Operating Schools in a Pandemic: Predicted Effects of Opening, Quarantining, and Closing Strategies

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About the authors

Brian Gill (Ph.D., Jurisprudence and Social Policy, and J.D., University of California at Berkeley), a senior fellow at Mathematica, directs REL Mid-Atlantic and leads its research alliance on accountability in the ESSA era. He has two decades of experience in a wide range of education research and policy issues, including charter schools, educator effectiveness, and the implementation and impacts of high-stakes testing and other accountability regimes. Much of his work has involved close collaboration with state and local education leaders, both through the REL and outside it. This work has involved assisting educators and officials with high-priority projects, including the refinement of accountability systems and the development of improved measures of educator performance. Dr. Gill has coordinated the REL's response to the COVID-19 pandemic, providing educators and policymakers in the mid-Atlantic region and beyond with timely information on remote learning, supports for families, implications for accountability systems, and tools to assess what is working to keep students engaged and learning while school buildings are closed.

Ravi Goyal (Ph.D., Biostatistics, Harvard University), a senior statistician at Mathematica, has 18 years of experience in applying data science techniques to deliver actionable insights to address public and social needs by investigating the diffusion of information and the spread of infectious disease. Dr. Goyal has developed an agent-based, stochastic dynamic network-based COVID-19 model for modeling disease spread. The model is being used the University of California, San Diego, to investigate policy to mitigate the spread of COVID-19 by limiting maximum class sizes and adjusting living situations. In addition, the model is used to aid in the design of vaccine trials. Previously, he served as the technical lead in the design and development of an agent-based mathematical model to measure the cost effectiveness of the Ryan White HIV/AIDS Program's system of care. As a doctoral student and research associate at the Harvard School of Public Health, he played an integral part in the design of the HIV agent-based model used to assess the feasibility of the Botswana Combination Prevention Program with regards to impact and statistical power. Dr. Goyal had several collaborations with Harvard University to develop novel statistical methods relevant to infectious disease. Previously, he has been a statistical consultant for the Clinton Foundation, Harvard Humanitarian Initiative, and Community Partners International, as well as an applied mathematician at the National Security Agency, where he gained field experience (deployed to Iraq) and experience with real-world complex data sets that included geospatial, longitudinal, and social network data.

John Hotchkiss (M.S., Data Analytics, Georgetown University), a data scientist at Mathematica, has five years of experience in building data science solutions to address public policy questions and needs. Mr. Hotchkiss is a SQL, R, Python, and Cloud expert specializing in data processing, machine learning methods, and translating results into actionable insights through visualization. Over the past three years, Mr. Hotchkiss has supported Dr. Goyal's work developing agent-based, stochastic, dynamic, network infectious disease models. Those models include a model being used the University of California, San Diego, to investigate policy to mitigate the spread of COVID-19 by limiting maximum class sizes and adjusting living situations, a model to help the World Health Organization design COVID-19 vaccine trials, and a model to measure the cost effectiveness of the Ryan White HIV/AIDS Program's system of care.

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Executive Summary

Schools across Pennsylvania and around the country are beginning the 2020–2021 school year while COVID-19 remains a threat in widely varying degrees, in different communities, and at different times. Every school that is opening its building to students—part-time or full-time, starting now or later in the school year—needs to contemplate the possibility that a student or staff member will become infected with COVID-19. Our previous work (Gill et al., 2020) suggests that hybrid operating approaches, with part-time attendance in the school building, can substantially slow the spread of infections, but schools still need to have a plan for what to do when someone is infected.

The Pennsylvania Department of Education (PDE) asked Mathematica to extend our previous work by simulating COVID-19 spread in schools under a range of different scenarios that vary based on community infection rate, grade level, operating strategy, local COVID-19 testing capacity, and the school's response to a confirmed infection—which is likely to include quarantining of close contacts of the infected person and may also include temporary closure of the school building.

This report provides the findings from those simulations. The simulations employed an agent-based computational model like the one used in our previous work, refined based on emerging evidence and extended to incorporate effects of quarantines and temporary school shutdowns in response to COVID-19 cases in the school community. We conducted approximately 400,000 simulations, predicting the spread of infections for hundreds of combinations of local circumstances and school operating and quarantine strategies.

Because we examined such a wide range of circumstances, the results of the simulations should be relevant well beyond Pennsylvania. Educators and policymakers elsewhere across the country can use these results to inform their own decisions about operating schools and setting policies for quarantining and/or closure in response to detecting COVID-19 cases among students or staff.

As with all simulations, the results depend on the validity of the assumptions informing the models, which are derived from emerging, uncertain science about the virus and from expectations about the behavior of students and school staff that involve a different kind of uncertainty. We model transmission of the virus in the school and on school buses—the places that are under the control of schools—but a rapid increase in infection rates outside the school can increase infections in the school (as is evident from our findings on schools in communities with higher infection rates). Educators and policymakers therefore should keep in mind the uncertainty of all predictions related to the pandemic.

The main body of this report presents results that describe general patterns related to school level, community infection rate, operating strategy, local COVID-19 testing capacity, and school policies for responding to detected infections. Appendix A provides detail on the agent-based model methods and assumptions underlying it. Appendix B provides customized results for sample schools with various particular characteristics using specific operating strategies and infection response policies. Specifically, Appendix B includes comparative results for 108 different school situations, so that any school can find a result relevant to its own circumstances. For each of these different circumstances, the appendix includes graphs showing the relative number of infections the school is likely to experience, the percentage of school days the typical student is likely to be able to attend in person, and the total number of likely infections in the school at the time the first infection is detected. Importantly, these graphs show not only the average results but also the range of random variation across schools in similar circumstances, which is important because no school can count on landing at the average.

Key findings from the main body of the report include the following:

- Cumulative infection rates in elementary schools are likely to be consistently lower than in secondary schools employing the same operating strategies, even if they are similar in size, because younger children are less likely to be infected.
- Precautions such as requiring masks can measurably reduce infection spread in schools.
- Hybrid operating approaches in which groups of students attend school in person part-time dramatically reduce the total number of likely infections in the school. Simulation results suggest that under a hybrid approach with precautions (including wearing masks, eliminating additional mixing of students outside of class, and putting six feet of distance between desks), most infections coming from outside the school will produce zero additional infections in the school.
- If all students are coming to school daily, temporarily closing the building every time an infection is detected modestly reduces the total number of infections. But temporary closures are far less effective in reducing infection spread than using a hybrid operating strategy from the start, and closures disrupt school schedules unpredictably.
- If the school is operating in part-time hybrid mode, quarantining the close contacts of individuals with detected infections is likely to keep the school's infection rate low; temporary closures reduce the number of days that students can attend with no demonstrable benefit in further reducing infections.
- Under part-time hybrid operating strategies, students come to school far fewer days by design, but because hybrid operation keeps infection rates low, the typical student in a secondary school using a hybrid approach (in a community with a low or moderate infection rate) is likely to experience little or no unplanned disruption in the days they can come to school. Students in school buildings operating full-time, in contrast, are more likely to be sent home for quarantine.
- At very low community infection rates (10 reported infections per 100,000 population over the last seven days), most students can expect to attend nearly every day even in schools operating full-time, as long as the schools implement precautions such as mask wearing.
- Delays in COVID-19 testing results are likely to increase infections in schools operating full-time without precautions. But faster turnaround of COVID-19 test results has no measurable impact on infection spread in schools operating on a part-time hybrid model, in which infections are likely to remain low regardless of the speed of receiving test results.
- Transmission of the virus has a large random element, which means that regardless of precautions taken, there is a chance that a school could have an infection on its first day of operation, underscoring the need for careful adherence to mitigation strategies to minimize the risk of spread in the school.
- Because many of those infected are asymptomatic or presymptomatic, all schools should expect that a single detected case may represent one or more additional undetected cases. In secondary schools operating with full-time attendance or in communities with high infection rates, there may be five or more infections in the school when the first case is detected.

I. Introduction

Schools across Pennsylvania and around the country are beginning the 2020–2021 school year while COVID-19 remains a threat—to widely varying degrees in different communities and at different times. Plans for how schools begin the school year also vary enormously, reflecting not only differences in the prevalence of the disease, but also differences in communities' views of the difficult tradeoffs between the public health risks of bringing students to school and the educational and other harms of leaving them at home (Center on Reinventing Public Education, 2020). Many schools are beginning the year with exclusively remote instruction, while some are bringing all their students into buildings on a regular schedule, and others are working out hybrid approaches that seek to balance costs and benefits by dividing students into smaller groups, each of which comes to school part-time and learns from home part-time (Center on Reinventing Public Education, 2020).

Any school that is opening its building to students—part-time or full-time, starting now or later in the school year—needs to contemplate the possibility that a student or staff member will become infected with COVID-19. As long as the disease exists in the community, no precautions in a school can eliminate the possibility that a student or staff member will be infected inside or outside of school. Our previous work (Gill et al., 2020) suggests that hybrid approaches with part-time attendance in the school building can substantially slow the spread of infections, but schools still need to have a plan for what to do when someone is infected.

PDE asked Mathematica to extend our previous work (conducted through the U.S. Department of Education's Regional Educational Laboratory [REL] Mid-Atlantic) by simulating COVID-19 spread in schools under a range of different scenarios that vary based on community infection rate, grade level, operating plan (full-time in-person attendance versus hybrid variants), local COVID-19 testing capacity, and the school's response to a confirmed infection.

This report provides the findings from those simulations. The simulations employed a similar agent-based computational model used in our previous work, refined based on emerging evidence and extended to incorporate effects of quarantines and temporary school shutdowns in response to COVID-19 cases in the school community. We describe these methods in the next section.

This report aims to allow schools in a variety of different circumstances to anticipate the implications of three different ways of responding to confirmed COVID-19 cases, which the Pennsylvania Department of Health (following published guidance from the federal Centers for Disease Control and Prevention [CDC]) indicated that schools might consider:

1. A two-week quarantine of the infected person and close contacts
2. A three-day shutdown of the school building for cleaning and disinfection, in addition to a two-week quarantine of the infected person and close contacts
3. A two-week shutdown of the school building

The effects of these strategies might differ for schools with different grade levels, schools operating under hybrid approaches versus full five-day attendance, schools in communities with different underlying infection rates, and schools in communities with different COVID-19 testing capacity (where COVID-19 test results might be delivered in two days or might be delayed a week or more). Our simulations explore the implications of all these variables, with the aim of allowing each school to identify a specific set of circumstances similar to its own. In total, we ran simulations for nearly a thousand different combinations of variables. Thus, a key part of this report is Appendix B, which provides simulation results for schools in many different circumstances. Educators can identify the specific set of circumstances that best fits their own school to assess the likely implications.

Because we examined such a wide range of circumstances, the results of the simulations should be relevant well beyond Pennsylvania. Educators and policymakers elsewhere across the country can use the results in the main body of the report and in Appendix B to inform their own decisions about operating schools and setting policies for quarantining and/or closure in response to detecting COVID-19 cases among students or staff.

For each set of circumstances, we report three outputs:

1. **Relative total number of infections among students and staff.** The agent-based model simulates infections among the school population from day to day over weeks and months, making it possible to compare the estimated cumulative infections among students and staff. This can help schools assess how much different operating strategies may reduce infection spread in the school, depending on the local community infection rate and other key variables.
2. **Percentage of days in the school building for a typical student**. Over the course of the school year, the percentage of days that students are actually in school may vary substantially from the plan, depending on how well the virus is contained, which in turn may depend on the operating strategy, the quarantine/closure strategy, the speed of receiving test results, and the community infection rate. We estimate the percentage of school days a typical student is likely to be in the school building over the course of the school year, which can help a school predict how much disruption the typical student is likely to experience.
3. **Estimated number of actual infections in the school based on recent detected infections**. Many COVID-19 infections go undetected because the infected person does not develop symptoms or does not get a test. When the school detects infections, there may be other undetected infections as well. Community infection rates, operating strategies, and the number of recently detected infections can provide information on the range of likely undetected infections in the school. We estimate how many infections may be in the school based when the first infection is detected. This information can help a school leader assess how widespread infections might be when the first one is detected.

