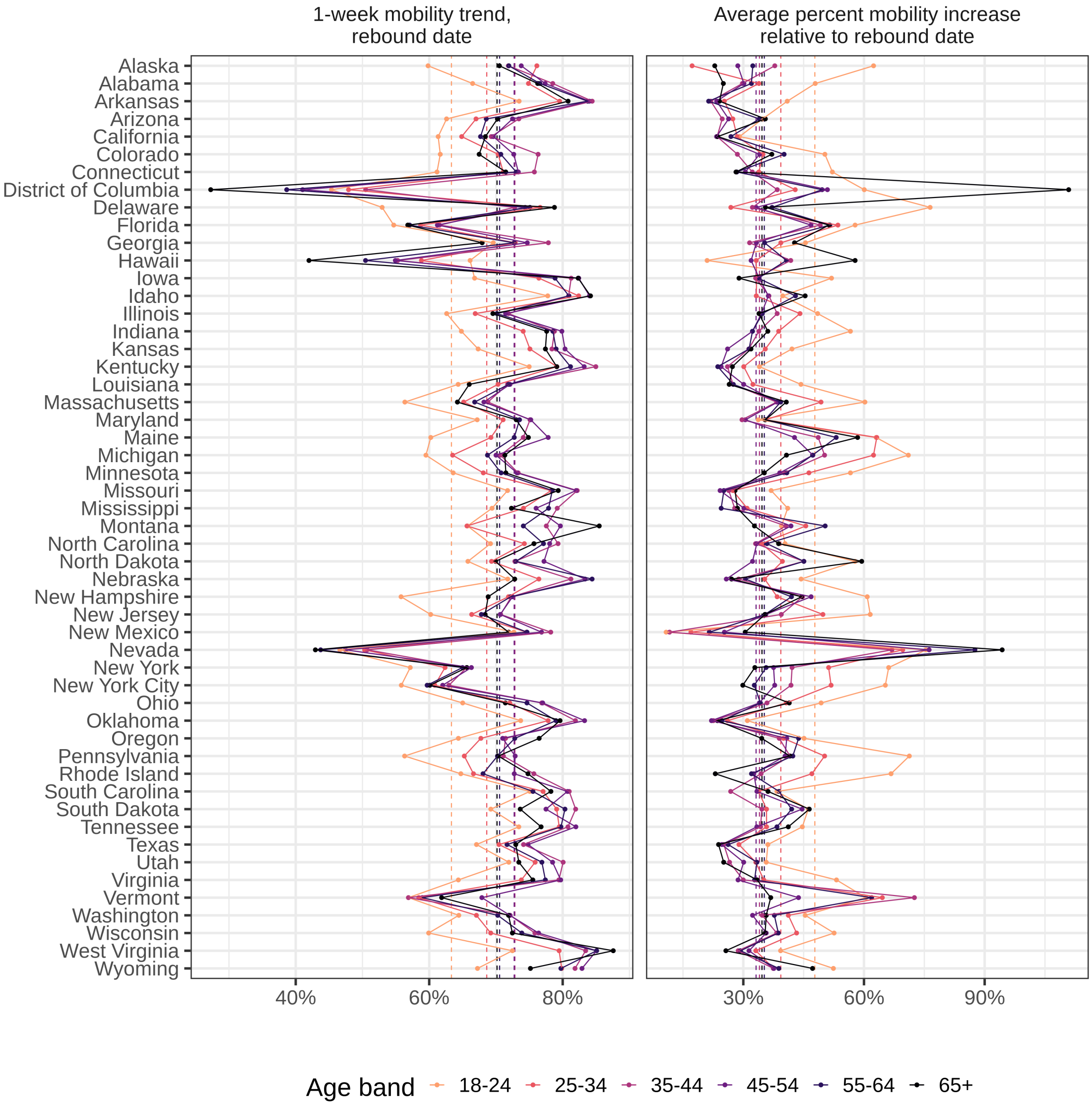


**Figure S3: Initial decline and surge in age-specific mobility trends in the United States.** (**A**) Longitudinal mobility trends for individuals aged $18-24$, $25-34$, $35-44$, $45-54$, $55-64$, $65+$ showed an initial decline and a subsequent increase across the United States. Rebound dates were estimated from the time series data, and to have occurred between March 30, 2020 to April 20, 2020. The figure shows age-specific mobility trends relative to the baseline period February 03 to February 09, 2020 for each location (state or metropolitan area). The 1-week mobility trend was calculated over the week prior to the rebound date. (**B**) Subsequent increases in mobility were quantified in terms of daily percent changes relative to the 1-week average prior to the rebound dates shown in Fig.A. The figure shows the average percent change in the last observation week October 19, 2020 - October 25, 2020 for each age band and each location.

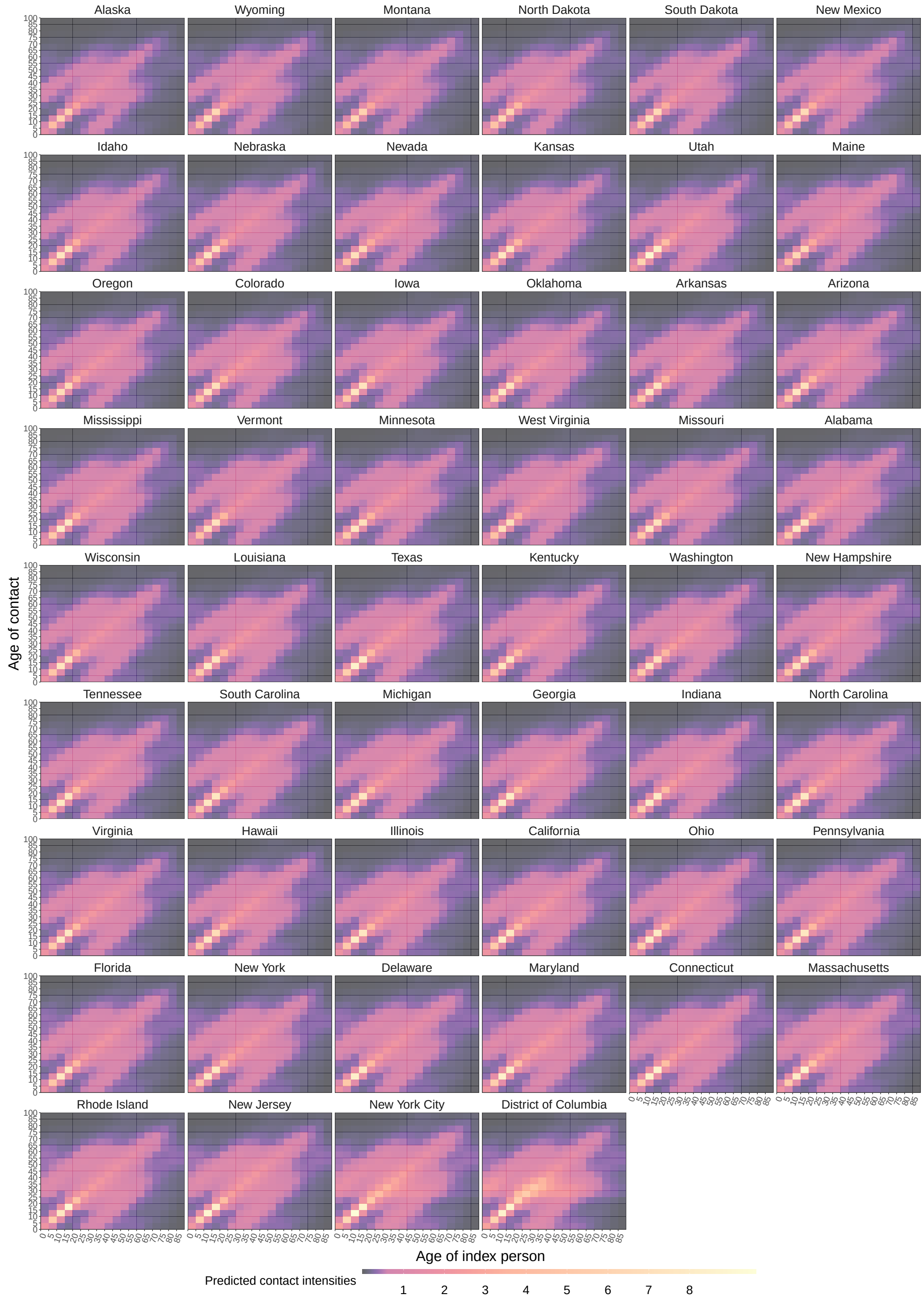


**Figure S4: Predicted age-specific contact matrices for the 50 US states, District of Columbia and New York City prior to the pandemic, on weekdays.** Shown in colour are the predicted number of contacts made by one index person of age $a$ with individuals of age $a'$ per day. Contacts were estimated from regression models using population demographics and fitted to contact survey estimates from the Polymod study. Locations ordered by population density.

