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## Original article

# Impact of changes in protective behaviors and out-of-household activities by age on COVID-19 transmission and hospitalization in Chicago, Illinois

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## ABSTRACT

**Purpose:** Even with an efficacious vaccine, protective behaviors (social distancing, masking) are essential for preventing COVID-19 transmission and could become even more important if current or future variants evade immunity from vaccines or prior infection.

**Methods:** We created an agent-based model representing the Chicago population and conducted experiments to determine the effects of varying adult out-of-household activities (OOHA), school reopening, and protective behaviors across age groups on COVID-19 transmission and hospitalizations.

**Results:** From September–November 2020, decreasing adult protective behaviors and increasing adult OOHA both substantially impacted COVID-19 outcomes; school reopening had relatively little impact when adult protective behaviors and OOHA were maintained. As of November 1, 2020, a 50% reduction in young adult (age 18–40) protective behaviors resulted in increased latent infection prevalence per 100,000 from 15.93 (IQR 6.18, 36.23) to 40.06 (IQR 14.65, 85.21) and 19.87 (IQR 6.83, 46.83) to 47.74 (IQR 18.89, 118.77) with 15% and 45% school reopening. Increasing adult (age  $\geq 18$ ) OOHA from 65% to 80% of pre-pandemic levels resulted in increased latent infection prevalence per 100,000 from 35.18 (IQR 13.59, 75.00) to 69.84 (IQR 33.27, 145.89) and 38.17 (IQR 15.84, 91.16) to 80.02 (IQR 30.91, 186.63) with 15% and 45% school reopening. Similar patterns were observed for hospitalizations.

This study was approved by the Institutional Review Board at the University of Chicago (IRB20–1656).

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**Conclusions:** In areas without widespread vaccination coverage, interventions to maintain adherence to protective behaviors, particularly among younger adults and in out-of-household settings, remain a priority for preventing COVID-19 transmission.

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## Introduction

Despite availability of safe and efficacious vaccines for COVID-19, protective behaviors such as social distancing and masking are necessary for preventing transmission until there is widespread vaccine distribution and uptake [1]. Due to widespread vaccine hesitancy across the United States [2–5], and more recently, infectious variants, there is a need for ongoing protective behaviors and appropriately tailored public health messages. The degree and rate of resumption of prepandemic activities vary across population subgroups and geographic areas, depending on individual characteristics such as age and occupation, and regional differences in local epidemics and policies. Effective local public health policies require understanding of how subpopulation changes in protective behaviors impact overall transmission under different scenarios of out-of-household activity (OOHA) resumption and school reopening.

Age-related differences in COVID-19 transmission and mortality have been widely documented [6–8]. Data suggest greater likelihood of symptomatic infection, disease severity, and case fatality among older adults, while children and young adults more commonly experience mild or asymptomatic infections [9,10]. Susceptibility also appears to increase with age [10]. Earlier in the pandemic, COVID-19 incidence was highest among older adults, but recent national data indicate a declining median age of COVID-19 cases (from 46 in May to 38 in August 2020) [11]. From June to August, the highest incidence was observed among young adults aged 20–29; this group accounted for 20% of all cases during this period [11].

Because young adults have more social contacts, different mixing patterns, and higher rates of mild and asymptomatic infections than older adults, it is plausible that they contribute disproportionately to overall transmission, particularly since transmission often occurs from individuals with asymptomatic or presymptomatic infection [12]. Age has been associated with varying degrees of adherence to behavioral risk reduction practices, social interactions,

mobility, and potential exposure venues (e.g., day-care facilities, schools, workplaces) [6–8,10]. Such age-related differences in susceptibility and behavioral and environmental risk may impact epidemic trends. However, existing data could be biased due to selection, changes over time in testing behaviors, and differential reporting by age due to differences in severity and symptoms. Questions therefore remain about the extent to which young adults contribute to population-level transmission.

This study used agent-based modeling to explore how interacting behavioral changes, individual risks, and contextual factors influence COVID-19 transmission to provide insights for public health policies and interventions. Agent-based models enable the development of endogenous transmission vectors that are dependent on age and other sociodemographic characteristics, facilitating comparisons across a broader range of potential scenarios than compartmental models allow. Such analysis is relevant for public policymakers, given the possibilities of continued COVID-19 transmission with the increasing presence of variants and particularly in areas with low vaccination rates. We examined the impact of age-related differences in protective behaviors (e.g., social distancing, masking) on COVID-19 transmissions and hospitalizations during a period when OOHA resumption was beginning in Chicago, a large diverse Midwestern city severely impacted early on in the pandemic and where there were large disparities in transmission and mortality from COVID-19.