In the main body of the report, we

present a selection of results for these three outputs, alongside additional outputs, to illustrate differences related to key variables, including grade level, operating strategy, quarantine/closure strategy, timing of test results, and community infection rate.

It is important to keep in mind that results are based on modeling the spread of infections in the schools themselves and on school buses. The models implicitly assume that the operating strategy chosen by the school does not substantially affect a student's likelihood of being infected outside the school. It is possible, however, that a school's operating strategy could affect other family decisions in ways that could increase students' chances of being infected elsewhere. For example, parents might respond to hybrid or remote schooling by putting their children in group child care centers on other days, or full-time operation of schools might cause parents to increase their own interactions in the broader community. Such actions could increase the chance that students will be infected outside of school. We do not have a way to model these second-order responses to school policy. Our results include infections that occur outside of school (based on community incidence rates), but they assume that the school's actions do not increase or decrease the number of infections experienced by students and staff outside of school.

Chapter 2 describes the methods used in the simulations, and Chapter 3 provides general results.

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II. Methods, operating scenarios, assumptions, and outcomes

A. Agent-based model

Mathematical models are currently providing predictions in various contexts to support evidence-based policymaking, including for primary and secondary schools (Aleta et al., 2020; Keeling et al., 2020). For this project, the simulations conducted to predict virus spread in schools used a similar agent-based model (ABM) employed in the previous REL Mid-Atlantic project (Gill et al., 2020), and much of the text in this methods section is borrowed from that work.

ABMs are computational models for simulating interactions of individuals ("agents") to assess their collective effects on a system. For purposes of this study, agents are defined as students, teachers, and other school staff such as bus drivers, learning and working in settings managed by the school. We simulate the interactions of individuals, incorporating available data on infection spread and mitigation strategies (such as increasing physical distance or wearing masks), to predict the likely spread of disease in a school. Compared to other models, ABMs more closely and reliably model reality for the spread of infectious diseases when it comes to person-to-person interactions (Koopman, 2002). Unlike traditional epidemic models that work from the top down with population-level data, ABMs work from the ground up by building on the specific nature of the interactions among different groups of people.

As with all estimates, an ABM's accuracy depends on the validity of the assumptions built into it. This analysis is based upon the best available information at the time it was developed, but much of that information remains uncertain. To address the uncertainty, our previous work included sensitivity tests to understand how violations of those assumptions affected model results (Gill et al., 2020).

Mathematica researchers previously developed an ABM that models the spread of HIV, including for the federal Department of Health and Human Services (Goyal et al., under review; Wang et al., 2014). The model used in this report was redesigned and reparameterized to represent the characteristics of the COVID-19 epidemic. More details on the model are provided in Appendix A.

B. Operating strategies (scenarios) for reopening schools

We used the ABM to investigate differences in COVID-19 infection rates that might be expected across seven operating scenarios (one baseline and six alternative scenarios). The seven operating scenarios were selected based on consultation with PDE staff, interviews with stakeholders across the state, and a review of school reopening plans that have been publicly proposed by various individuals and organizations. These are not, of course, all the possible ways that schools might operate during the pandemic, nor are they formally defined as options by the state, but they capture a wide range of different approaches.

- **Operating Scenario A (baseline).** This scenario predicts the growth of COVID-19 infections in the unlikely circumstance that a school tried to operate as if the pandemic had not occurred. It provides a worst-case baseline scenario against which improvements resulting from mitigation strategies can be gauged. In this scenario and all others, we assumed that 20 percent of students will stay home from school voluntarily; this assumption is based on findings from surveys suggesting that many parents remain very concerned about infection risk and are considering keeping their children home (Murrieta

Valley Unified School District 2020; Page, 2020).[1] We apply the same quarantining and closure approaches to Scenario A as to the other scenarios.

Scenarios B–D assume all students (other than the 20 percent who are staying home voluntarily) are in school every day, with different combinations of strategies designed to reduce COVID-19 infections while students are in school.

- **Operating Scenario B (daily attendance with precautions).** Students and staff wear masks on the bus and throughout the school day.[2] Students interact with other students only in their class(es); elementary students remain with the same class all day (nondepartmentalized instruction), while middle and high school students take six classes during the day. Lunch is eaten in classrooms rather than cafeterias that could involve more mixing of students. If recess occurs, it involves only the students who are in class together, preventing mixing with other classes. This scenario represents a relatively modest change to regular school routines.
- **Operating Scenario C (daily attendance with precautions and block scheduling).** Same as Scenario B, with an additional shift to block scheduling for middle and high schools, meaning each class meets only every other day for double the amount of time. This would have the effect of reducing the number of other students that each student contacts by half each day. (For nondepartmentalized elementary schools, Scenario C is not relevant.)
- **Operating Scenario D (daily attendance with precautions and students "podded" in one classroom).** Same as Scenario B, except there is no mixing of students across classes during the day. This has the effect of making middle and high schools operate more like nondepartmentalized elementary schools, as the same group of students is kept together for all classes. Departmentalized instruction is implemented by teachers moving between classrooms during the day. The only contact that students have with other students outside their homerooms is on the bus. (For nondepartmentalized elementary schools, Scenario D is not relevant.)

Scenarios E–G involve part-time hybrid approaches in which students are in school some days and learning at home other days.

- **Operating Scenario E (rotating two days per week).** Same as Scenario B, except that students are divided into two groups, with half coming to school on Mondays and Wednesdays and the other half coming on Tuesdays and Thursdays. All students remain at home on Fridays for remote instruction. We assume that reducing the school population by one-half each day—in addition to having 20 percent of students stay home full-time voluntarily—is likely to be sufficient to allow six feet of distance between desks in most classrooms. It also reduces the frequency of contacts by 60 percent and cuts in half the number of other students that each student contacts—both in the classroom and on the bus. But we assume Scenario E will not reduce bus ridership enough to achieve the space suggested by the CDC (2020a), which would seem to require buses to run at 20 percent or less of normal capacity.

[1] Page (2020) reports results of a *USA Today*/Ipsos survey that asks a question about the likelihood of pursuing online/home education without specifying whether that would be a substitute for attending school in person or a complement (for example, if schools are partly open). This suggests that their finding overestimates the number of parents who would keep their children home if schools are open part-time. Murrieta Valley is a local school district that found that 12 percent of parents preferred a fully online option over hybrid and traditional approaches. We think 20 percent is plausible, but it is of course uncertain.

[2] In our previous report, we assumed that students wore masks on buses but not in class. In light of increased public attention to the value of masks, we have modified that assumption for this report.

- **Operating Scenario F (weekly four-day rotations).** Same as Scenario E, except that instead of a daily rotation, the two groups of students are on a weekly rotation. One group of students attends Monday through Thursday in Week 1, and the second group of students attends Monday through Thursday in Week 2. The cumulative amount of time each student spends in the school building is the same as in Scenario E, but rotating through four days in school followed by 10 days out of school might lead to lower COVID-19 infection rates because most students who become infected during their in-school period would not become infectious until they were back home, at which point they would have 10 days to show symptoms (and possibly recover) (Alon et al., 2020).
- **Operating Scenario G (rotating one day per week).** Students are divided into five (very small) groups with each group coming to school only one day per week, with all other learning conducted at home. This is the only scenario that is sure to reduce daily bus ridership enough to implement the physical distancing suggested by the CDC.[3]

Many schools may be using an operating approach that combines elements of the operating scenarios described above. For example, some schools may have enough students opting for remote instruction and enough space in their buildings to allow six feet of physical distance for all students attending in person even if they attend five days a week. Although our models do not explicitly examine such a scenario, it is reasonable to expect that infection spread in such schools would be reduced somewhat relative to full-time in-person attendance without six feet of distance (Scenario B) but not as much as in the hybrid approaches that involve fewer contacts in school and only two days of contact rather than five.

C. Assumptions and outcome measures

For the ABM used in this study, the agents represent students, teachers, administrators, and support staff; the agents interact with other students and staff within the school and on school buses. The ABM investigates “typical” elementary, middle, and high schools in the Commonwealth of Pennsylvania for the 2020–2021 school year, with the assumption that 20 percent of students will remain at home, as discussed previously. Appendix Table A.1 shows the current estimates for relevant values as well as the forecasted numbers for the 2020–2021 school year that include the 20 percent reductions used in the model. Table A.1 also includes the current average number of teachers and support staff in a school. Based on Pennsylvania Department of Transportation and enrollment data, 79 percent of students typically ride a school bus. The Pennsylvania School Bus Association (private correspondence) estimates that on average a school bus transports 40 students, which we decrease by 20 percent for the model.

During the simulation, infectious individuals (students, teachers, administrators, and support staff) transmit to uninfected individuals through interactions. The ABM includes five modes of transmission. First, there are interactions within the classrooms; these include interactions among students and between students and the teacher. In addition, students can have contact with other students during lunch and recess (second) (depending on the scenario) or on the school bus (third). Teachers, administrators, and support staff can have contact with each other during staff meetings (fourth). Students, teachers, administrators, and support staff can also acquire COVID-19 outside the school based on a community-level infection rate (fifth).

[3] Scenarios that split students into two groups (E and F), with no more than half of students coming to school each day, might in some instances leave buses sufficiently empty to follow CDC suggestions for physical distancing, if substantial numbers of students choose to stay home or find other ways to get to school. We have conservatively assumed that this will not generally be possible, however, unless group sizes are reduced more.

A substantial percentage of infected people are asymptomatic, and even those who develop symptoms are contagious before symptoms become evident (Oran & Topol, 2020). The proportion of infected people who are asymptomatic is uncertain and a matter of considerable debate. The CDC and the Office of the Assistant Secretary for Preparedness and Response estimate that between 20 and 50 percent of those infected are asymptomatic (CDC, 2020b). However, some estimates are as high as 80 percent, and infected children may be asymptomatic at even higher rates than adults (Keeling et al., 2020; Oran & Topol, 2020). Our models assume that 50 percent of those infected are asymptomatic. Sensitivity analyses in our previous work suggest that the relative effectiveness of different operating strategies is similar if asymptomatic rates are higher or lower than this (Gill et al., 2020).

The model follows infected individuals from infection to contagiousness and then randomly assumes that half of those infected develop symptoms. Those who do not develop symptoms remain in the school, while those who develop symptoms are assumed to be likely to be sent home (with a return home probability each day as described in Appendix Table A.3). Most of those who are sent home with symptoms are expected to be tested for COVID-19, with test results coming from zero to 10 days after the test (in different simulations).

As discussed in Chapter 1, the simulations assume that a positive test result that is reported to the school leads to a quarantine of the infected person's direct contacts, defined in the model as all students and staff who shared a class or a bus with the infected person. We model three different school responses to detected infections: quarantining of close contacts without school closure, quarantining of close contacts with a three-day closure for deep cleaning, and quarantining of close contacts with a 14-day closure to (temporarily) eliminate the possibility of further transmission in the school.

The results we present are generally based on simulations that sought to examine the progression of infections for 200 calendar days (including weekends), which would encompass a substantial part of the 2020–2021 school year. We also ran simulations for 500 days to test the sensitivity of the results given the uncertainty of the daily transmission rate; results for 500 days do not lead to qualitatively different conclusions than results for 200 days.