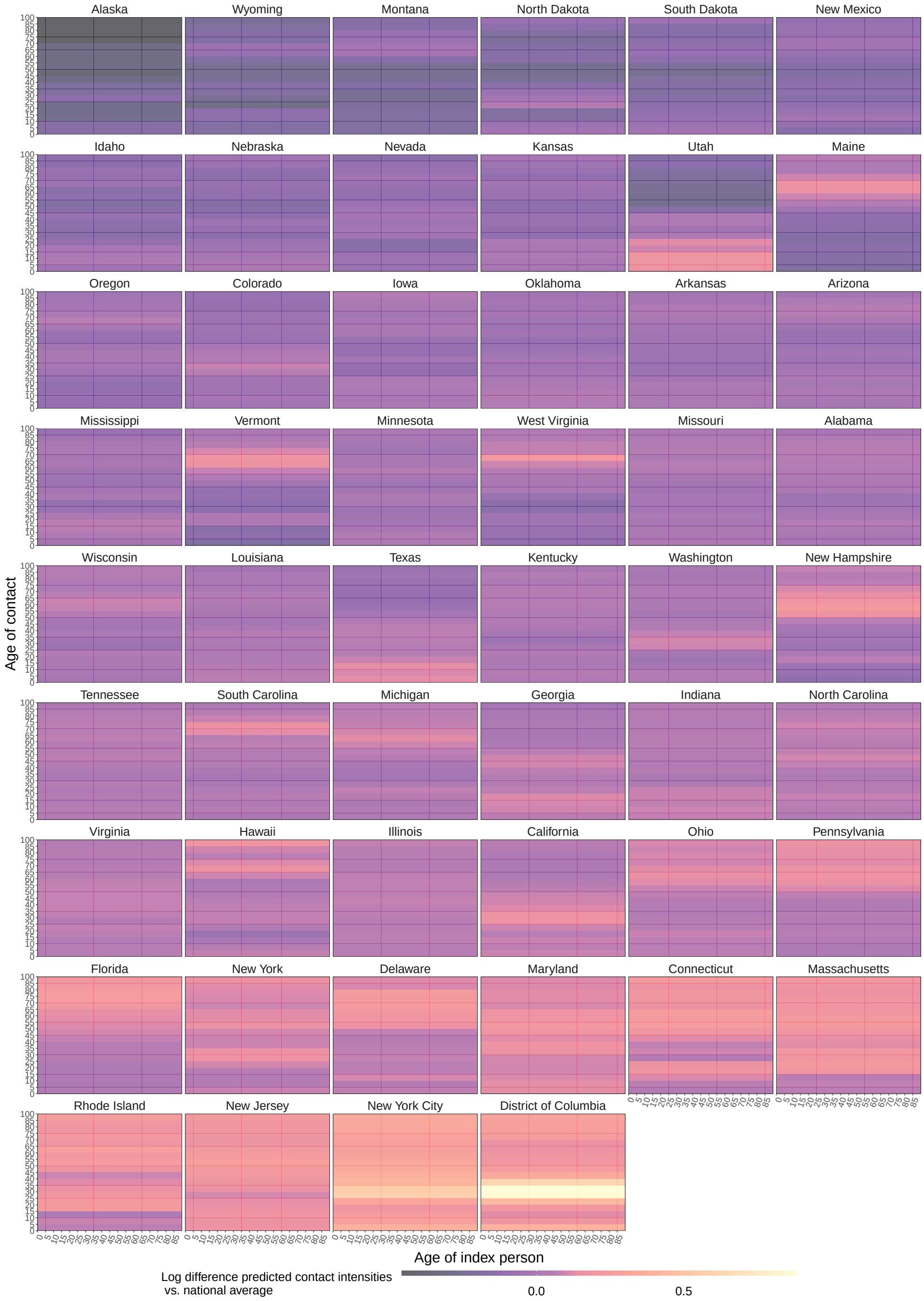


**Figure S5: Difference in predicted age-specific contact matrices for the 50 US states, District of Columbia and New York City prior to the pandemic relative to the national average, on weekdays.** Shown in colour are the log ratio of the contact intensities in each location compared to the contact intensities for the national population. Locations ordered by population density.

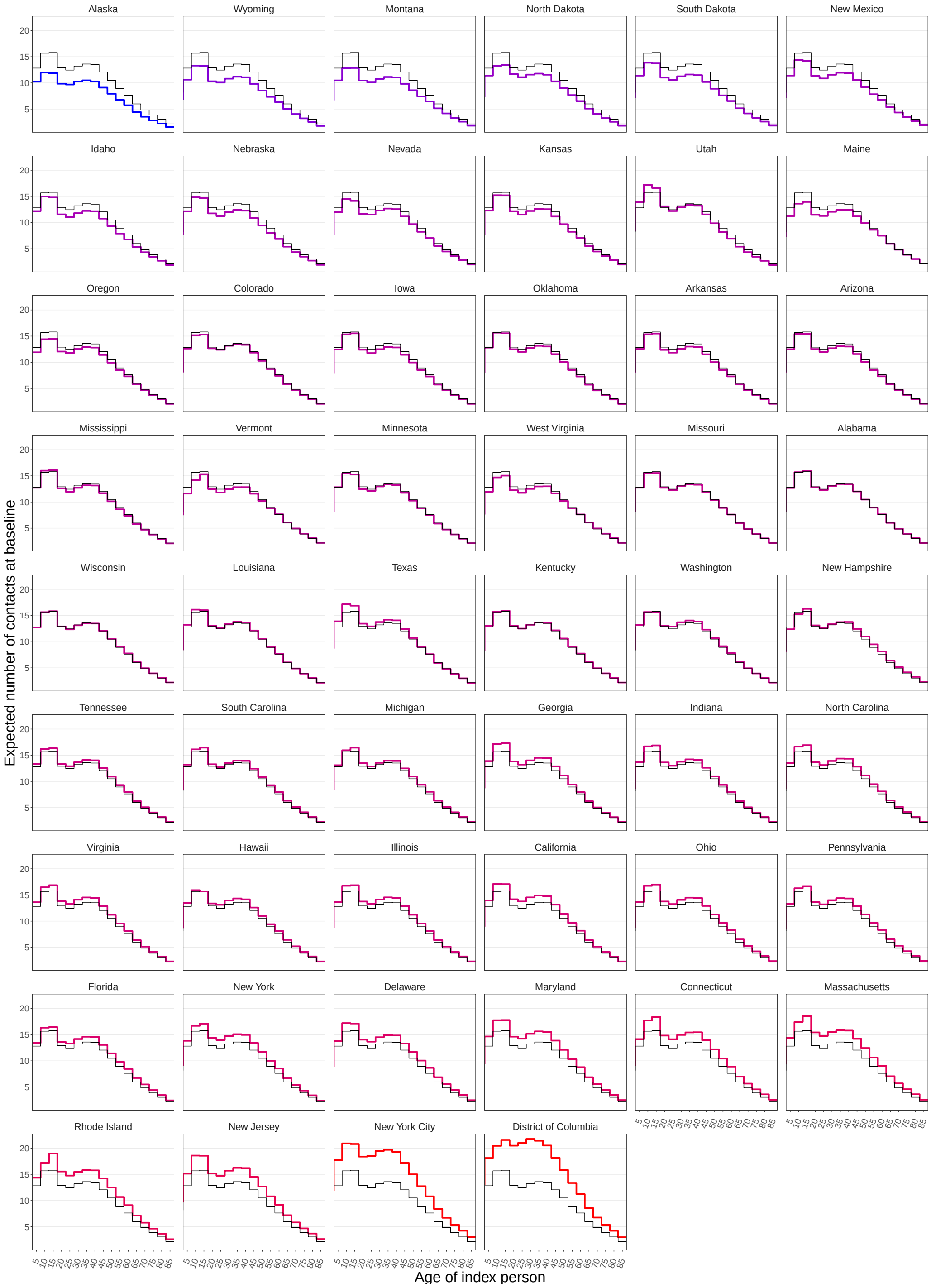


**Figure S6: Predicted number of expected contacts by one index individual of age $a$ per day.** Locations ordered by population density, national average shown in black. Predictions shown for weekdays.