## Methods

### Model population and processes

We built a stochastic agent-based modeling, CityCOVID, based on our previously developed research [13–15]. CityCOVID contains 2.7 million agents representing the population of Chicago in terms of behaviors and social interactions and 1.2 million unique geolocations, including households, schools, workplaces, and hospitals. CityCOVID incorporates individualized disease progression dynamics with transitions between COVID-19 disease states that depend

**Table 1**  
Effects of school reopening and adult behavior change on COVID-19 infections and hospitalizations as of November 1, 2020

Scenario			Exposed*			Hospitalized		
	School reopening	Adult behavior change	Prevalence per 100,000(IQR)	PR (behavior change) <sup>†</sup>	PR (school reopening) <sup>‡</sup>	Prevalence per 100,000(IQR)	PR (behavior change) <sup>†</sup>	PR (school reopening) <sup>‡</sup>
S1	15%	0%	15.93 (6.18, 36.23)	1.00 (Ref)	1.00 (Ref)	2.05 (0.76, 4.76)	1.00 (Ref)	1.00 (Ref)
S2	15%	25%	26.43 (9.79, 60.47)	1.66 <sup>§</sup>	1.00 (Ref)	2.97 (0.92, 6.42)	1.45 <sup>§</sup>	1.00 (Ref)
S3	15%	50%	40.06 (14.65, 85.21)	2.51 <sup>§</sup>	1.00 (Ref)	3.67 (1.17, 8.46)	1.79 <sup>§</sup>	1.00 (Ref)
S4	30%	0%	16.14 (6.71, 38.77)	1.00 (Ref)	1.01 <sup>§</sup>	2.32 (0.81, 5.33)	1.00 (Ref)	1.13 <sup>§</sup>
S5	30%	25%	27.91 (10.32, 67.11)	1.73 <sup>  </sup>	1.06 <sup>#</sup>	3.06 (1.11, 6.92)	1.32 <sup>  </sup>	1.03 <sup>#</sup>
S6	30%	50%	44.21 (17.73, 99.24)	2.74 <sup>  </sup>	1.10 <sup>**</sup>	4 (1.32, 9.02)	1.72 <sup>  </sup>	1.09 <sup>**</sup>
S7	45%	0%	19.87 (6.83, 46.83)	1.00 (Ref)	1.25 <sup>§</sup>	2.63 (0.77, 5.77)	1.00 (Ref)	1.28 <sup>§</sup>
S8	45%	25%	30.89 (11.47, 79.4)	1.55 <sup>§</sup>	1.17 <sup>#</sup>	3.59 (1.03, 7.8)	1.37 <sup>§</sup>	1.21 <sup>#</sup>
S9	45%	50%	47.74 (18.89, 118.77)	2.40 <sup>§</sup>	1.19 <sup>**</sup>	4.67 (1.54, 10.51)	1.78 <sup>§</sup>	1.27 <sup>**</sup>

IQR = interquartile range; PR = prevalence ratio.

\* Exposed refers to the latent state in the SEIR model, in which an individual is infected but not infectious.

<sup>†</sup> Prevalence ratio for behavior change represents the PR associated with decreases in protective behaviors for a given level of school reopening.

<sup>‡</sup> Prevalence ratio for school reopening represents the PR associated with increases in school reopening for a given level of adult behavior change.

<sup>§</sup> Reference category = S1.

<sup>||</sup> Reference category = S4.

<sup>§</sup> Reference category = S7.

<sup>#</sup> Reference category = S2.

<sup>\*\*</sup> Reference category = S3.

on agent attributes and exposure to infected individuals through colocation, place-based risks, and protective behaviors such as social distancing, masking, and handwashing.

The agent population was built by extending existing synthetic population databases [16,17] to statistically match Chicago’s demographic composition. Agent activity schedules were derived from the American Time Use Survey and the Panel Study of Income Dynamics. The model was calibrated to local data obtained from the Chicago and Illinois Departments of Public Health of daily COVID-19 attributed hospitalizations and death counts. CityCOVID was developed to support City of Chicago, Cook County, and State of Illinois COVID-19 mitigation and planning and represents collaboration between the local health departments, Argonne National Laboratory, and the University of Chicago. The study was approved by the Institutional Review Board at the University of Chicago.

**Model assumptions**

The model assumes, based on calibration, that average adult OOHA levels were reduced after Chicago’s March 21, 2020 stay-at-home order to 57% (SD 8%) of pre-COVID-19 activity levels. OOHA included any activities that occurred at a place other than the agent’s household, including going to work, school, grocery shopping, etc. Separately, the reduction in transmission risk (i.e., probability of transmission) due to engagement in protective behaviors was estimated to be 90% (SD 3%). After reopening began on June 3, 2020, adult OOHA were gradually increased such that they asymptotically approached 65% of pre-pandemic levels by September 1, 2020, which is consistent with published estimates [18]. During the summer, we assumed that school-age children (age <18) engaged in peer-to-peer activities at a 50% lower rate than activities during the typical (pre-pandemic) school year. School reopening scenarios reflect situations where a given proportion of students return to in-person classes, in which they interact with children of the same age group, or alternatively, primarily online instruction with informal out-of-school mixing with peers. Thus, for a 15% school reopening scenario, during weekdays, only 15% of pre-pandemic activities involving peer-to-peer interactions among school-age children occur. This could involve interactions in classrooms, or, for students engaged in remote learning, could reflect a sce-

nario in which they maintain contact with other children at 15% of their typical pre-pandemic interactions. All scenarios assume that school-age children engage in protective behaviors inside and outside of school.