Whether an infection occurs in any particular school is partly a function of random factors. One of the advantages of ABMs is that they can incorporate random variation. As a result, multiple simulations of an ABM will produce different results even when scenario parameterizations are identical. To account for random variation in ABM results, we ran 200 simulations of each scenario at each school level for every combination of variables related to community infection rate, closing strategy, and the timing of receiving test results. In total, this involved running approximately 400,000 simulations. For each of the combinations of variables, we show average results across the 200 simulations. We also show the upper and lower boundaries for 90 percent of simulations, using the 5th and 95th quantile results of those simulations. These bars provide information on the range of outcomes likely to be experienced by similar schools.

Apart from school characteristics and random variation, the ABM assumes that transmission rates vary systematically by the amount of time spent with an infected person (for example, one class period or bus ride versus a full day); the type of individuals in the interaction (young children, older children, adults); whether physical distancing is maintained; and whether masks are worn. In a change from our previous work, our primary analyses now assume that both students and staff wear masks on the bus and in school, in a nod to the growing public consensus about the value of masks. In light of new findings about the relative susceptibility of younger versus older children (Park et al., 2020), we also modified assumptions for elementary versus secondary students: secondary students are assumed to be as susceptible as adults, while elementary students are assumed to have half the susceptibility as adults. Appendix Table A.2 provides values for the transmission probabilities used in the model, which are derived from available external evidence on COVID-19 and mitigation factors.

The evidence on COVID-19 that informs the values used in the simulations is emergent, imperfect, and sometimes contested. Given these uncertainties, our previous work included sensitivity analyses to examine how model results change under different assumptions. We found that the results on the relative effects of different operating strategies are largely consistent across a range of assumptions related to the transmissibility of the virus in different contexts, the proportion of infected individuals who develop symptoms, the relative contagiousness of symptomatic versus asymptomatic individuals, and the effectiveness of masks in reducing transmission (Gill et al., 2020).

The results of our prior sensitivity analyses provide confidence that the model findings are robust, but it is impossible to be certain that the simulations will accurately predict the progress of the disease in schools, given uncertainties about the disease itself and human responses to it. For example, the simulations assume that the risk of infection increases linearly with the time spent near an infected person; the accuracy of this assumption depends on unknown factors related to the intensity of the dosage needed to infect, the rate at which the virus dissipates in spaces with different levels of ventilation, and the movements of students and teachers in the room. These uncertainties suggest the need for some caution in interpreting results—and particularly suggest that readers should not make too much of small differences in results.

Finally, it is important to keep in mind that, without a vaccine, there is no measure that will eliminate all infections among the school population. Even closing the school will not prevent students and teachers from acquiring COVID-19 in their home or community. Therefore, the ABM results focus on the probable *relative* effectiveness of different mitigation strategies in reducing the number of infections that occur in the school and on school buses (and thus the total number of infections).

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III. Results

We conducted simulations for elementary (nondepartmentalized, grades K–5), middle (departmentalized, grades 6–8), and high (departmentalized, grades 9–12) schools, using average grade-level enrollments and staffing characteristics for Pennsylvania as noted in Appendix Table A.1. We also ran simulations for large high schools with three times the population of the average high school. Results for typical middle and high schools are nearly indistinguishable, because both have departmentalized instruction, their average size is not dramatically different, and their students are in an age range regarded as equally susceptible to COVID-19; accordingly, results for the average Pennsylvania high school can be viewed as predictive of results for the average Pennsylvania middle school. We therefore use the results from typical high schools to represent results for secondary schools broadly.

A. Initial infections in schools

Before conducting the modeling, it was necessary to estimate the likely number of infected students and staff in each school at the beginning of the school year, based on infection rates in local communities. We estimated this based on a formula (detailed in Appendix A) that adjusts reported current infection rates in the population for (a) estimates of under-reporting derived from emerging literature and (b) estimates of differences in infection rates by age group. We estimated the initial number of cases in the school for five different levels of reported community infection rate—from 10 to 175 detected cases per 100,000 population over the last week.

In August, the statewide average infection rate was approximately 40 detected cases per 100,000 per week, and reported county-level infection rates ranged from zero to approximately 200 detected cases per 100,000. The Pennsylvania Departments of Education and Health deem fewer than 10 detected cases per 100,000 over seven days to represent low levels of infection that can permit full-time reopening of schools. About 10 of Pennsylvania's 67 counties had infection rates below this level in August. Communities with infection rates of 10 to 99 cases per 100,000 are deemed by the state as having moderate rates of infection that could allow hybrid operation of schools for part-time attendance in small groups. The large majority of Pennsylvania counties had infection rates in this range in August. The state recommends fully remote instruction in communities with rates at or above 100 cases per 100,000, which included only a single county in mid-August. (We use 175 cases per 100,000 as the high end of our simulations because it is the highest rate recommended for any in-person instruction by any outside experts we are aware of; this rate is the threshold identified by the Harvard Global Health Institute.)

Table 1 provides an estimate of the number of infections that are likely to be occurring in a typical school's population of students and staff at the time the school year begins, using the assumptions described in Appendix A on the ratio of detected to undetected cases and the relative infection rates of young children, older children, and adults. Secondary schools are expected to have more infections than elementary schools, even at the same size, because older children have higher rates of infection than younger children. Within the elementary and secondary categories, the likely number of initial infections at the beginning of the school year scales proportionally to school size.

Table 1. Likely number of infected students and staff at school opening, by school type and local community infection rate, including symptomatic and asymptomatic individuals

	Reported community infection rate per 100,000 population over the last seven days				
School type	10	25	50	100	175
Typical elementary (~450 students and staff)	0	0	1	2	3
Typical secondary (~550 students and staff)	0	1	2	4	7
Large secondary (~1,600 students and staff)	1	3	6	11	19

Note: Calculations assume the reported community infection rate underestimates true infections by a factor of five. Total infections in the school account for different underlying infection rates for young children, older children, and adults.

As the table indicates, schools in communities with low local infection rates are likely to start the year with few if any infected staff or students. Larger schools and schools in communities where infection rates exceed 50 per 100,000 per week are likely to have several infected students and/or staff members at the beginning of the school year. These estimated initial infection counts include people with and without symptoms; many infected staff and students may not know they are infected.

B. Infection spread over the school year

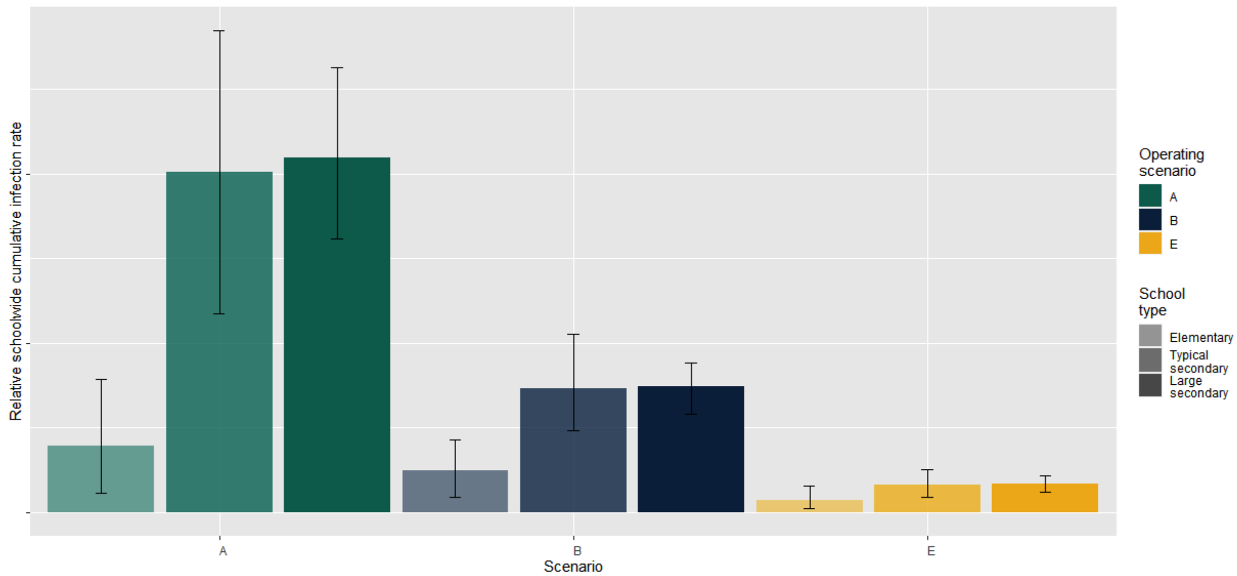
As noted in the preceding chapter, many critical factors affecting disease spread remain highly uncertain. The model must make assumptions about these factors, as we discuss in the methods section. Given the uncertainty of these assumptions, we believe it would be a mistake to focus too much on the precise number of infections predicted for a school, and instead we focus on *relative* number of infections a school is likely to experience under different operating scenarios and in different circumstances. We represent the relative number of infections by the height of the bars in each chart, omitting number labels to avoid implying more precision than can be justified regarding the absolute infection rate.

1. Cumulative infections in elementary versus secondary schools

First, we examine differences between elementary and secondary schools in likely infection spread. As previously shown in Table 1, infection rates among younger students have been substantially lower than infection rates among older students, which leads to a smaller number of likely infections in elementary schools at the time of school opening (even if elementary schools have as many students in total). In addition, as noted in the preceding chapter, recent evidence (Park et al., 2020) suggests that when infected, younger children are only about half as likely to transmit the virus to others. In our simulations, these differences mean that the virus spreads more slowly in elementary schools relative to secondary schools. For any particular operating scenario, closing strategy, and community infection rate, the cumulative fraction of students and staff who become infected is lower in elementary schools than in secondary schools.

In Figure 1 we illustrate the differences in school types by showing the relative fraction of the school's population that is infected for three typical operating scenarios: Scenario A (full-time, business as usual); Scenario B (full-time, with precautions including masks); and Scenario E (hybrid, with students divided into two groups each attending two days per week, plus precautions). School type is represented by shading, with the lightest shading indicating a typical elementary school, medium shading indicating a typical secondary school, and dark shading (the right-most bar for each operating scenario) indicating a large secondary school. The results in the figure are based on a moderate community infection rate of 50 per 100,000 per week, quarantines without school closures, and a two-day COVID-19 testing response time. The differences by school type in Figure 1 are consistent for different circumstances and closure policies.

Figure 1. Relative schoolwide cumulative infection rate among students and staff by operating scenario and school type



Note: The whisker lines for each bar show the range of expected outcomes from the 5th to the 95th percentile. These simulations assume that the detected community infection rate is 50 per 100,000 over the last week, that COVID-19 test results are returned in two days and that detected infections lead schools to quarantine close contacts but not to shut down. Scenario A represents a "business as usual" approach with full-time attendance and no changes to operations except quarantining of infected individuals and their close contacts.

As Figure 1 indicates, cumulative infection rates in elementary schools (represented by the first, lightest-shaded bar in each operating scenario) are consistently lower than in secondary schools employing the same operating strategies. The elementary-secondary difference in infection rates is largest for schools that are trying to operate without substantial changes to mitigate infection spread (Scenario A).

Notably, cumulative infection rates in large secondary schools (represented by the third, darkest-shaded bar in each scenario)—with three times as many students and staff—are essentially indistinguishable from the cumulative infection rates in typical (smaller) secondary schools, regardless of whether the school is operating full-time, business as usual (Scenario A), full-time with precautions (Scenario B), or part-time hybrid (Scenario E). Under the assumptions of the model, the total number of students and staff in a school is far less important than their underlying susceptibility and factors that affect the probability that any infected individual will transmit the virus to someone else.