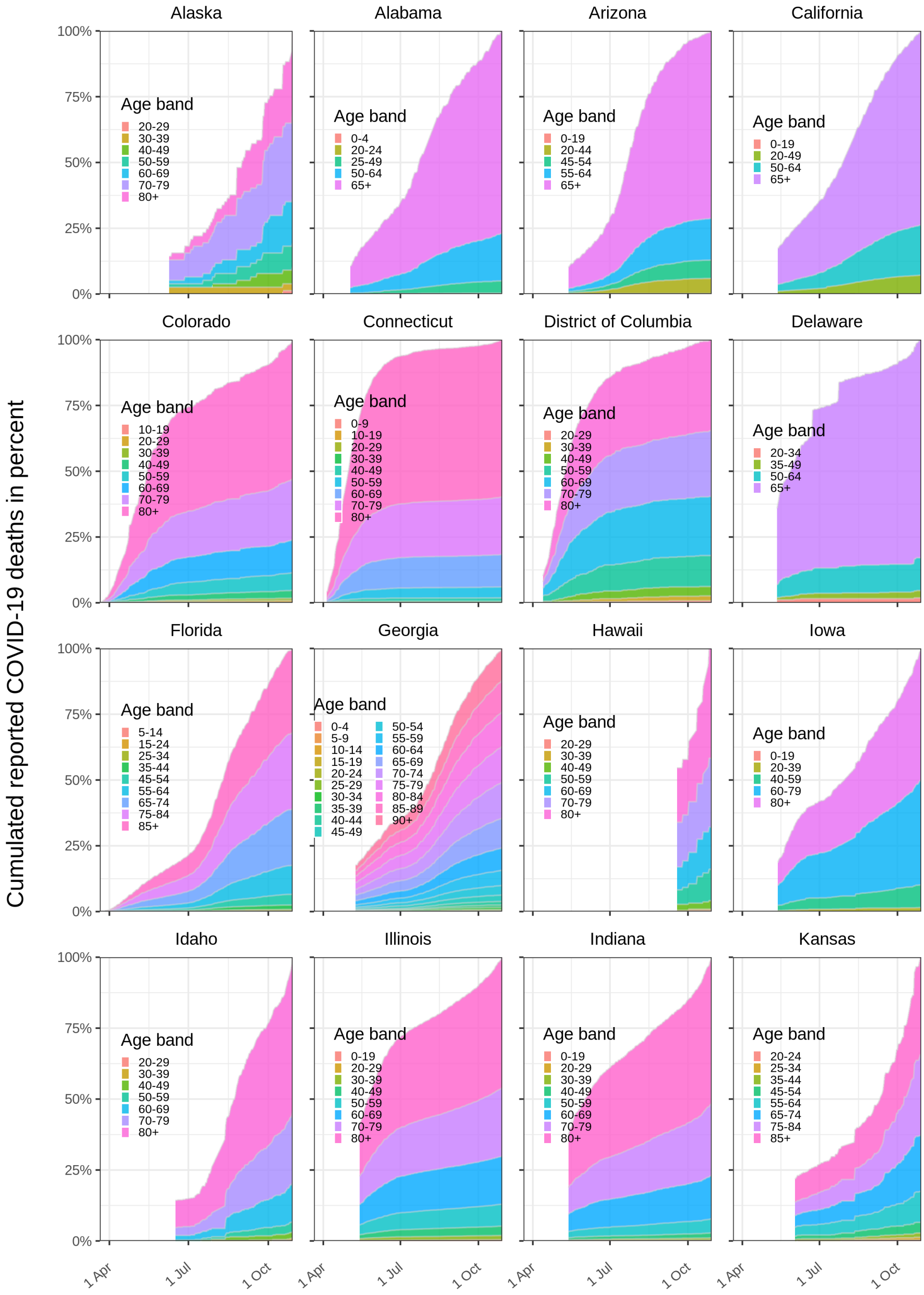


**Figure S7: Age-specific COVID-19 mortality data in the US (part 1).** COVID-19 attributable deaths were recorded as reported by city or state DoH. Shown is the percent contribution of age groups to cumulated deaths (colours) from the first day on which the death by age was recorded. The start of the x-axis is the same in every figure and corresponds to the day with the first observation of death by age across all locations (states and metropolitan areas).

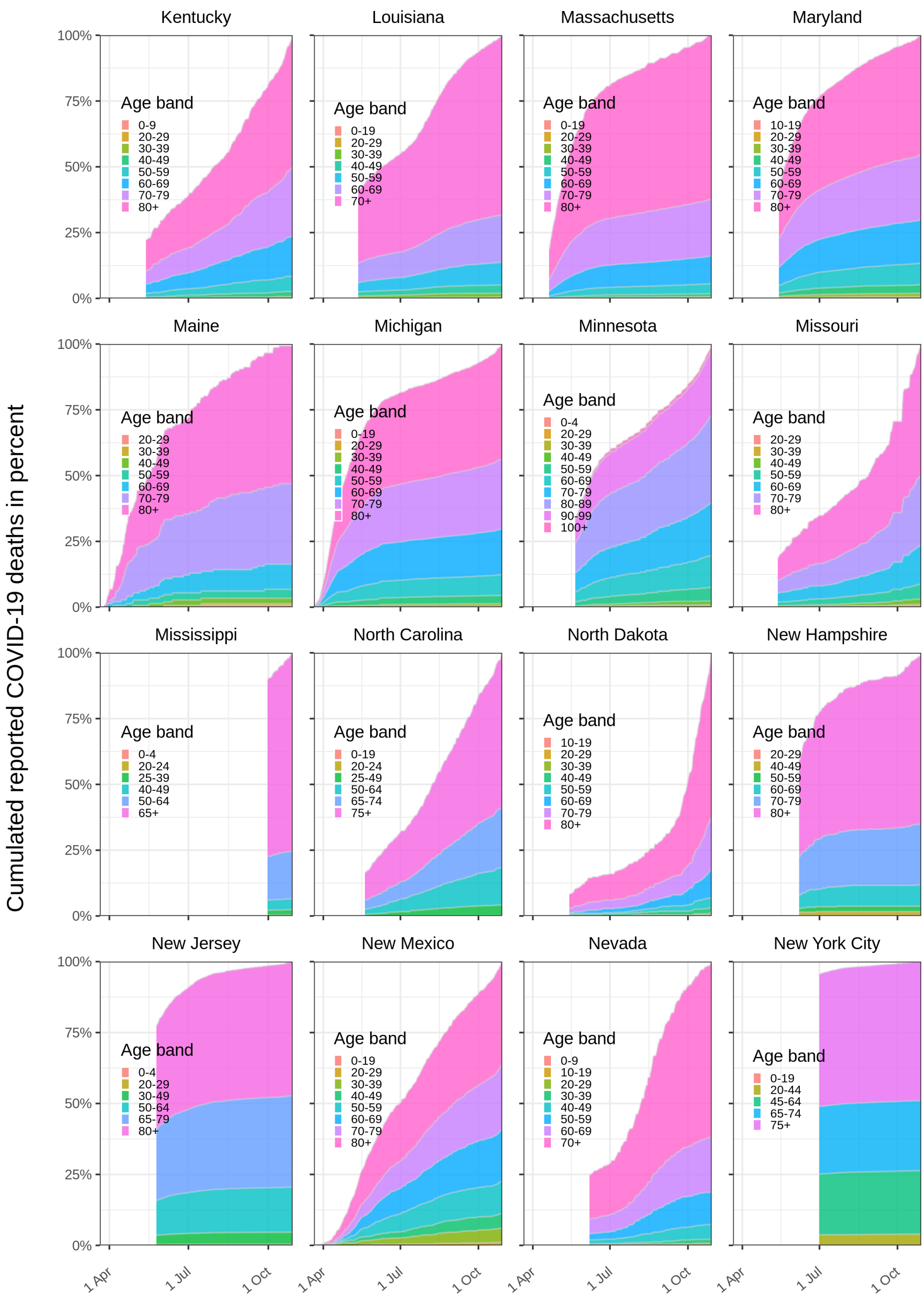


**Figure S7: Age-specific COVID-19 mortality data in the US (part 2).** COVID-19 attributable deaths were recorded as reported by city or state DoH. Shown is the percent contribution of age groups to cumulated deaths (colours) from the first day on which the death by age was recorded. The start of the x-axis is the same in every figure and corresponds to the day with the first observation of death by age across all locations (states and metropolitan areas).