**Model experiments**

Using the baseline assumptions described above, we experimented with independently varying adult protective behaviors and OOHA under different school reopening scenarios to determine their relative and combined impact on overall and age-specific COVID-19 transmission and hospitalization. Outcomes for analysis are expressed as point prevalence of latent infection (i.e., the exposed state in the susceptible, exposed, infectious, recovered model in which individuals are infected but not yet infectious) and hospitalizations. We developed multiple scenarios in which we examined: 1) the impact of differential relaxation of adult protective behaviors (from 90% to 87.5% to 85% transmission reduction due to protective behaviors) by age category (<18, 18–40, 40–60, ≥60) over a 90 day period beginning September 18, 2020 under 15%, 30%, and 45% school reopening levels (scenarios S1–S9; Table 1), and 2) the effects of maintaining vs. increasing adult OOHA from 65% to 70%, 75%, and 80% of pre-pandemic levels after further easing of business restrictions on October 1, 2020 under 15%, 30%, and 45% school reopening levels (scenarios A1–A12; Table 2). The levels of relaxation in protective behaviors were chosen to represent medium (25%) and large (50%) changes in protective behaviors relative to the baseline level (90%), which was determined by model calibration. For example, a 25% relaxation in adult protective behaviors to a change from 90% to 87.5% transmission reduction (i.e., transmission probability = 1-transmission reduction; 90% transmission reduction translates to 10% transmission probability, which is relaxed by 25%–12.5%). Similarly, a 50% relaxation in adult protective behaviors represents an increase in transmission probability from 10% to 15%. The baseline school reopening scenario of 15% reflected what was occurring in Chicago during September–December 2020, when most schools implemented remote learning. The 30% and 45% school reopening scenarios reflect medium and large increases in-person learning compared to the baseline scenario. For the original calibration period (through June 3, 2020) we

**Table 2**  
Effects of school reopening and adult out-of-household activities on COVID-19 infections and hospitalizations as of November 1, 2020

Scenario			Exposed*			Hospitalized		
	School reopening	Adult OOHA	Prevalence per 100,000 (IQR)	PR (OOHA)†	PR (school reopening)‡	Prevalence per 100,000 (IQR)	PR (OOHA)†	PR (school reopening)‡
A1	15%	65%	35.18 (13.59, 75)	1.00 (Ref)	1.00 (Ref)	3.81 (1.31, 7.9)	1.00 (Ref)	1.00 (Ref)
A2	15%	70%	45.01 (20.44, 94.58)	1.28§	1.00 (Ref)	4.52 (1.58, 8.71)	1.19	1.00 (Ref)
A3	15%	75%	58.13 (23.6, 116.58)	1.65§	1.00 (Ref)	4.88 (1.76, 9.89)	1.28	1.00 (Ref)
A4	15%	80%	69.84 (33.27, 145.89)	1.99§	1.00 (Ref)	5.56 (2.19, 11.24)	1.46	1.00 (Ref)
A5	30%	65%	42.62 (16.26, 81.78)	1.00 (Ref)	1.21§	3.9 (1.38, 8.2)	1.00 (Ref)	1.02§
A6	30%	70%	51.83 (22.06, 102.31)	1.22	1.15#	4.54 (1.79, 9.32)	1.16	1.00#
A7	30%	75%	60.92 (24.69, 127.91)	1.43	1.05**	5.12 (2.05, 10.32)	1.31	1.05**
A8	30%	80%	80.99 (29.95, 154.82)	1.90	1.16††	6.15 (2.35, 12.09)	1.58	1.11††
A9	45%	65%	38.17 (15.84, 91.16)	1.00 (Ref)	1.08§	4.2 (1.44, 8.82)	1.00 (Ref)	1.10§
A10	45%	70%	47.39 (20.31, 111.64)	1.24§	1.05#	4.39 (1.73, 9.9)	1.05§	0.97#
A11	45%	75%	62.15 (25.2, 143.83)	1.63§	1.07**	5.5 (1.94, 11.42)	1.31§	1.13**
A12	45%	80%	80.02 (30.91, 186.63)	2.10§	1.15††	6.06 (2.31, 13.16)	1.44§	1.09††

IQR = interquartile range; OOHA = out-of-household activities; PR = prevalence ratio.  
 \* Exposed refers to the latent state in the SEIR model, in which an individual is infected but not infectious.  
 † Prevalence ratio for OOHA represents the PR associated with increases in OOHA for a given level of school reopening.  
 ‡ Prevalence ratio for school reopening represents the PR associated with increases in school reopening for a given level of adult OOHA.  
 § Reference category = A1.  
 || Reference category = A5.  
 # Reference category = A9.  
 # Reference category = A2.  
 \*\* Reference category = A3.  
 †† Reference category = A4.

selected the eight best candidate parameter combinations and ran ten replicates for each combination over each of the three baseline scenarios, resulting in 240 base case simulations. The number of parameter combinations and replicates were chosen to provide an adequate range of model behaviors consistent with empirical data and stable mean estimates while still being computationally feasible. Experimental scenarios were applied to each of the 240 simulations, and we computed the median, 50th and 95th percentile simulation intervals across all simulations. Details of baseline scenarios and model experiments are shown in the Appendix.

### Effective reproductive number ( $R_t$ )

We used the model to track secondary infections and calculated the effective reproductive number ( $R_t$ ), defined as the average number of secondary infections resulting from an infected individual [19].  $R_t = 1$  represents the threshold needed for an epidemic to be sustained.  $R_t$  less than 1 indicates that an epidemic is dying out, while  $R_t$  more than 1 indicates that the epidemic is growing. As the epidemic progresses and the size of the susceptible population declines,  $R_t$  can also decline due to the decreased likelihood of contact between an infectious individual and susceptible individuals. For each infected agent, we calculated the total number of secondary infections generated from the initial infection over their entire infectious career and averaged over the population to obtain  $R_t$ , where the time  $t$  is associated with the start of an agent's infectious career. This approach is consistent with the case or cohort reproductive number described by Gostic et al. [20] based on methods of Wallinga and Teunis [21]. This method of calculating  $R_t$  aligns with our goal of understanding how newly infectious individuals at different time points contribute to overall spread of infection over their entire infectious career and how this may vary according to individual characteristics [20].  $R_t$  was calculated by decadal age category to assess whether certain age groups contributed disproportionately to overall transmission.