Despite these age-based differences in infection rates, the simulations show that *relative* differences in results by operating scenario and infection response follow similar patterns across all school types. For example, elementary schools have lower infection rates than secondary schools across the board, but the different operating scenarios and quarantining/closing strategies produce proportionally similar reductions in infections. To simplify the presentation, in the rest of the main body of the report, we focus on the typical Pennsylvania secondary school, while noting cases in which findings on the relative effects differ substantially for elementary schools or large secondary schools. In the detailed results in Appendix B, we present results separately for typical Pennsylvania elementary schools, typical secondary schools, and large secondary schools so that educators in each type of school can examine outcomes for schools similar to their own.

2. Cumulative infections by operating scenario and community incidence

Next, we examine how the local community's infection rate and the school's operating scenario affect the relative number of infections among students and staff over several months. Figure 2 shows the relative proportion of infected individuals in the school, stratified by scenario and community infection rate. The height of the bars shows the average effect, while the whiskers show the likely range in which 90 percent of individual schools would land (5th percentile to 95th percentile), given chance variation of the disease itself. For each of the operating scenarios (A–G), the number of infections among the school population rises steadily as the local community's reported infection rate increases from 10 per 100,000 per week to 175 per 100,000 per week. These results assume that COVID-19 tests are returned in two days and that schools quarantine close contacts but do not shut down when cases are detected. Trends are similar for strategies that involve temporary school closings and circumstances that involve slower reporting of test results.

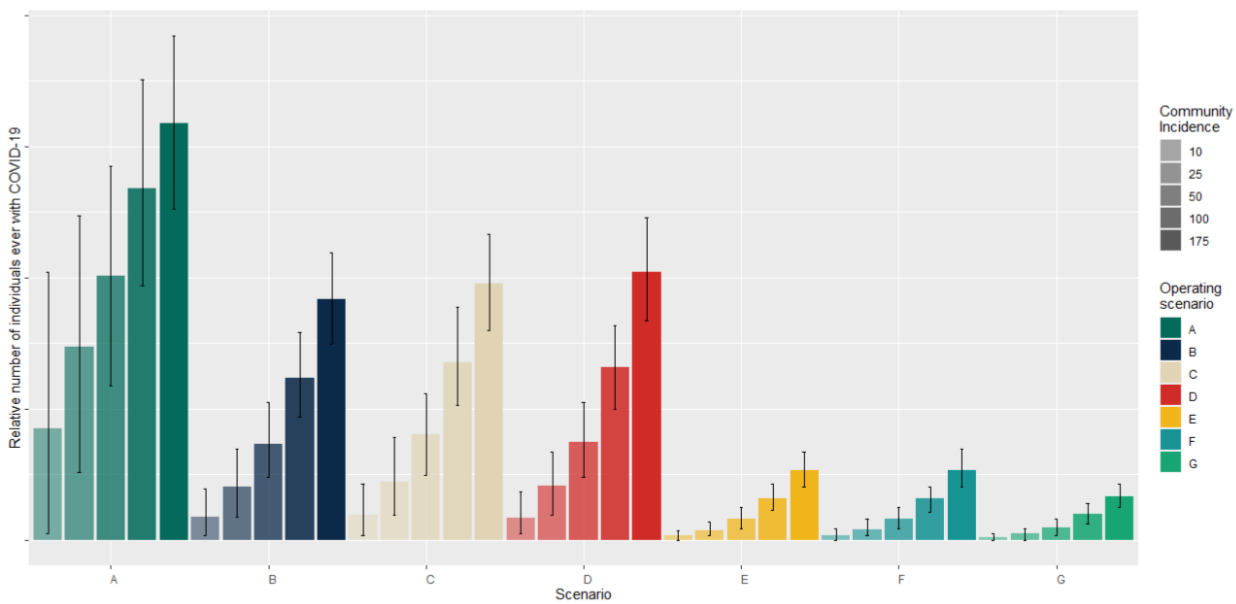
The results in Figure 2 also demonstrate the importance of infection precautions and the school's operating strategy. Precautions such as mask wearing and lunch in classrooms (Scenario B) substantially reduce total infections relative to operating without precautions (Scenario A). Consistent with the results in our prior work (Gill et al., 2020), hybrid approaches in which students are divided into groups, each of which attends part-time (operating scenarios E, F, and G), dramatically reduce the total number of infections over time. For example, a hybrid approach with students in two groups, each attending 40 percent of days (Scenarios E or F) can reduce the number of predicted infections in a school where the community rate is 50 per 100,000 per week to a level comparable to a school running five days a week with precautions (Scenario B) in a community where the local infection rate is only one-fifth as high (10 per 100,000 per week) (as can be seen by comparing the height of middle bar for Scenario E or F to the lowest bar for Scenario B).

Moreover, the local community infection rate has a much larger effect on infections in the school when schools are operating full-time than if they operate in a part-time, small-group hybrid approach. The mitigating effects of part-time, small-group instruction are especially large at community infection rates above 50 per 100,000 per week.

Precautions and hybrid scenarios also shrink the amount of random variation in infection spread, reducing the likelihood that a school will experience unusually high numbers of infections due to bad luck. This can be seen in the fact that the high end of the whisker range for each bar is substantially lower in Scenarios B–D (full-time with precautions) than in Scenario A (full-time without precautions), and much lower still in Scenarios E–G (part-time hybrids).

The results in Figure 2 do not suggest observable differences in infection rates between the three full-time strategies with precautions (Scenarios B, C, and D). Under the assumptions of the model, block scheduling (Scenario C) does not reduce infections because the increase in the length of classes cancels out the benefit of reducing the number of classes per day. The same tradeoff—time exposed to an infected person versus number of infected people potentially contacted—explains why Scenario D (which involves keeping students in a single classroom all day, while teachers rotate) does not show reduced infections relative to the more conventional scheduling of Scenario B. More generally, our current model results for Scenarios C and D are similar to those of Scenario B in all analyses we conducted for all outcomes. But these results are contingent on the assumption (noted in the preceding chapter) that the risk of transmission increases linearly with time spent near the infected person. That assumption is uncertain and dependent not only on the virus itself but also on ventilation in the space and on the behavior of students and staff as they move around the room during a class period or school day. If the transmission risk declines somewhat with each additional hour in a class (as seems likely), then our results will underestimate the benefits of block scheduling and single-classroom pods.

Figure 2. Relative cumulative infections among students and staff, by community incidence (per 100,000 population over seven days) and operating scenario, in a typical Pennsylvania secondary school



Note: The whisker lines for each bar show the range of expected outcomes from the 5th to the 95th percentile. These simulations assume that COVID-19 test results are returned in two days and that detected infections lead schools to quarantine close contacts but not to shut down. Scenario A represents a "business as usual" approach with full-time attendance and no changes to operations except quarantining of infected individuals and their close contacts.

Unfortunately, we are aware of no evidence that would allow us to quantify the relationship between time in a classroom and risk of transmitting the infection. We have conducted alternative analyses that assume classroom interaction for a full day is no greater than interaction for one period; these suggest that block scheduling (Scenario C) or podding (Scenario D) would reduce infections somewhat relative to a more typical secondary schedule (Scenario B), but the reductions would be much smaller than reductions from hybrid approaches.[4] Given that our current primary results probably slightly underestimate the benefits of

[4] This is evident in findings from our previous work (Gill et al., 2020), in which we had assumed equal transmission risk regardless of the amount of time in contact.

Scenarios C and D, we omit those scenarios from the charts in the remainder of this report. Readers should expect that secondary schools operating with Scenarios C or D are likely to observe results slightly better than those of Scenario B.

Finally, Figure 2 also shows no notable differences in infections between the two 40 percent attendance hybrid strategies: Scenario E, which involves daily rotations of the two student groups; and Scenario F, which involves weekly rotations. Results for Scenarios E and F are generally similar in various circumstances (as will be seen throughout the report) and for sensitivity analyses.

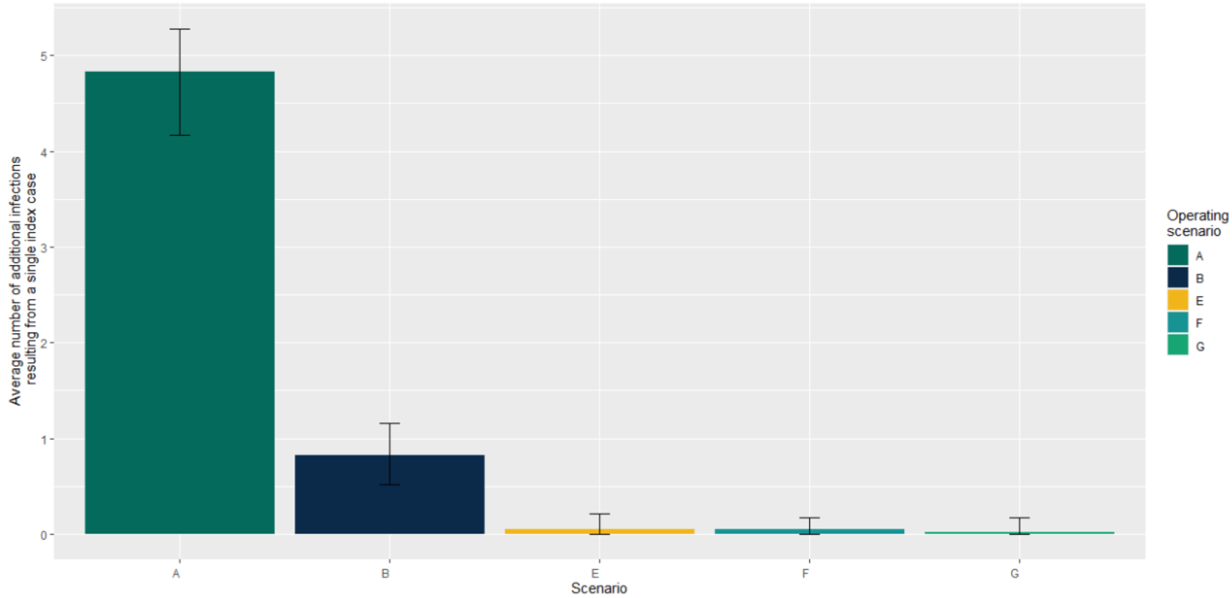
3. Operating strategies and in-school transmission of infections

Since schools cannot control the infections that occur outside of school, their aim in mitigation strategies is to reduce the number of additional infections produced by their own operations—infections that occur in school or on the school bus. Although the simulations seek to estimate the total number of infections among students and staff occurring inside or outside the school, they also allow us to focus specifically on the secondary infections attributable to the schools themselves. This provides an indication of the additional risks created by opening school buildings under different operating strategies.

In Figure 3, we show the average number of additional infections produced in the school or on the bus from each infection brought in from the outside. The results powerfully demonstrate the importance of precautions and the additional mitigation produced by part-time hybrid strategies. Specifically, in communities with moderate local infection rates (50 per 100,000 per week), secondary schools that try to operate full-time without precautions (Scenario A) are likely to accelerate infection growth, with about five new secondary and tertiary infections in the school produced by each infection brought in from outside—even if such schools are quarantining those with detected infections and their classmates. (In elementary schools, the average number of additional infections produced is substantially smaller due to lower susceptibility of young children.)