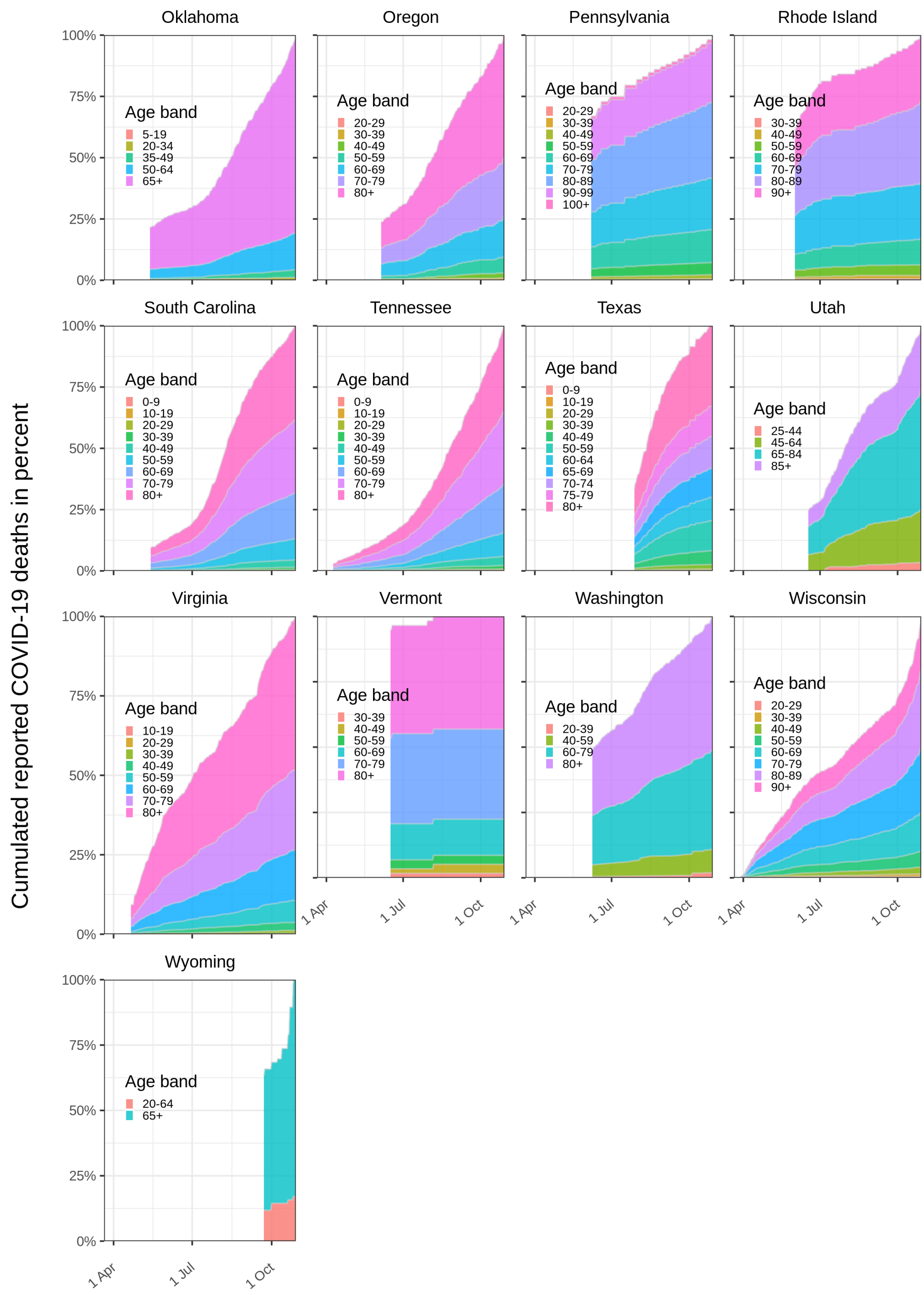


**Figure S7: Age-specific COVID-19 mortality data in the US (part 3).** COVID-19 attributable deaths were recorded as reported by city or state DoH. Shown is the percent contribution of age groups to cumulated deaths (colours) from the first day on which the death by age was recorded. The start of the x-axis is the same in every figure and corresponds to the day with the first observation of death by age across all locations (states and metropolitan areas).

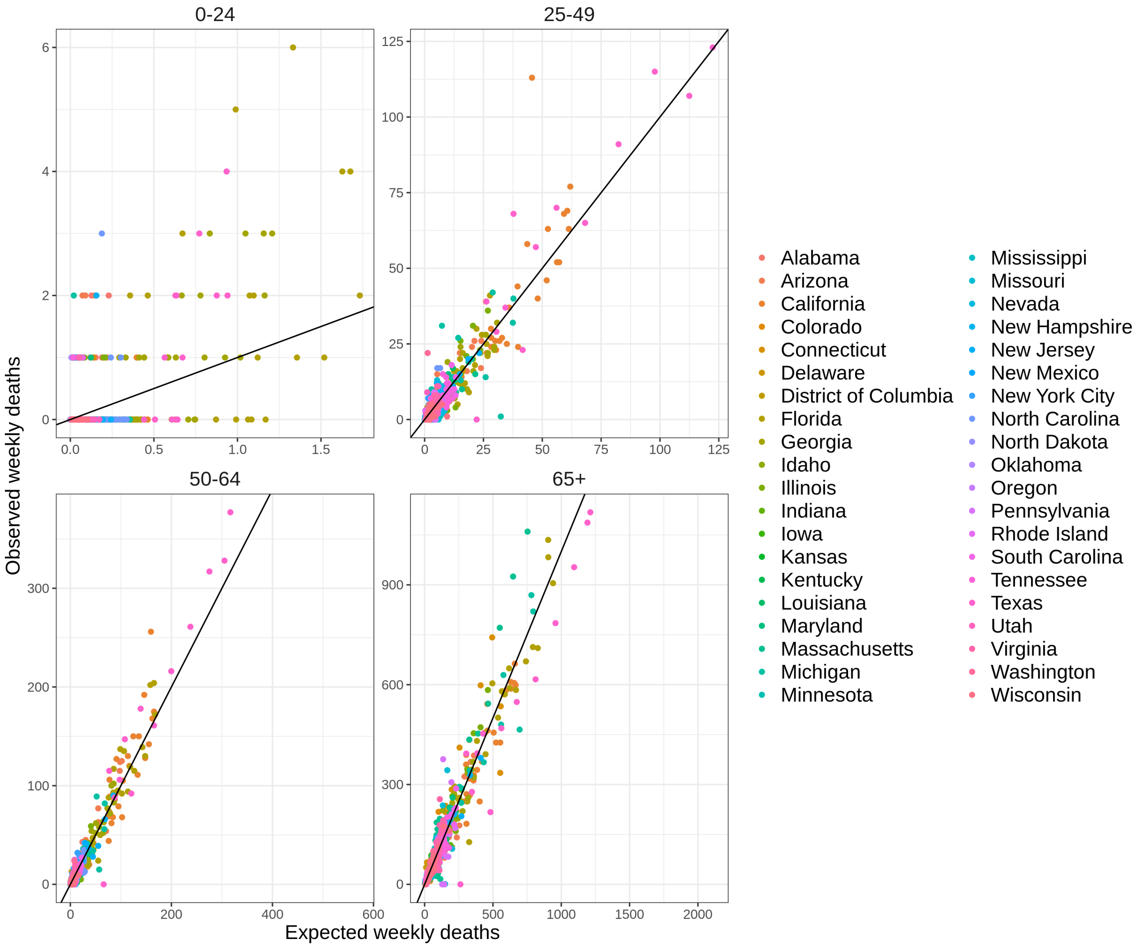


**Figure S8: Summary of model fit to age-specific COVID-19 attributable mortality data.** To investigate model fit, observed weekly deaths are plotted against posterior median estimates of the expected number of weekly deaths. Locations (states and metropolitan areas) are shown in color. For clarity, the data and weekly estimates are grouped into four age bands.