## Results

In the baseline scenarios (maintaining protective behaviors and current OOHA levels among adults) the model predicted overall declines in infections and hospitalizations through the end of October 2020 (Figs. 1 and 2). However, trends varied widely depending on adult protective behaviors and OOHA, with several scenarios suggesting upward trends in infections and hospitalizations by the end of October.

### Impact of reductions in adult protective behaviors under various school reopening scenarios

From Sept 1, 2020 to November 1, 2020, latent infection prevalence (i.e., exposed state in the susceptible, exposed, infectious, recovered model) declined from 85.69 (IQR 48.23–133.9) to 15.93 (IQR 6.18, 36.23) per 100,000 and hospitalizations declined from 6.94 (IQR 4.68–9.51) to 2.05 (IQR 0.76, 4.76) per 100,000 for the scenario with 15% school reopening and no reductions in adult protective behaviors. Given high adherence to protective behaviors among 18 to 40-year-old adults, increased school reopening had relatively little impact on overall transmission or hospitalizations (Fig. 1, column 1). As of November 1, 2020, the model predicted latent infection prevalence of 15.93, 16.14, and 19.87 per 100,000 for school reopening scenarios of 15%, 30%, and 45% respectively when adult protective behaviors were maintained (Table 1: S1, S4, S7; Figure 4). The downward trend in infections and hospitalizations was reduced in a scenario with 45% school reopening coupled with large reductions in protective behaviors among 18 to 40-year-old

adults (lower right-most panel of Fig. 1, Table 1: S9). Latent infection prevalence was 47.74 (IQR 18.89, 118.77) in S9 vs. 15.93 (IQR 6.18, 36.23) in S1). For each level of school reopening, reductions in adult protective behaviors had a substantial impact on transmission (Figure 4). Latent infection prevalence ratios (PR) for 25% and 50% reductions versus no change in protective behaviors were 1.66 and 2.51 (S2 and S3 vs. S1; Table 1) for the 15% school reopening scenario and 1.55 and 2.40 for the 45% school reopening scenario (S8 and S9 vs. S7).

### Impact of increased adult OOHA under various school reopening scenarios

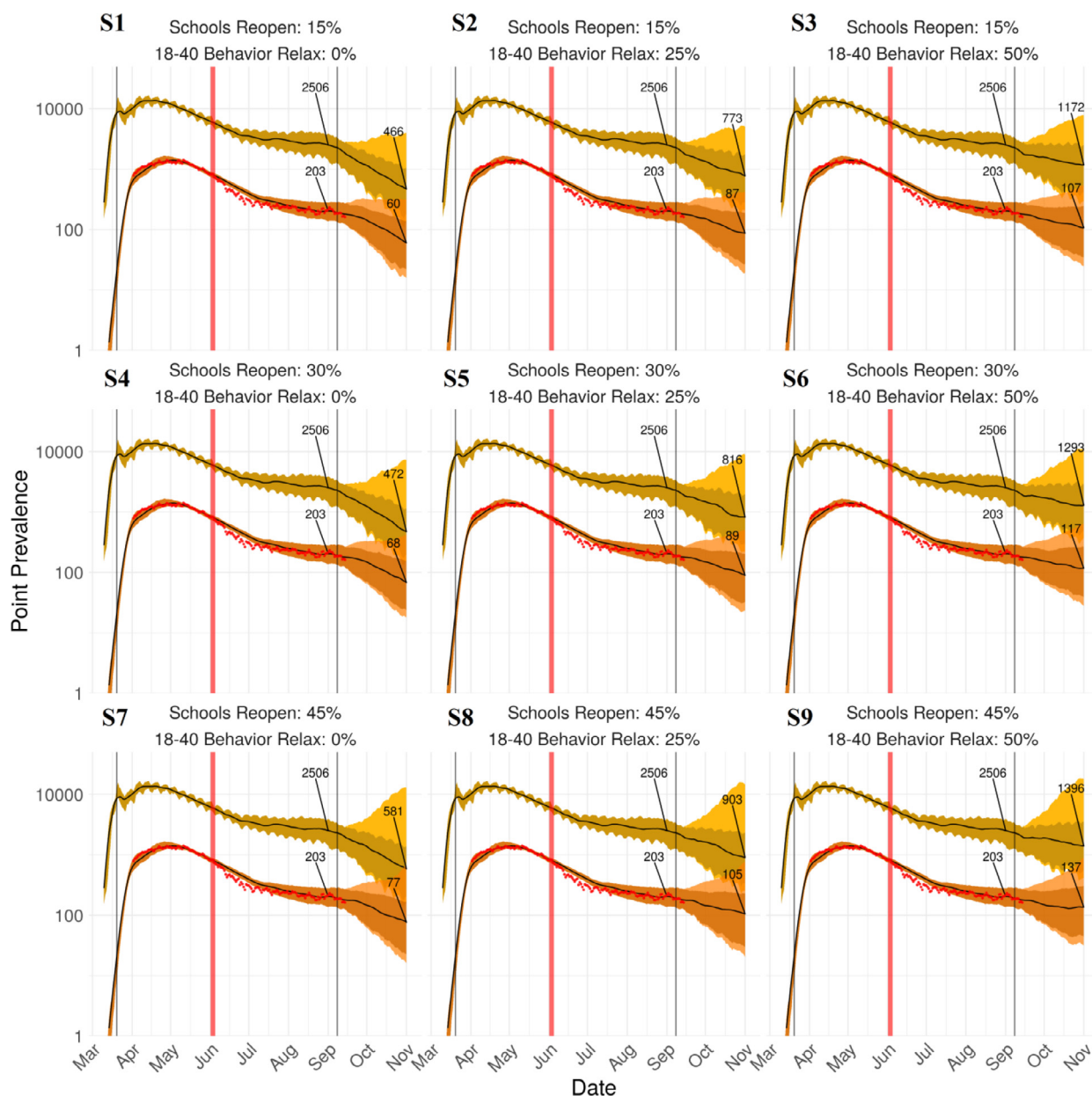
School reopening had little impact on infections or hospitalizations when current levels of adult OOHA were maintained (Fig. 2, column 1). Point prevalence of latent infection was 35.18 (IQR 13.59, 75), 42.62 (IQR 16.26, 81.78), and 38.17 (IQR 15.84, 91.16) per 100,000 for school reopening scenarios of 15%, 30%, and 45% when adult OOHA levels were maintained at 65% of pre-pandemic levels (Table 2 scenarios A1, A5, A9). Even in the presence of increased OOHA among adults beginning October 1 (vertically from top to bottom, columns 2–4 of Fig. 2; Table 2) increasing school reopening had little impact on infections and hospitalizations. In contrast, within each school reopening scenario, increasing adult OOHA had a substantial impact on infections and hospitalizations, with the largest impact of adult OOHA observed at school reopening levels of 45% (left to right, rows 1–3 of Fig. 2). Latent infection prevalence ratios for adult OOHA of 70%, 75%, and 80% vs. 65% were 1.28, 1.65, and 1.99 with 15% school reopening (scenarios A2–A4 vs. A1) and 1.24, 1.63, and 2.10 with 45% school reopening (scenarios A10–A12 vs. A9, Table 2). As OOHA approached 80% of prepandemic levels, the model suggested a reversal of downward trends where both infections and hospitalizations began to increase by November 2020.