Meanwhile, precautions such as wearing masks and eliminating mixing in cafeterias (Scenario B) can dramatically reduce the school's role in spreading infection, so that each infection from outside produces only about one additional infection in the school (Figure 3). As can be seen from the results for Scenarios E, F, and G, *part-time hybrid approaches in conjunction with masks reduce the effect of school operations on infection spread so that most infections coming from outside the school are likely to produce* <u>*zero*</u> *additional infections in the school*.

Figure 3. Average number of additional infections among students and staff for each infection coming from outside the school, by operating scenario, in a typical Pennsylvania secondary school



Note: The whisker lines for each bar show the range of expected outcomes from the 5th to the 95th percentile. These simulations assume that COVID-19 test results are returned in two days, that the reported community infection rate is 50 per 100,000 per week, and that detected infections lead schools to quarantine close contacts but not to shut down. Scenario A represents a "business as usual" approach with full-time attendance and no changes to operations except quarantining of infected individuals and their close contacts.

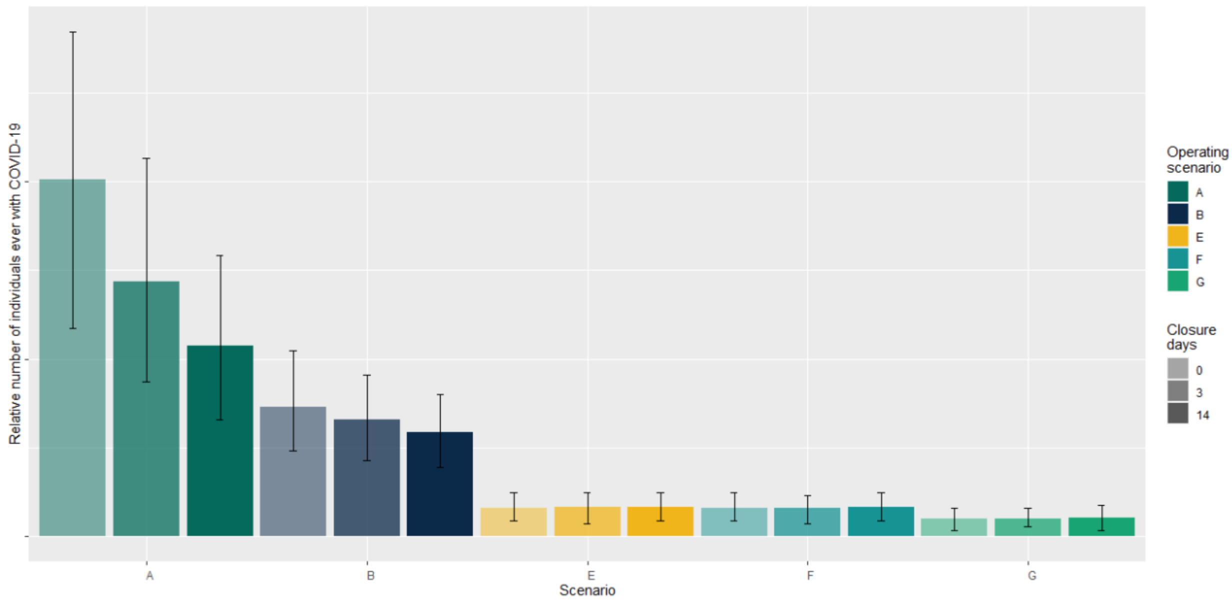
4. Cumulative infections by operating strategy and closing policy

In addition to the operating strategy, the ways in which schools respond to detected infections may affect the spread of the virus in the school. As discussed in Chapter 1, we examine three possible responses: (1) quarantining the infected person's close contacts (that is, students and teachers in the same classes and on the same school bus with the infected person); (2) quarantining close contacts and closing the school for three days for intense cleaning; and (3) quarantining close contacts and closing the school for two weeks for intense cleaning and to shut down any further infection spread in the school.

Simulation results in Figure 4 show that in the typical secondary school, if all students are attending every day, temporarily closing the school every time an infection is detected modestly reduces the total number of infections. Closures substantially reduce infections in typical secondary schools that are otherwise operating without precautions (Scenario A). Schools operating with precautions and open full-time (Scenario B) see a more modest reduction in infection from closures from a lower starting point. In larger secondary schools that are operating full-time, closures have a somewhat larger effect in reducing infection spread (not shown).

Figure 4 also shows that if the school is operating in part-time hybrid mode from the start (Scenarios E, F, and G), schoolwide closures do not measurably reduce infections relative to simply quarantining the close contacts of the infected person. In typical and large secondary schools, infection rates under part-time hybrid operating scenarios remain substantially below infection rates in schools open full-time regardless of the closing approach. Indeed, in secondary schools in communities with moderate infection rates, hybrid operating strategies *without* temporary closures are likely to keep cumulative infection numbers substantially lower than full-time operation *with* temporary closures for each detected infection.

Figure 4. Relative cumulative number of infected individuals, by operating scenario and school closure duration, in a typical Pennsylvania secondary school



Note: The whisker lines for each bar show the range of expected outcomes from the 5th to the 95th percentile. These simulations assume that COVID-19 test results are returned in two days and that the reported community infection rate is 50 per 100,000 per week. Scenario A represents a "business as usual" approach with full-time attendance and the same quarantining and closing policies as the other scenarios.

The simulation results suggest that temporary schoolwide closures should rarely be needed to reduce infections in schools operating in hybrid mode, because infection spread is kept low through the combination of the part-time hybrid approach, precautions such as masking, and quarantining close contacts of those infected. But the simulations do not address outlier cases in which substantial numbers of students or staff are simultaneously infected through a super-spreader event such as a party or sporting event. Detection of a substantial number of cases in a short period of time might indicate that the school community has experienced a super-spreader event that has taken it beyond the typical range of variation resulting from random individual transmissions of the virus.

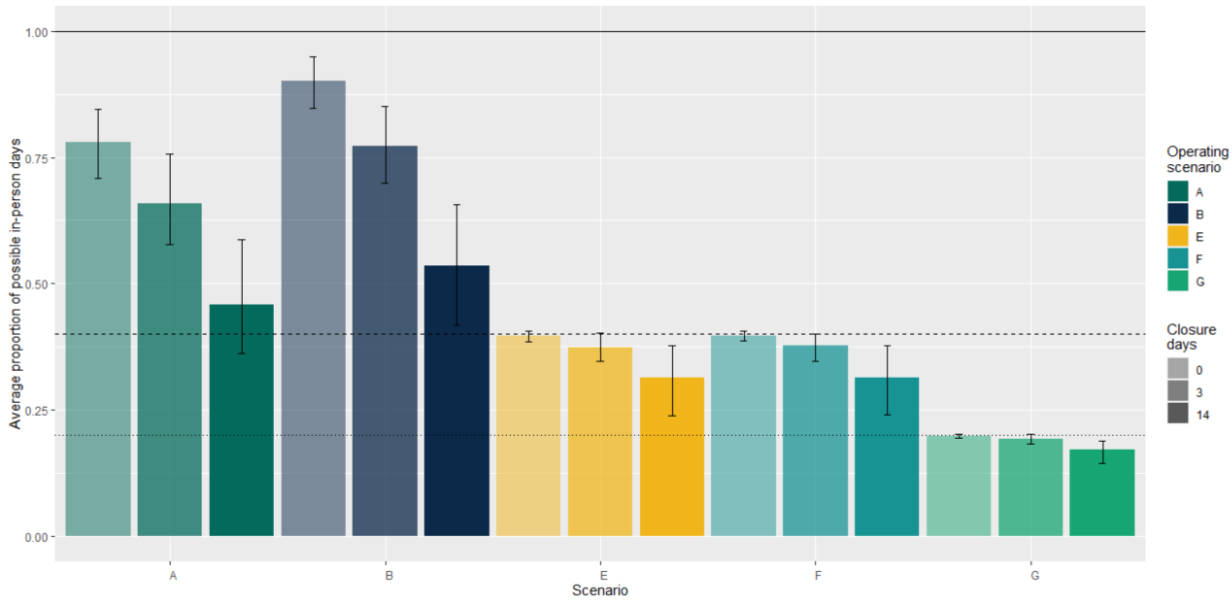
C. In-school attendance over the school year

Next we examine how operating scenarios, closing policies, and community infection rates affect the percentage of possible school days that the typical student will be able to come to school. Here we are interested both in the fraction of all school days (Monday through Friday) that a student can attend and in the fraction of *intended* school days based on the school's operating scenario. From the perspective of students and families, there is value in coming to school more days in total (based on the operating scenario) and in being able to count on having a consistent schedule. While hybrid approaches involve fewer total days in school by design, they substantially reduce infection rates and therefore might reduce the number of *unplanned* days out of school due to quarantines or temporary closures.

1. In-school attendance by operating strategy and closing policy

Not surprisingly, policies that close the school (for 3 days or 14 days) when infections are detected substantially reduce the total number of days that students can attend in person (Figure 5). These effects are larger in schools operating full-time than in schools using hybrid approaches because schools using hybrid approaches experience fewer infections that lead to quarantines or closures. In secondary schools where students are attending daily and the community infection rate is at a moderate level (50 per 100,000 per week), closing the school for 14 days for each detected infection would be highly disruptive, such that the typical student would be able to attend only about half of all school days (as seen in the third bar in Scenarios A and B). Even in the absence of a school closure policy, quarantines of the classmates and bus-mates of infected students are likely to reduce in-person attendance for the typical student by about 10 percent in a school open full-time with precautions (Scenario B, first bar).

Figure 5. Proportion of school days attended in-person by a typical student, by operating scenario and school closure duration, in a typical Pennsylvania secondary school



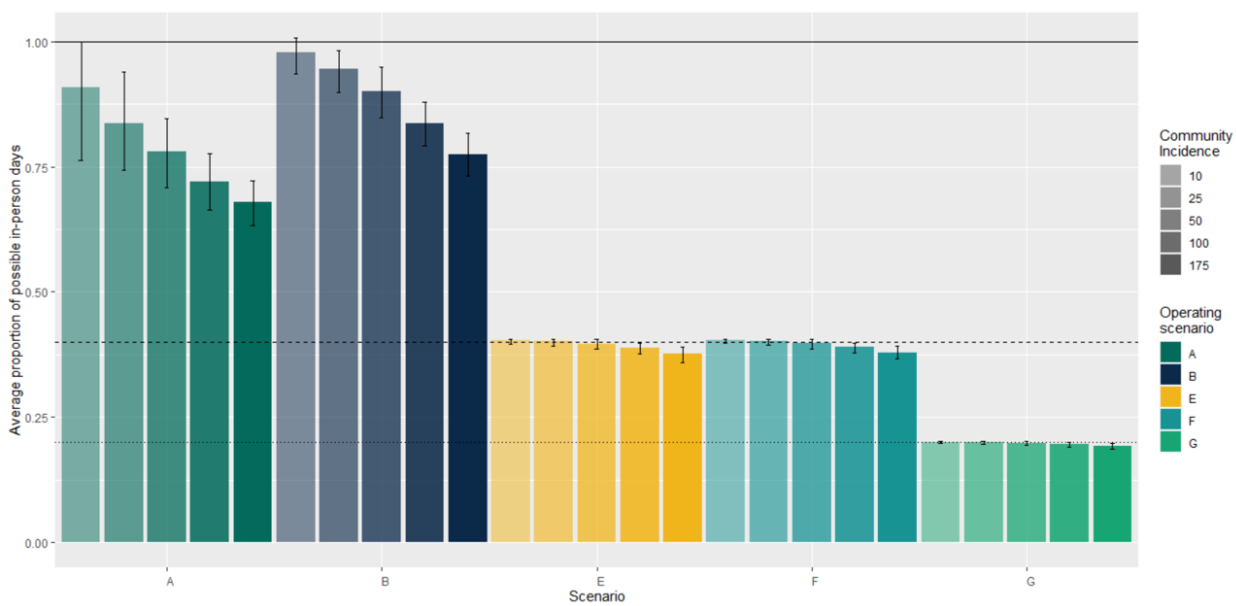
Note: The whisker lines for each bar show the range of expected outcomes from the 5th to the 95th percentile. These simulations assume that COVID-19 test results are returned in two days, that the reported community infection rate is 50 per 100,000 per week, and that detected infections lead schools to quarantine close contacts but not to shut down. Scenario A represents a "business as usual" operating approach with full-time attendance and the same quarantining and closure policies as the other scenarios. The dotted (bottom) line shows 20 percent in-person attendance, which is the maximum possible for Scenario G; the dashed (middle) line shows 40 percent in-person attendance, which is the maximum possible for Scenarios E and F, and the solid (top) line shows 100 percent attendance Monday through Friday.