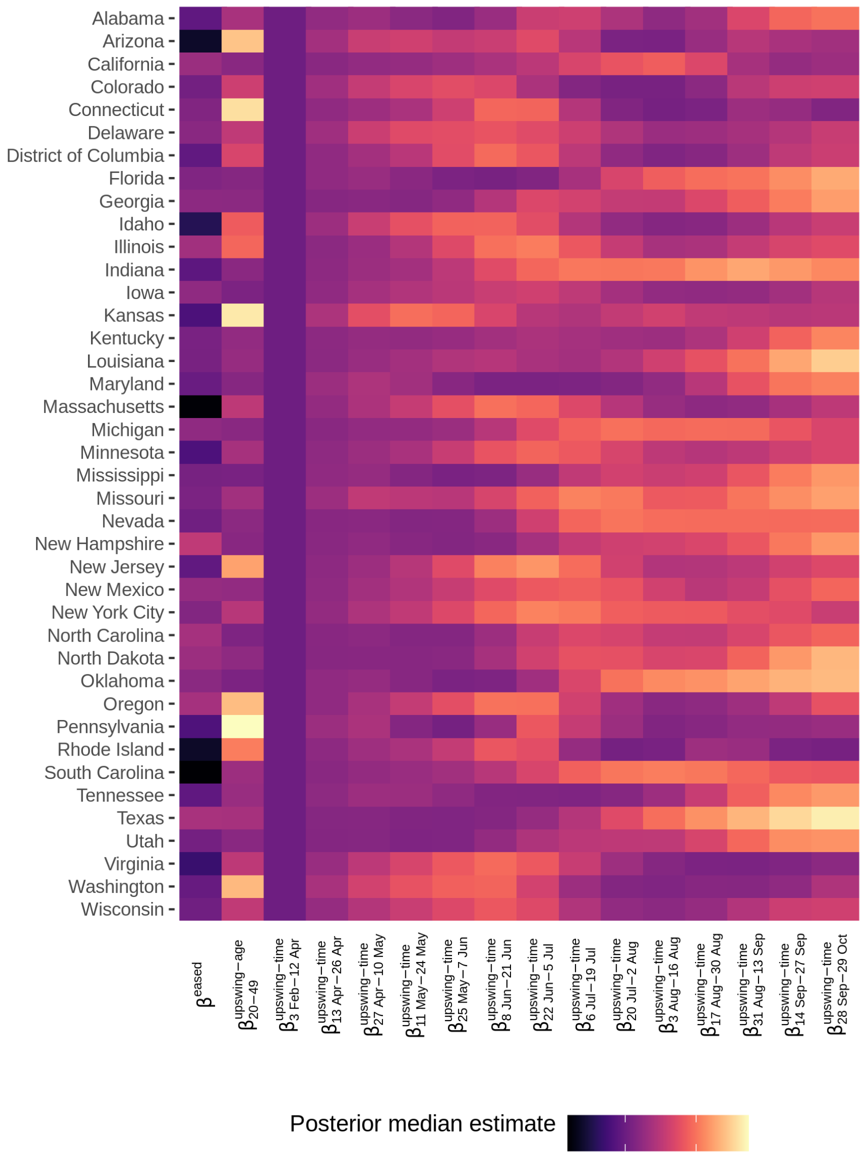


**Figure S9: Summary of space, time and age random effects in the model that capture inferred age-specific differences in transmission risk not captured in the observed mobility data.** Shown are posterior median estimates of the space, time, and age random effects of the contact-and-infection model, see further Materials and methods and Supplementary materials.

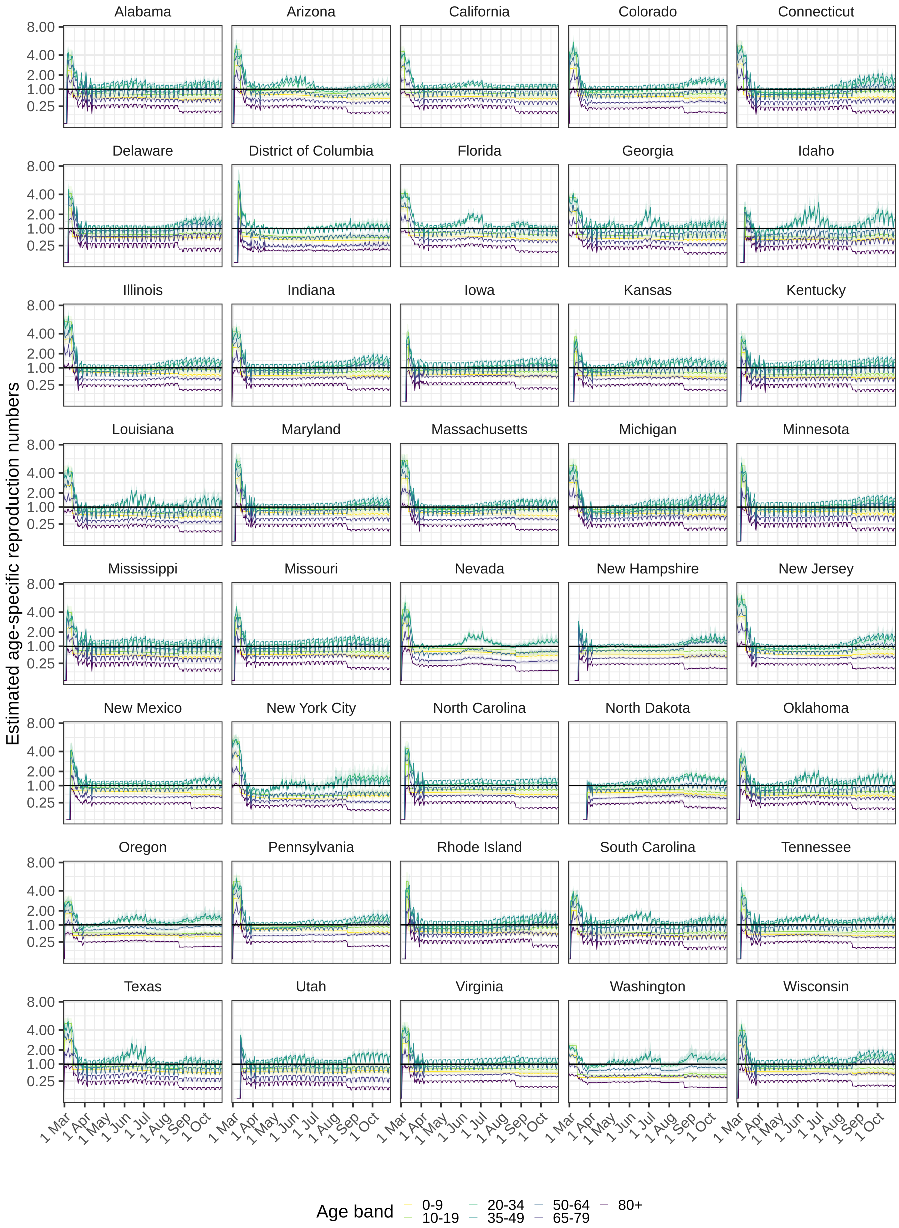


**Figure S10: Estimated age-specific reproduction numbers.** Posterior median estimates of the reproduction number for each age group with 95% credible intervals.