### Age-specific contributions to COVID-19 transmission

There was a high degree of heterogeneity in the effective reproductive number ( $R_t$ ) by age, suggesting important age differences in contribution to overall transmission.  $R_t$  values for June–October 2020 suggest that children and young adults (age groups 0–10, 10–20, and 20–30) contributed the most to transmission, with lower contribution from adults 60 and older (Fig. 3). From June to August,  $R_t$  values more than 1 were observed for children and young adults (ages <30). Among adults ages 20–30, increasing  $R_t$  values were observed beginning in mid-September with values remaining above 1 for this age group through October 2020.

## Discussion

Our model results are consistent with empirical data and suggest that there was higher COVID-19 transmission among young adults (ages 20–30) compared to those aged more than 30 in Chicago over the study period. We also observed  $R_t$  more than 1 for children (ages 0–10 and 10–20) during the summer of 2020. The fact that empirical data trends were corroborated by the model suggests that the observed elevated rates among younger age groups were not due exclusively to testing bias, because the model tracks all infections, not just those that are detected through testing. Because empirical data on case counts are known to underestimate the true number of cases due to under-reporting and lower probability of detection of asymptomatic or mild infections, the model was calibrated to COVID-19 deaths and hospitalizations, which are more consistently and accurately reported. Thus, the model helps to answer an important scientific question that is not directly measured or measurable by empirical data.