Under part-time hybrid operating strategies, students come to school far fewer days by design (40 percent of days in Scenarios E and F and 20 percent of days in Scenario G). As we saw in the preceding section, schools using hybrid approaches are not likely to need to shut down, since their infections remain low with quarantines of close contacts. In consequence, *the typical student in a secondary school using a hybrid approach (in a community with a moderate infection rate) is not likely to experience any unplanned disruption in the days they can come to school.* This can be seen in Figure 5 in the left-most bars for Scenarios E, F, and G. In all three cases, those bars are reaching the theoretical maximums for days that can be attended, indicated by the dotted line at 20 percent for Scenario G and the dashed line at 40 percent for Scenarios E and F.

2. In-school attendance by operating strategy and community infection rate

As the community infection rate increases, the number of in-person days decreases due to quarantining of those infected and their close contacts, even if the school building does not close (Figure 6). But high community infection rates are more disruptive to schools operating full-time in person than to schools using hybrid approaches, as can be seen in the slower rate of attendance decline for Scenarios E, F, and G as the community infection rate increases from low (10 cases per 100,000 per week, on the left of each scenario's set of bars) to high (175 cases per 100,000 per week, on the right of each scenario's set of bars). Even at 100 reported community infections per 100,000 per week (represented by the fourth of the five bars in each operating scenario), the typical student in a hybrid secondary school (Scenarios E, F, and G) can expect to miss only a very few days due to quarantines, while the typical student in a secondary school open full-time with precautions (Scenario B) might be sent home for about 15 percent of possible days due to quarantines.

Figure 6. Proportion of school days attended in-person by a typical student, by community incidence (per 100,000 population over seven days) and operating scenario, in a typical Pennsylvania secondary school



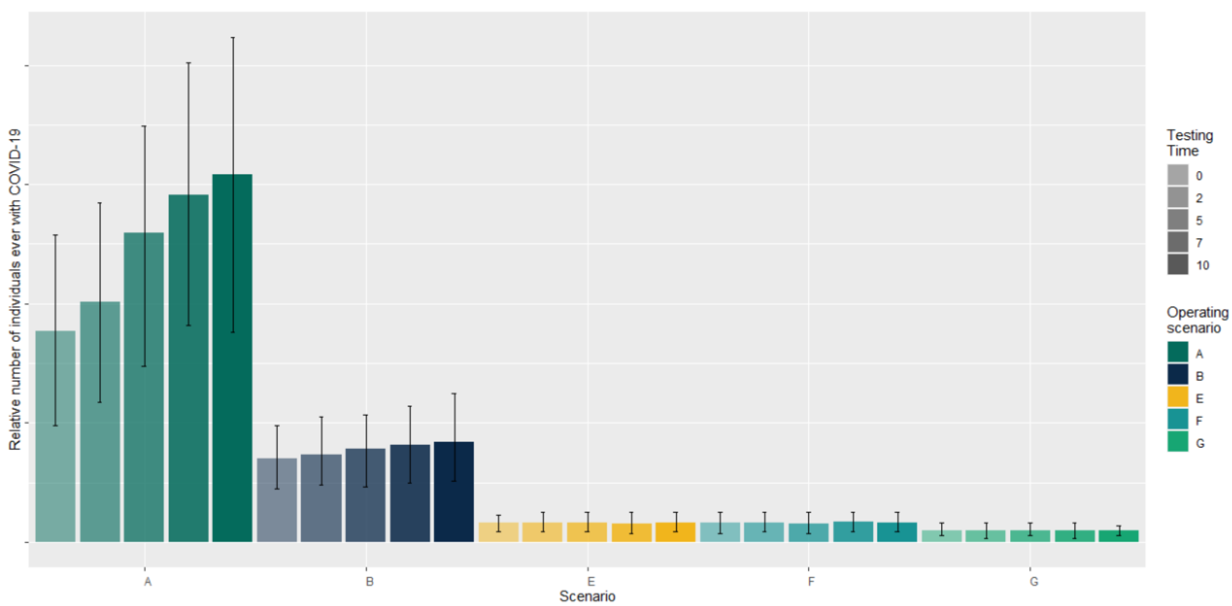
Note: The whisker lines for each bar show the range of expected outcomes from the 5th to the 95th percentile. These simulations assume that COVID-19 test results are returned in two days and that detected infections lead schools to quarantine close contacts but not to shut down. Scenario A represents a "business as usual" approach with full-time attendance and no changes to operations except quarantining of infected individuals and their close contacts. The dotted (bottom) line shows 20 percent in-person attendance, which is the maximum possible for Scenario G; the dashed (middle) line shows 40 percent in-person attendance, which is the maximum possible for Scenarios E and F, and the solid (top) line shows 100 percent attendance Monday through Friday.

At very low community infection rates (10 per 100,000 population over the last seven days), most students can expect to attend school nearly every day, even in schools operating full-time, as long as precautions are implemented. This can be seen in the left-most bars of Scenario B in Figure 6, in which the typical student can attend nearly 100 percent of possible days. Students in elementary schools in communities with very low infection rates are likely to experience even fewer disruptions, since they experience fewer infections requiring quarantines (not shown).

D. Effect of variation in COVID-19 testing response time

In principle, the turnaround time for COVID-19 test results might substantially affect the total number of infections in the school because quarantines of close contacts cannot be implemented until an infection is confirmed. In practice, we find that delays in testing would have large effects in schools implementing no precautions, as shown in the steep slope of the results for Scenario A in Figure 7: as testing turnaround time increases from zero to 10 days from left to right, the number of infections in the school increases substantially (in a community with a moderate infection rate of 50 per 100,000 per week and a school that is quarantining close contacts but not shutting down).

Figure 7. Relative cumulative infections by time to receive COVID-19 test results and operating scenario, in a typical Pennsylvania secondary school



Note: The whisker lines for each bar show the range of expected outcomes from the 5th to the 95th percentile. These simulations assume that the reported community infection rate is 50 per 100,000 per week and that detected infections lead schools to quarantine close contacts but not to shut down. Scenario A represents a "business as usual" approach with full-time attendance and no changes to operations except quarantining of infected individuals and their close contacts.

In secondary schools operating full-time with precautions, faster turnaround of test results modestly reduces infection rates, as indicated in the gradually rising left-to-right slope of the bars for Scenario B. In typical elementary schools, testing turnaround time has no influence on infection rates under any scenario that includes precautions (B–G) (not shown). Similarly, in secondary schools operating on a part-time hybrid model, faster turnaround of test results has no measurable impact on infection spread because infections remain low regardless of the speed of receiving test results (Figure 7).

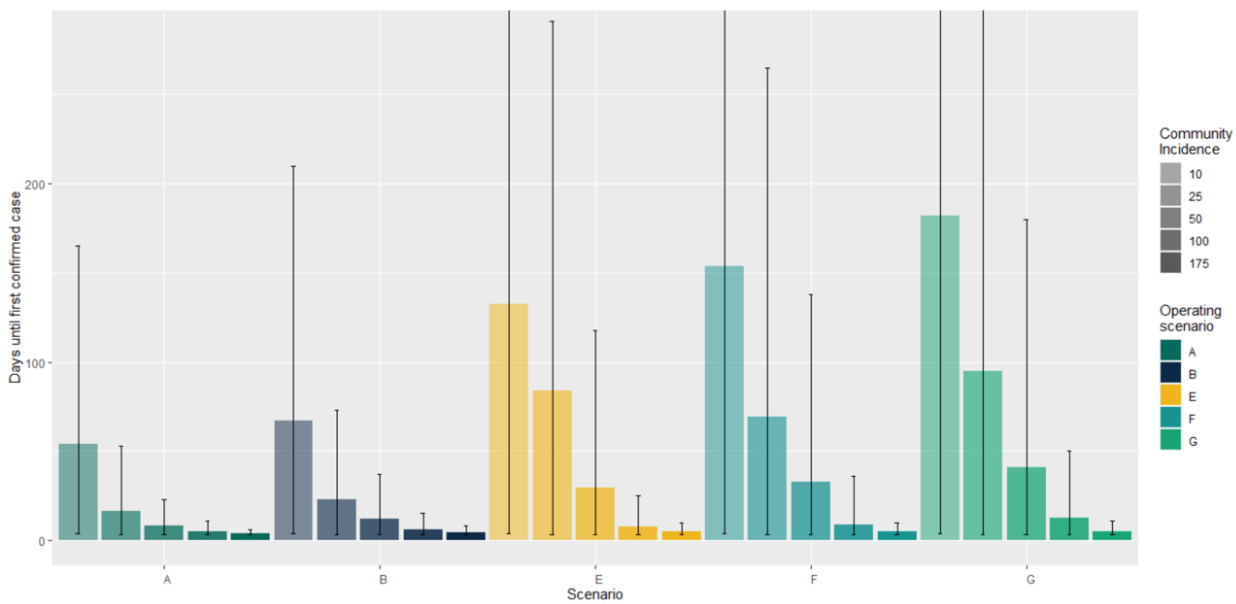
E. Detected and undetected infections

1. Time to first detected case, by operating scenario and community infection rate

Next we examine the effects of operating strategy and community infection rate on the amount of time it is likely to take before a school detects an infection among its students and staff—keeping in mind that some infections will go undetected because the infected person does not have symptoms (or because a family fails to report a positive test result to the school, which might occur for a small fraction of student infections).

The underlying local community infection rate has a large effect on the average time to the first detected infection (Figure 8). At a very low local infection rate (10 per 100,000 population in the last week), many schools might observe no infections for months, as indicated by the left-most bar for each operating scenario in Figure 8. In contrast, with local infection rates at the highest levels that the state of Pennsylvania and outside experts have considered acceptable for opening (the two right-most bars for each operating scenario, at 100 and 175 cases per 100,000 per week), most schools are likely to have at least one infected person at the time of opening or shortly thereafter.