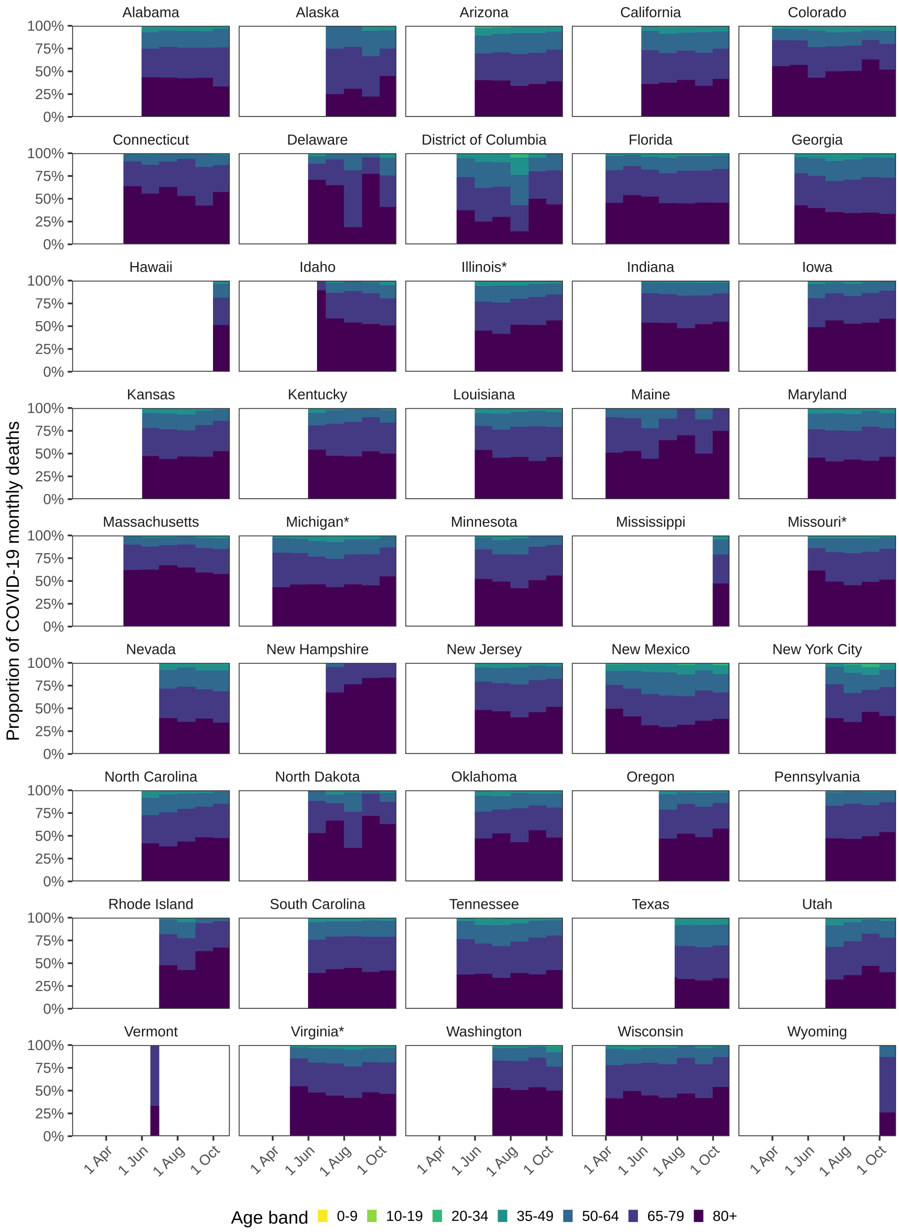


**Figure S11: Empirical analysis of the share of age groups among observed COVID-19 attributed deaths.** Age-specific COVID-19 attributable deaths were recorded from state or city DoH. DoH used their own age stratification, and the observed data were re-estimated into common age groups across states with a Dirichlet-Multinomial model; see the Supplementary materials. The figure shows the proportion of monthly deaths by age. A star (*) next to a location's name indicates that there was was a statistically significant shift in the share of individuals aged 80+ among deaths in the corresponding location. Note these are empirical estimates that do not rely on the contact and infection model.

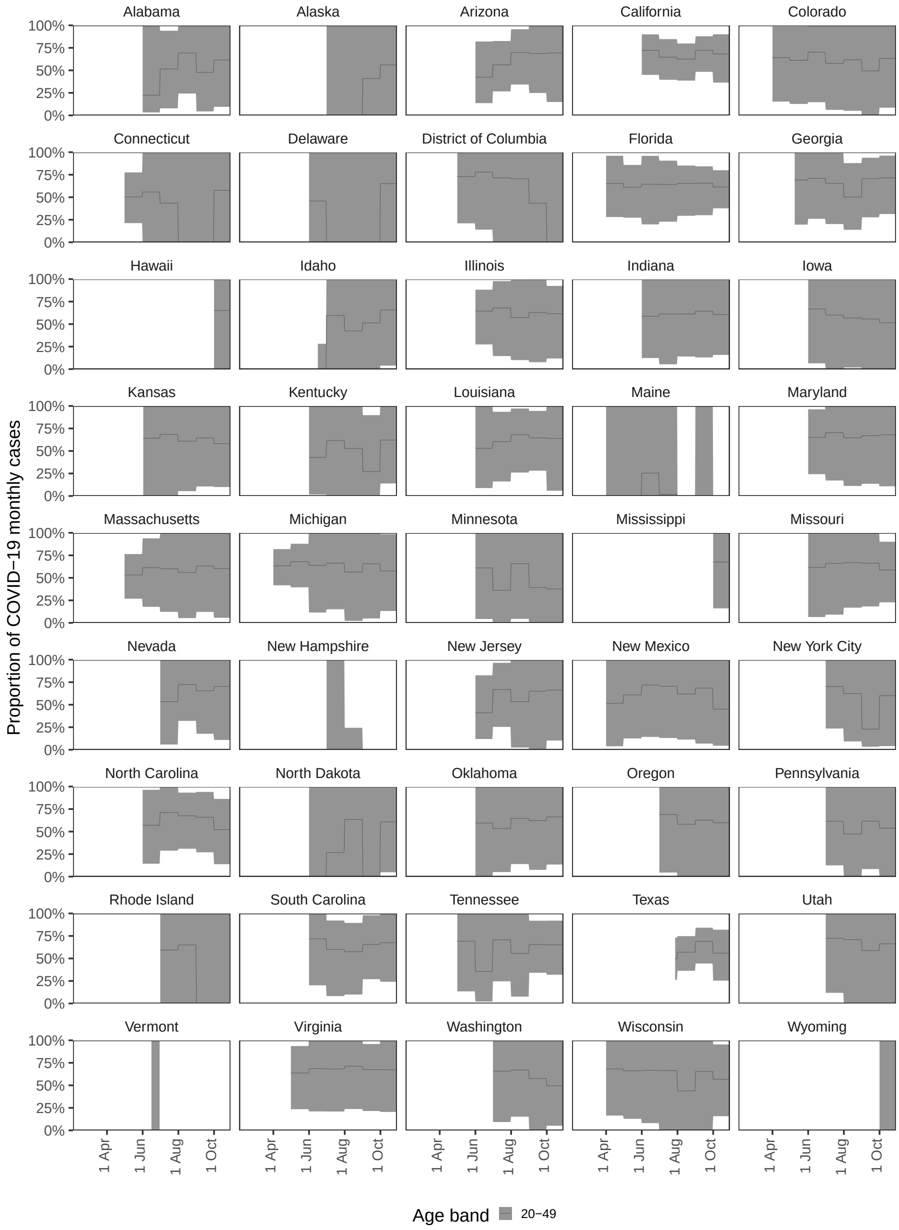


**Figure S12: Empirical analysis of the estimated share of individuals aged 20 to 49 among COVID-19 attributed cases.** Monthly cases were back-calculated from the empirical proportion of age groups among deaths based on the meta-analysis infection fatality rate estimates of [20]; see the Supplementary materials. The figure shows the estimated share of individuals aged 20 to 49 among monthly cases. A star (*) next to a location's name indicates that there was was a significant shift in the share of individuals aged 20 − 49 among deaths in the corresponding location. Note these are empirical estimates that do not rely on the contact and infection model.