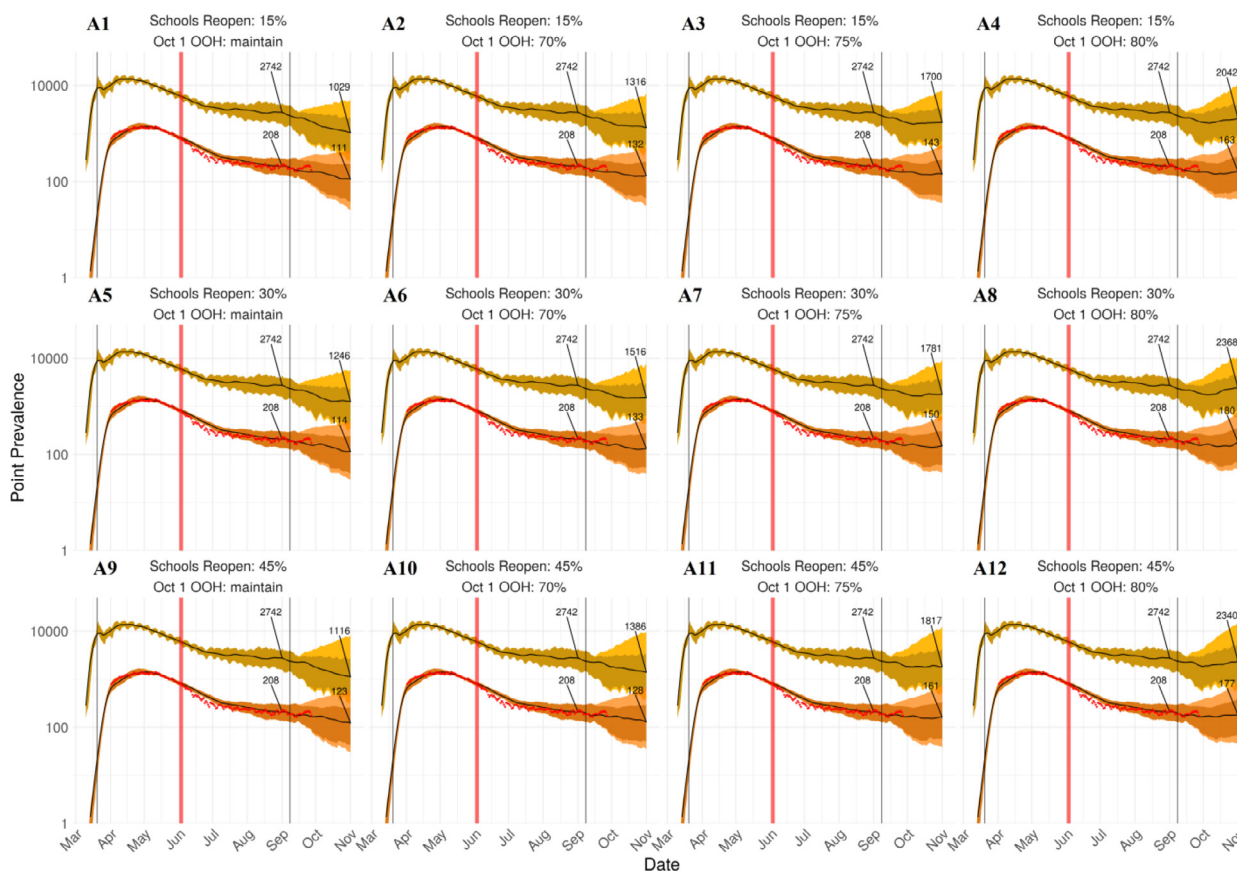


**Fig. 1.** Impact of decreases in protective behaviors on COVID-19 infections and hospitalizations under various school reopening scenarios. Horizontally from left to right, effects of reductions (0%, 25%, 50% reduction) in protective behaviors among 18–40-year-old adults for a given level of school reopening (15%, 30%, and 45% reopening), from March 2020 to November 2020. Vertically from top to bottom, effects of increasing school reopening for a given level of protective behaviors among 18–40-year-olds. Yellow plots indicate point prevalence of latent infections and red plots indicate point prevalence of hospitalizations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

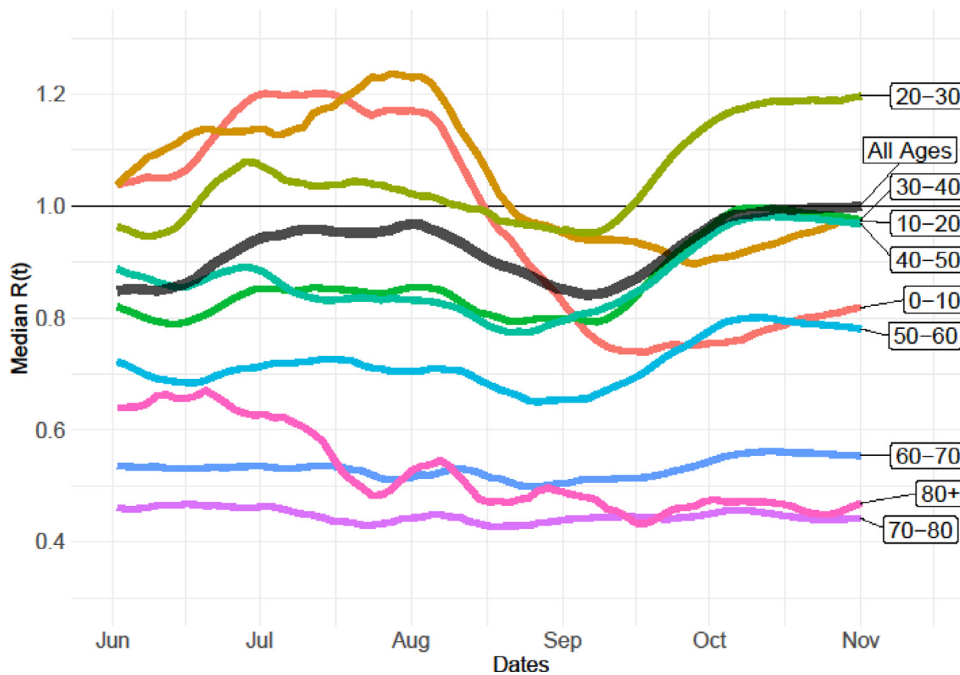
The disproportionate contribution by young adults to overall transmission reflects both behavioral patterns and economic roles, as they are likely to be more mobile, have more social interaction, and are more likely to be employed in service industry jobs [22]. Our results suggest that changes in protective behaviors such as social distancing and masking among adults aged 18–40 can markedly influence population COVID-19 transmission, with or without increases in school reopening. Furthermore, increased OSHA had an important impact on transmission, even with relatively high adherence to protective behaviors. Interventions to increase the proportion of children and adults of all ages who are fully vaccinated (including appropriate boosters) with age-appropriate messaging about the importance of ongoing protective behaviors are a key public health priority.