Figure 8. Time to first confirmed COVID-19 case, by community incidence (per 100,000 population over seven days) and operating scenario, in a typical Pennsylvania secondary school



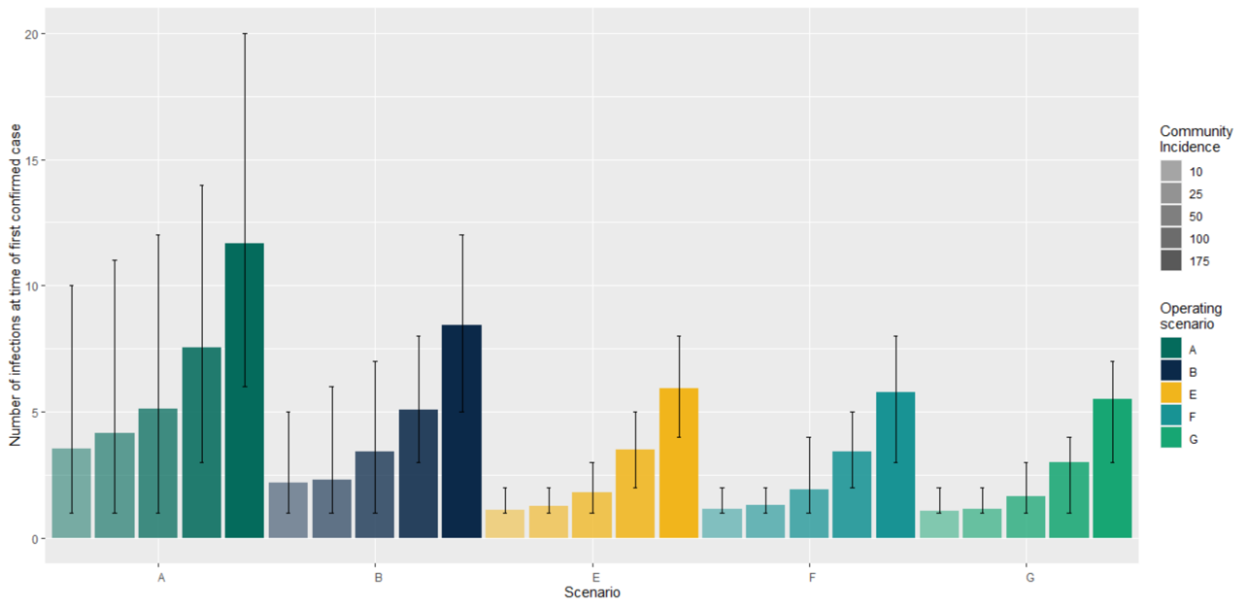
Note: The whisker lines for each bar show the range of expected outcomes from the 5th to the 95th percentile. These simulations assume that COVID-19 test results are returned in two days and that detected infections lead schools to quarantine close contacts but not to shut down. Scenario A represents a "business as usual" approach with full-time attendance and no changes to operations except quarantining of infected individuals and their close contacts.

The results in Figure 8 also show that, on average, hybrid approaches with part-time attendance (Scenarios E, F, and G) substantially increase the average length of time before schools detect their first infection. Unfortunately, however, *the average time to the first detected infection provides little information about when any individual school will detect its first infection, due to large random variation that means that any school could have an infection from the day it opens.* From the perspective of an individual school, the most important thing to notice in Figure 8 is the extremely wide variation around all the averages, as indicated by the whiskers around each bar. Those whiskers show the range of random variation from the 5th percentile to the 95th percentile.

2. Number of likely total infections when first infection is detected

Because many infected people are asymptomatic, by the time the first confirmed COVID-19 case is identified, several unidentified or unconfirmed cases may be present in the school. More specifically, regardless of the community infection rate, secondary schools in all scenarios should expect that there is at least one undetected case in the school when they detect a case (Figure 9). In secondary schools that are operating with full-time attendance or in communities with high local infection rates, there may be five or more infections in the school when the first case is detected. In elementary schools, in contrast, under most of the operating scenarios and community infection rates, there is typically not more than one additional undetected infection for each detected infection (not shown).

Figure 9. Number of infected individuals at the time of the first confirmed case, by community incidence (per 100,000 population over seven days) and operating scenario, in a typical Pennsylvania secondary school



Note: The whisker lines for each bar show the range of expected outcomes from the 5th to the 95th percentile. These simulations assume that COVID-19 test results are returned in two days and that detected infections lead schools to quarantine close contacts but not to shut down. Scenario A represents a “business as usual” approach with full-time attendance and no changes to operations except quarantining of infected individuals and their close contacts.

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Appendix A

Agent-based model methods and assumptions[5]

[5] Much of this text is borrowed from our previous work (Gill et al., 2020).

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A. Agent-based model

ABMs' ability to model complex interactions among individuals differentiates ABMs from top-down epidemic models (Dimitrov & Meyers, 2010). Therefore, ABMs are ideal for informing policy decisions that influence complex social systems, such as the interactions among members of a school community and the spread of COVID-19 among them (Willem et al., 2017). An ABM allows investigators to leverage their expertise about the complex social systems by enabling the explicit inclusion of important societal structures (such as a high degree of contact among students in the same classroom) into the model. Furthermore, policymakers must consider these societal structures in the measurement and evaluation of interventions targeted at mitigating the spread of COVID-19 (such as physical distancing and self-isolation) to obtain valid results (Lai et al., 2020).

There are four key components to the ABM: (1) specifying the agents, (2) interactions among the agents, (3) transmission between agents, and (4) disease progress of an infected agent. As discussed in the main text, here the agents are categorized into three types: students, teachers, and other staff. The model assumes students attend grades K–5 for elementary school, 6–8 for middle school, and 9–12 for high school.

The number of students by grade as well as the number of teachers and staff are specified in Table A.1. Each elementary student is assigned a single class, while middle and high school students are assigned six classes that they attend each day (Scenario C assumes block scheduling where those six classes are spread over two days); all classes are assumed to contain the same number of students. Except for Scenario D, middle and high students are assigned their six classes and classmates at random (within grade), which results in students of the same grade randomly mixing across their classes; for Scenario D, students have the same classmates for all six classes.

The number of classes or students per teacher does not vary by scenario. Only the frequency of the class (every other day in Scenario C) and proportion attending in-person varies (Scenarios E and F have 50 percent in-person attendance Monday through Thursday and 0 percent on Friday, while Scenario G has 20 percent in-person attendance each day). A single teacher is assigned to each of the classes.

A percentage of students are assigned to ride the school bus. All school buses are assumed to transport the same number of students, randomly distributed across grades and classrooms.

The ABM includes the four types of interactions (second component) listed below.

- **Classrooms**: During each in-person school day, all students within the same class interact with each other. The students also interact with the single teacher in the classroom. Students in middle or high school interact this way in each of their classes each in-person school day.
- **School bus**: During each in-person school day, all students within the same bus interact with each other.
- **Lunch/recess**: During each in-person school day, students interact with students in the school. The number of interactions for a student during a day is governed by a negative binominal distribution (r = 5; p = 0.1). The students that a particular student interacts with changes each day.
- **Teachers, administrators, and support staff**: During each school day, teachers and staff can have contact among themselves; this is in addition to teachers interacting with students in their classroom (see classroom interaction above). The number of interactions a teacher has with other teachers is

governed by a negative binominal distribution (r = 5; p = 0.625). The same holds for the number of interactions for a teacher with staff and a staff member with other staff.

Each individual also has a probability of acquiring COVID-19 from interactions outside the school community (that is, other than in the school or on the school bus). This probability represents the background risk of acquiring COVID-19 from their nonschool community and is in addition to the four types of interactions (described above) among the school population.

Figure A.1. Illustration of a potential contact network for a K–5 school

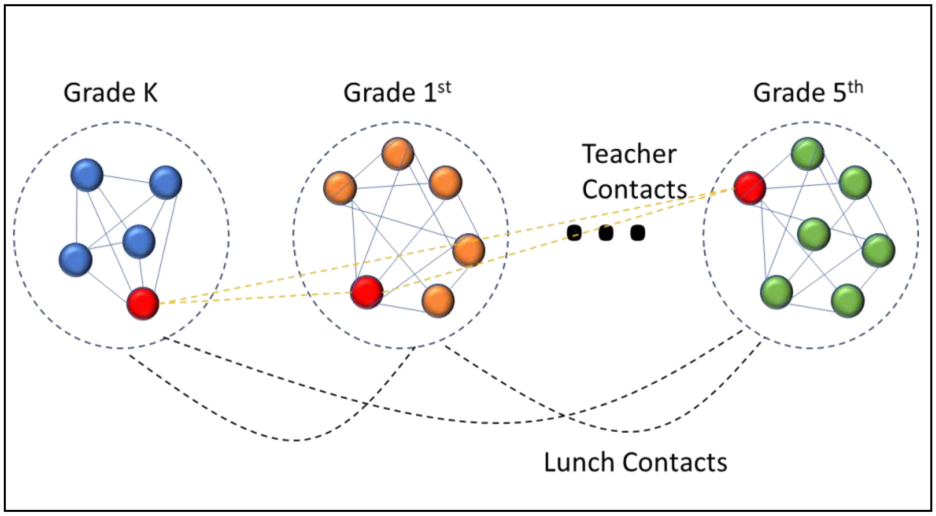
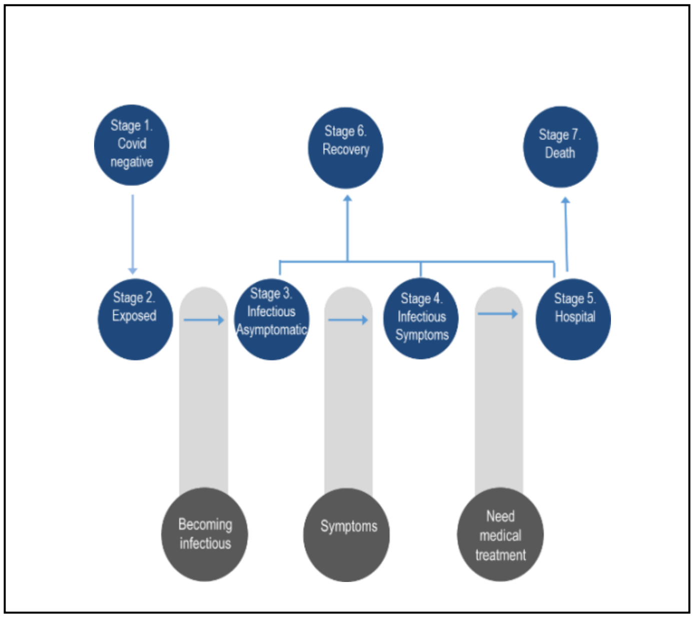


Figure A.1 shows an illustration of interactions for a K–5 school for the classroom, lunch/recess, and teacher contacts (bus and administrators/support staff contacts are not shown).

The third component is the transmission of COVID-19 between agents. Each type of interaction has a probability of transmitting COVID-19 from an infected to an uninfected individual; this probability can be modified based on characteristics of the individual (such as student versus adult and asymptomatic versus symptomatic), as well as precautions taken by the individual (such as adhering to six feet physical distance and wearing masks). The transmission probabilities for each interaction are provided in Table A.2, as well as modifications based on characteristics and precautions; as there is uncertainty in several of the transmission probabilities, sensitivity analyses were conducted to investigate the robustness of the findings. In addition to the interactions listed above, students, teachers, administrators, and support staff can also acquire COVID-19 outside the school based on a community-level infection rate.

Figure A.2. Model for COVID-19 stages of care and possible transition pathways between stages



Regarding the fourth component, the model simulates an individual's disease progression. The progression is based on a Susceptible-Exposed-Infectious-Recovered epidemic model, which is commonly used to model COVID-19 (Prem et al., 2020). Specifically, an individual progresses through seven stages: (1) COVID-19 negative, (2) COVID-19 positive incubation, (3) infectious but asymptomatic (for individuals that ultimately develop symptoms this would be their presymptomatic phase), (4) infectious with symptoms, (5) hospitalized, (6) recovery, and (7) death. Individuals contribute to the accrual of the first five infected cases once they transition to Stage 2 from Stage 1. Once an individual transitions into Stages 5, 6, or 7 they do not infect other individuals in the school. Only individuals in Stage 4 are able to self-isolate (that is, remain at home).