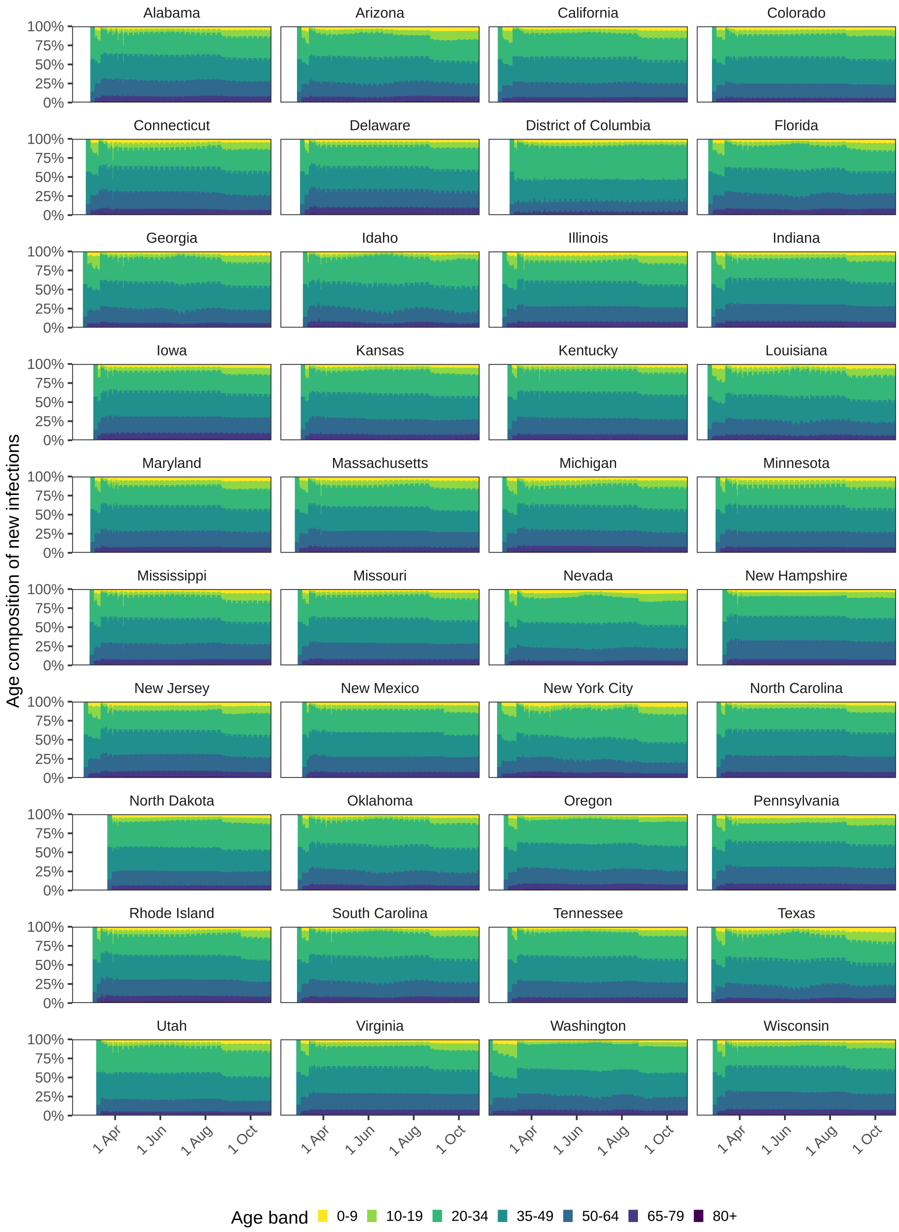


**Figure S13: Model-based, estimated percent contribution of age groups to SARS-CoV-2 infections.** Posterior median estimates are shown for each age band (colours). In the first 6 days of reconstructed transmission dynamics, cases were assumed to originate from adults aged 20-54, and trends at the beginning of March reflect a transition from the assumed age composition of initial cases. Note the estimates presented in this figure are derived from the fitted contact and infection model.

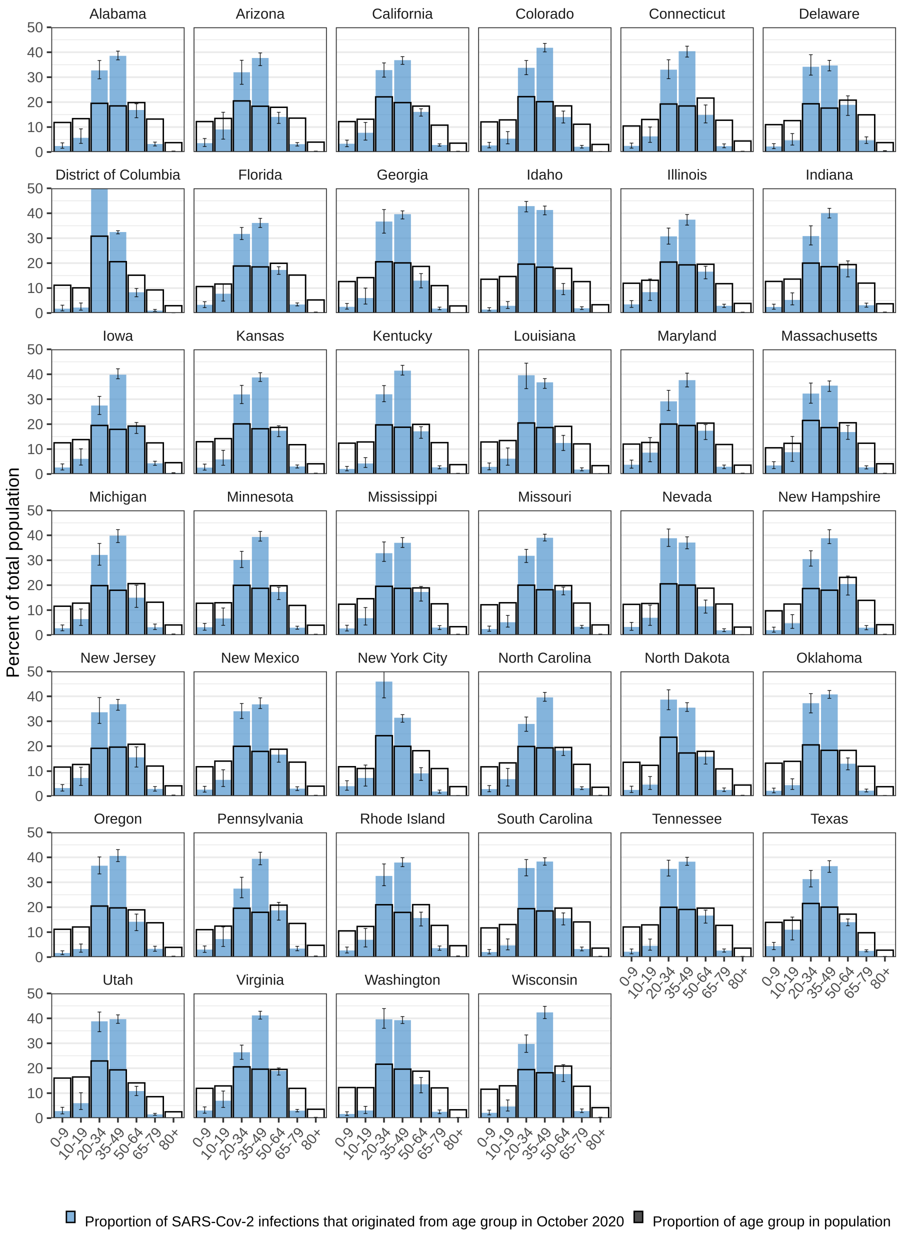


**Figure S14: Estimated cumulated contribution of age groups to SARS-CoV-2 infections for October, versus the proportion of the population in the same age group.** Posterior median estimates of the contributions from each age group (blue fill bars with 95% credible intervals) are compared against the population age composition of each state (black contour bars).