School reopening had little impact on epidemic trajectories in scenarios with strong adherence to protective behaviors among 18–40-year-olds, suggesting that schools could safely reopen if protective behaviors are maintained among adults, assuming protective behaviors are practiced among children while at school. School reopening had only slightly greater impact on overall transmission at lower levels of protective behaviors among adults. This suggests that there was not a synergistic effect (i.e., interaction) between school reopening and adult behavior change, at least under the existing assumptions. Nonetheless, our findings underscore the importance of maintaining protective behaviors with increases in safe school reopening and widespread return to prepandemic OSHA levels.

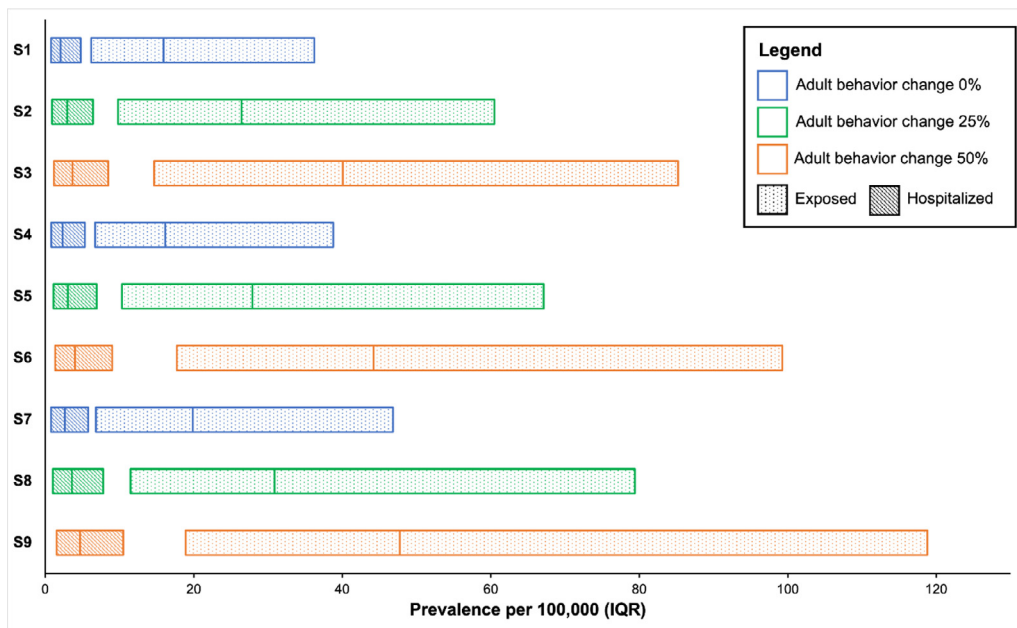
Evidence suggests that vaccination of adults aged 20–49 (i.e., those with the highest transmission) is most effective for reduc-



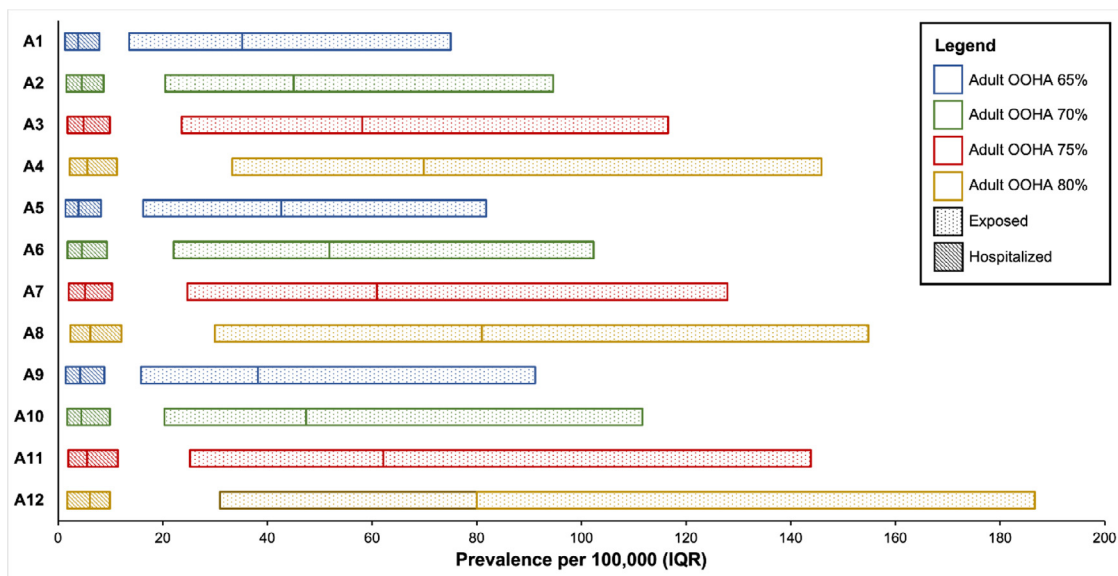
**Fig. 2.** Impact of increases in adult OOHA on COVID-19 infections and hospitalizations under various school reopening scenarios. Horizontally from left to right, effect of increasing adult OOHA (65%, 70%, 75%, and 80% of prepandemic levels) for a given level of school reopening, from March 2020 to November 2020. Vertically from top to bottom, effect of increasing school reopening for a given level of adult OOHA. Yellow plots indicate point prevalence of latent infections and red plots indicate point prevalence of hospitalizations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