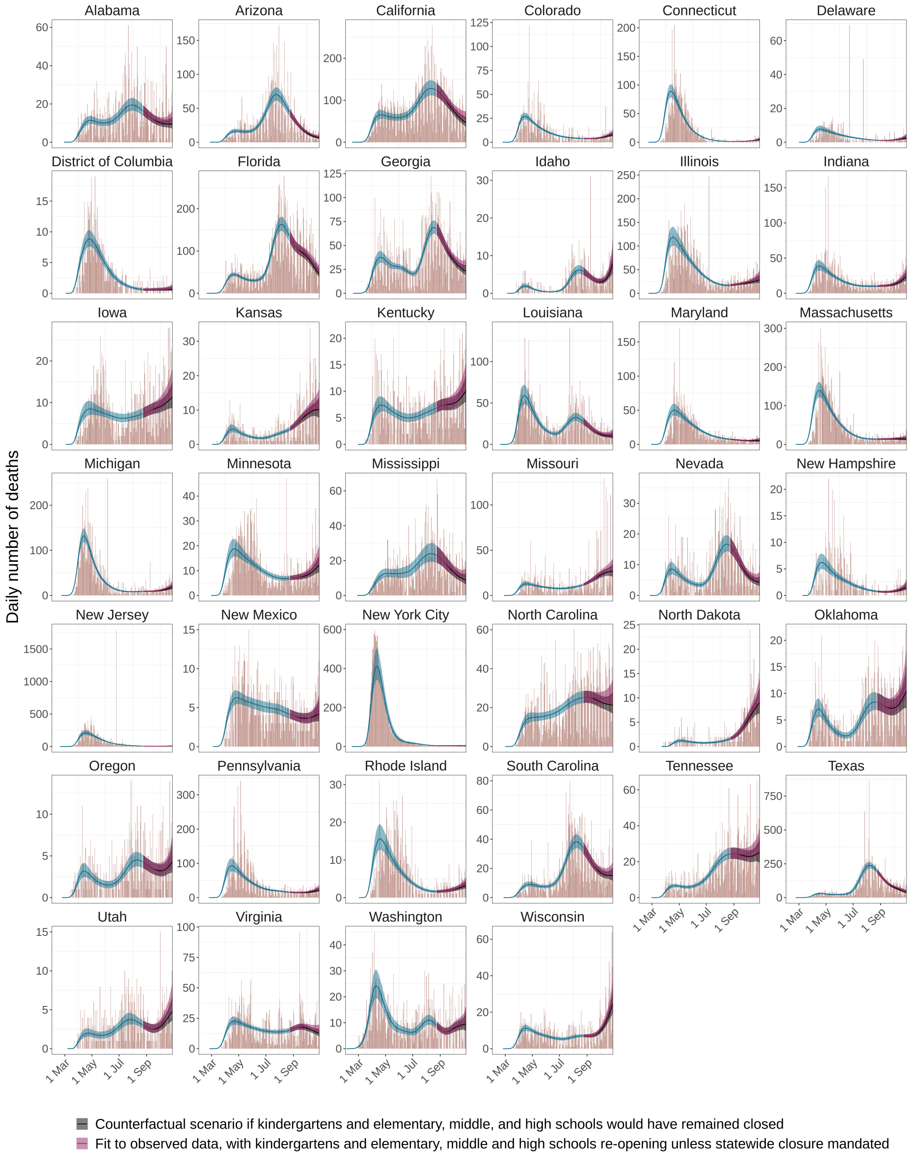


**Figure S15: Retrospective counterfactual modelling scenarios exploring the impact of school reopening on COVID-19-attributable deaths.** Shown in blue are estimated, daily COVID-19 deaths (posterior median: blue line, 95% credible interval: blue ribbon) under the model until October 29, 2020 for states in which state-wide school closures were no longer mandated since August, 2020. In counterfactual modelling scenarios, the retrospective impact of continued school closures was explored until October 29, 2020, and the predicted death trajectories are shown (posterior median: red line, 95% credible interval: red ribbon), revealing no statistically significant differences. Brown bars illustrate reported all-age COVID-19-attributable deaths [3].

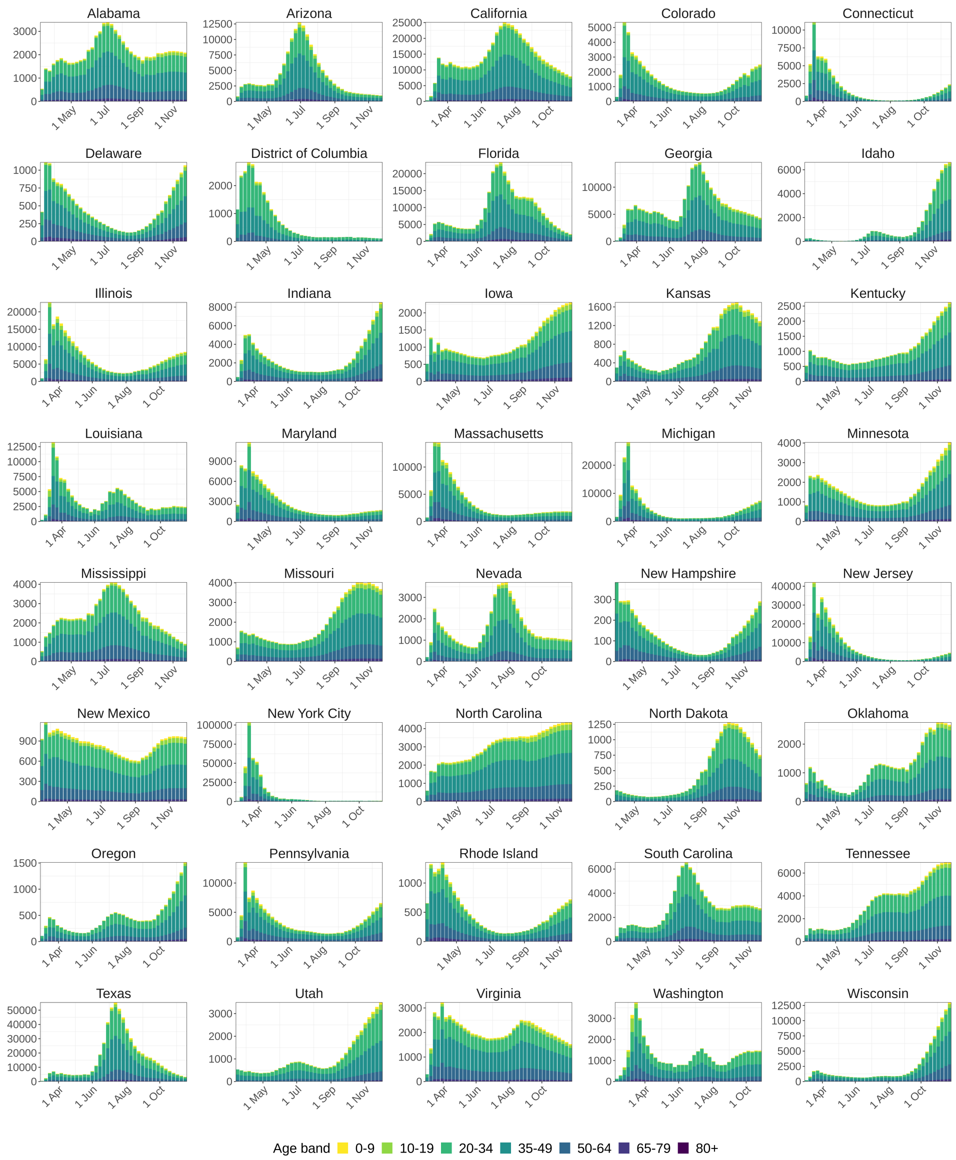


**Figure S16: Estimated age-specific daily SARS-CoV-2 infections.** Shown are the estimated, daily SARS-CoV-2 infections by age group (posterior median) .