**Fig. 3.** Effective reproductive number ( $R_t$ ) by age group assuming 45% school reopening beginning September 3, 2020.  $R_t$  is defined as the average number of secondary infections resulting from an infected individual in a population where not all individuals are susceptible. A value of 1 represents the threshold needed for an epidemic to be sustained; values less than 1 indicate that the epidemic is dying out and values more than 1 indicate that the epidemic is growing. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



**Fig. 4.** Effects of school reopening and adult behavior change on COVID-19 infections and hospitalizations as of November 1, 2020. Scenarios S1–S3 represent 15% school reopening, scenarios S4–S6 represent 30% school reopening, and scenarios S7–S9 represent 45% school reopening. Center vertical lines represent medians; left and right edges represent 25% and 75% quartiles respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



**Fig. 5.** Effects of adult OOHA on COVID-19 infections and hospitalizations under different school reopening scenarios as of November 1, 2020. Scenarios A1–A4 represent 15% school reopening, scenarios A5–A8 represent 30% school reopening, and scenarios A9–A12 represent 45% school reopening. Center vertical lines represent medians; left and right edges represent 25% and 75% quartiles respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

ing cumulative incidence, whereas vaccination of adults aged 60 and older (i.e., those with greatest risk for severe disease) has the greatest impact on mortality [23]. Our results are consistent with studies showing that young adults appear to contribute disproportionately to COVID-19 incidence, but it is unclear whether and how age-related differences in vaccine availability, acceptability and uptake will impact disease trends. Furthermore, there is much heterogeneity in transmission and mortality risk within age groups. Focusing on subgroups within younger and older populations with greater mobility, larger contact networks, or those living in more densely populated housing could help to minimize

population-level disease burden while optimizing use of limited vaccine resources. Future modeling studies could provide insights about how to combine such approaches to develop more nuanced vaccine targeting strategies.

It is important to note that there was divergence between the model results and empirical trends in COVID-19 in Chicago during the period from September to November 2020. There was a small peak in infections around September 1, after which cases declined slightly before a significant upward trend beginning in mid-October with a peak in mid-November, in contrast to the downward trends reflected by the median trend lines in the model.



The divergence between the model predictions and observed data trends is not surprising, and the goal of the study was not to make longer-term predictions, which would not be warranted given the rapidly changing landscape of COVID-19 and the sensitivity of models to behavioral changes in response to the epidemic. Indeed, this highlights the differing goals of forecasting and scenario studies and the inherent difficulties of long-term forecasts in epidemiological modeling. Rather, we sought to understand the potential impact of different scenarios involving varying levels of behavior and activity changes among children and adults, and to present an approach for use of such analyses in other settings to generate information that could be useful in planning for future pandemics. For example, scenario analyses can help to identify levers or thresholds for intervention targets, as well as identifying variables that have little impact on model behavior. They can thus be useful for efficiently utilizing limited public health resources. (<https://covid19scenariomodelinghub.org>)

### Limitations

Our results reflect Chicago's local epidemic, and may not generalize to other places, though similar modeling approaches could be applied elsewhere to understand how protective behaviors in various population subgroups impact transmission dynamics. The results should be interpreted in light of the model assumptions that if altered could produce different results. For example, we assumed that protective behaviors were maintained among children while at school. This assumption appears plausible given that children's behavior in school is closely monitored and peer-to-peer interactions are relatively constrained, making it easier to enforce protective measures. However, altering this assumption might influence the relative impacts of school reopening and adult behavior change. The model does not distinguish between behaviors of teenagers and younger children, though adherence to social distancing and masking likely varies between younger and older children both inside and outside of school. Because younger children have less autonomy they are potentially also less at risk for exposure through peer-to-peer interactions that occur outside of classroom settings as compared to older children. Results may also be sensitive to seasonal changes or localized events that could increase new infections, such as large sporting events, increasing time spent indoors in winter, holiday travel or gatherings, or natural disasters (tornadoes, hurricanes, wildfires). Further research is needed to understand how such events could impact transmission overall and within subgroups over time. Our model did not incorporate differences in protective behaviors by other factors, such as occupation, household composition, or socioeconomic status, that likely impact individuals' ability to effectively reduce risk. Such factors may explain the disproportionate burden of COVID-19 in Black and Hispanic communities that have been widely documented since the beginning of the epidemic [24,25]. Understanding how environmental and structural factors increase risk among certain subgroups is important for efficiently utilizing intervention resources and deploying strategies for increasing testing and vaccination. Additional modeling is underway to explore how relationships between race/ethnicity, occupational risk, prevention behaviors, and vaccine uptake impact COVID-19 transmission. Our model incorporates a high degree of complexity and granularity which were not fully utilized in the current analysis but will allow us to take advantage of increasingly detailed data on mobility, health outcomes, and behaviors to model the population level impact of individual behaviors and their interactions. This is an ongoing area of work, and we also plan to more fully exploit the granularity of the model in future work, including analyses of mobility patterns and occupational vs. household transmission.

### Conclusion

Our results add new information on the impact of increasing school reopening and changes in adult protective behaviors and OOHA on COVID-19 transmission in Chicago. Our findings demonstrate how increased OOHA among younger adults can substantially impact epidemic trends, particularly if combined with decreases in protective behaviors and more widespread school reopening. Until complete vaccination is widespread, focused interventions to promote adherence to protective behaviors in out-of-household settings among younger adults are a public health priority.

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