Each day, an agent either remains in the current stage or transitions to another stage. Figure A.2 depicts these stages as well as possible transition pathways between stages. Individuals stochastically transition between stages in daily increments. The daily probability of moving from Stage 1 (uninfected) to Stage 2 (exposed) is determined by the values shown in Table A.2. The daily probabilities of an exposed person with COVID-19 transitioning from Stage 2 to Stage 3 (that is, being asymptomatic but infectious) follows a geometric distribution based on Imperial College London's estimate that the mean time from exposure to infectiousness is 4.6 days (Ferguson et al., 2020). Once an individual enters Stage 3, they can recover (Stage 6), develop symptoms (Stage 4), or remain in Stage 3. The daily probability of transitioning from Stage 3 to Stage 4 is based on a geometric distribution derived from Imperial College London's estimate of an average of half a day from infectiousness to symptoms for those who become symptomatic (Ferguson et al., 2020).

We have relied on estimates from CDC and the Office of the Assistant Secretary for Preparedness and Response to assume that 50 percent of students and teachers/staff are asymptomatic for the entire duration of their infection (CDC, 2020b); asymptomatic individuals transition directly from Stage 3 to Stage 6. The remaining 50 percent of students and teachers/staff eventually develop symptoms, which transitions them to Stage 4. As some estimates are as high as 80 percent, and infected children may be asymptomatic at even higher rates than adults (Keeling et al., 2020; Oran & Topol, 2020), sensitivity analyses (specified in Table 3) were conducted that assumed that lower and higher percentages of those infected are symptomatic. If an individual is in Stage 4, they can recover (Stage 6), require hospitalization (Stage 5), or remain in Stage 4. Only if an individual enters the hospital can they move to Stage 7 (death). For children, hospitalization and death are very rare. Additional information on the probabilities related to progression through the stages is available on request.

Integration of the fourth component (disease progress of an infected agent) with the other three components is necessary to simulate the spread of COVID-19 as well as strategies to mitigate the spread. For instance, it is important for the simulation to know whether an individual is in their infectious phase (specifically, Stages 3 or 4) when they have an interaction with other members of the school. This is particularly relevant for Scenarios C and E–F, where infected students do not interact with all their classmates daily. All the code and data visualizations were created in R (R Core Team, 2020).

B. Community background infection rate

Each individual has a daily probability of contracting SARS-CoV-2 from interactions they have outside of school, varying with the infection rate in the local community. The model includes differential community background infection rates based on age; in particular, the model has three categories for the following populations: elementary school students, middle and high school students, and adults. The following description provides the technical details to calculate the three community background infection rates.

The Pennsylvania COVID-19 Early Warning Monitoring System Dashboard provides weekly incidence in Pennsylvania. (As of mid-August 2020, the weekly incidence was 43.2 individuals per 100,000). In order to estimate the number of weekly incidence cases by the three population categories, we use the COVID-19 Data for Pennsylvania, which provides the total cases (not weekly) by age category as well as a joint report from the American Academy of Pediatrics and the Children's Hospital Association, which stated that the percentage of cases concerning children has been increasing and estimated this percentage to be approximately 11.5 percent nationwide during July 2020. We used this percentage to represent children from 0 to 19. To estimate the percentage of weekly incidence cases per 100,000 for elementary school students and high school students, we scale up the percentage of Pennsylvania's total cases that are associated with individuals between ages 0 and 9 (2,107 of 110,416 as of August 2, 2020) and with individuals between ages 10 and 19 (5,968 of 110,416 as of August 2, 2020) by an equal proportion to get a total of 11.5 percent. This leads to an estimate of 3 percent of cases for children ages 0 to 9 and 8 percent for those ages 10 to 19. To estimate the number of weekly incidence cases per 100,000 for elementary school students, we multiply the weekly incidence by 3 percent. For middle and high school students, we multiply the weekly incidence by 8.5 percent. For school staff, we use the percentage of total cases that are between ages 20 and 69 for adults (83,723 of 110,416, as of August 2, 2020), but we adjust this percentage proportionally downwards to reflect the increase in children-related cases. We convert the weekly incidence to daily incidence by dividing by 7.

These calculations result in the daily incidence for elementary school students, middle and high school students, and adults of 0.208, 0.590, and 5.03, respectively, per 100,000. To adjust for underreporting, each daily incidence is multiplied by 5 based on underreporting estimates from Penn State's Center for Infectious Disease Dynamics (2020) (estimated between 4 and 7) and the University of Texas (Fox et al., 2020) (estimated at 5); we refer to these quantities as the adjusted daily incidence.

To calculate the community background infection rates, we use the following equation to convert each of the adjusted daily incidence to a daily probability that a susceptible individual in the associated age category will acquire SARS-CoV-2 and develop COVID-19:

$$CBIR_{pop} = \frac{(Pop\ of\ Pennsylvania/100{,}000) * daily\ incidence_{pop}}{number\ susceptible_{pop}},$$

where "pop" is the population of interest (elementary school students, middle and high school students, or adults). To estimate the number of susceptible individuals, we subtract the number infected (adjusted for underreporting) from the total population for each population of interest. Based on U.S. Census data, 1,555,749 individuals in Pennsylvania are between ages 0 to 9, 1,714,835 are between ages 10 to 19, and 7,575,941 are between ages 20 and 69. These calculations result in the community background infection rates for elementary school students, middle and high school students, and adults of 8.63e-05, 2.24e-04, and 4.49e-04, respectively.

C. Infections at start of school

To estimate the probability that an individual is infected at the start of school (referred to as PIS), we use the following equation:

$$PIS_{pop} = (1 - \left(1 - CBIR_{pop}\right)^{14}),$$

where "pop" is the population of interest (elementary school students, middle and high school students, or adults) and 14 is the average length of the infection. Therefore, we anticipate the number of individuals who are infected at the start of school to be $PIS_{pop} * N_{pop}$, where N_{pop} is the number of individuals associated with that category at the school of interest. We assigned 6/14 of these individuals to Stage 2 (exposed) and the remaining to Stage 3 (infectious). The individuals in Stage 3 are stratified into asymptomatic and symptomatic based on the specified proportions.

Table A.1. Inputs for the characteristics of students, teachers, and support staff (reprinted from Gill et al., 2020)

Category	Parameter	Current estimates	Forecasted 2020-2021 school year[7]
Elementary school: total number of students in per grade	Kindergarten	71[1]	57
	1st grade	75[1]	60
	2nd grade	75[1]	60
	3rd grade	76[1]	61
	4th grade	78[1]	64
	5th grade	86[1]	69
Middle school: total number of students in per grade	6th grade	112[1]	90
	7th grade	128[1]	103
	8th grade	123[1]	99
High school: total number of students in per grade	9th grade	149[1]	120
	10th grade	153[1]	123
	11th grade	150[1]	128
	12th grade	147[1]	118
Students per class	K–5	21[2]	17
	6–8	23[2]	19
	9–12	22[2]	18
Professional and support staff per school	Teachers	36[3]	36
	Administrators and staff	37[4]	37
School bus	Students per bus	40[5]	32
	Percent riding the bus	79%[6]	79%

[1]Source: 2018-2019 Public School Enrollment Report restricted to LEA type school district (https://www.education.pa.gov/DataAndReporting/Enrollment/Pages/PublicSchEnrReports.aspx).

[2]Source: U.S. Department of Education, National Center for Education Statistics, National Teacher and Principal Survey (NTPS), "Public School Teacher Data File," 2017–2018. (http://blogs.edweek.org/edweek/inside-school-research/2020/05/crowding_and_the_coronavirus_b.html).

[3]Source: 2018-19 Professional Staff Summary Report (https://www.education.pa.gov/DataAndReporting/ProfSupPers/Pages/SupportStaffSum.aspx)

[4]Source: 2018-2019 Public School Support Personnel (https://www.education.pa.gov/DataAndReporting/ProfSupPers/Pages/SupportStaffSum.aspx)

[5]Based on communication with the Pennsylvania Bus Association on June 5, 2020.

[6]Based on the fraction of the 1,520,999 students who ride the bus daily (https://www.dmv.pa.gov/Pages/Pennsylvania-School-Bus-Statistics.aspx) over the 1,924,189 total student enrolled. (https://nces.ed.gov/ccd/elsi/expresstables.aspx?bridge=quickFacts&tableid=13&level=State&year=2018-19). These estimates are used for elementary, middle, and high schools.

[7]We have assumed that 20 percent of students will stay home from school voluntarily; this assumption is based on findings from surveys suggesting that many parents remain very concerned about infection risk and are considering keeping their children home (Murrieta Valley Unified School District, 2020; Page, 2020)

Table A.2. Inputs for the transmission probabilities

Category	Parameter	Parameter Value
Daily transmission rate for symptomatic adults per contact	Within classroom per period	0.16%[1]
	At lunch or recess	0.16%[2]
	Among teachers, administrators and staff at meetings	0.22%[3]
	On school buses	0.16%[4]
	Outside of school	Varies depending on local infection rate
Proportion asymptomatic	Children	50%[5]
	Teachers, administrators, and staff	50%[6]
Reduction in transmission	Infected individual is asymptomatic	50%[7]
	Infected and noninfected individual wearing a protective mask	40%[8]
	Infected individual practicing physical distancing (6 feet)	75%[9]
	Relative susceptibility of elementary school children versus adults of acquiring COVID-19	50%[10]
	The proportion of infected individuals that would self-isolate if they present with symptoms	95% of staff; 75% of students
	Proportion of positive test results reported to school	100% of staff; 90% of students

[1]Converted to a daily transmission probability based on a secondary attack rate of 12.8 percent for individuals with frequent close contacts (Bi et al., 2020). Assumes an entire school day is equivalent to having frequent close contacts with an individual.

[2]There is limited data on transmission rates due to contacts during lunch and recess. The only study we identified calculated a daily transmission probability of approximately 12 percent for their specific setting (Lu et al., 2020). However, this estimate is probably high due to selection bias in the settings investigated. To be conservative in estimating the impact of Scenario B, we set the daily transmission probability to be equivalent to estimates for individuals with frequent close contacts.

[3]Converted to a daily transmission probability based on a secondary attack rate of 3.0 percent for individuals with moderate contacts (Bi et al., 2020)

[4]There is limited data on transmission rates due to contacts on public transportation. To be conservative in estimating the impact of Scenario B, we set the daily transmission probability to be equivalent to estimates for individuals with frequent close contacts. We assumed a bus ride has a transmission risk approximately equivalent to a class period.

[5]CDC and the Office of the Assistant Secretary for Preparedness and Response: COVID-19 Pandemic Planning Scenarios from https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html

[6]CDC and the Office of the Assistant Secretary for Preparedness and Response: COVID-19 Pandemic Planning Scenarios from https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html

[7]At time of analysis, there is no clear evidence comparing the infectiousness of asymptomatic to symptomatic (Davies et al., 2020). For influenza, asymptomatic infections are about a third as infectious per social contact as persons with symptomatic infections (Van Kerckhove et al., 2013). Based on conversations with infectious disease modelers, a value of half (50 percent) was selected as plausible.

[8]Based on a conservative estimate from Leung et al., 2020.

[9]Based on a conservative estimate from https://www.livescience.com/face-masks-eye-protection-COVID-19-prevention.html, which reported a 88 percent reduction due to social distancing of 6ft.

[10]Park et al. 2020. Keeling et al. 2020 had estimated 63 percent for children across all ages, which is generally consistent with Park et al.'s subsequent finding of 50 percent for young children and no difference in susceptibility for older children.

Table A.3. Inputs for testing, tracing, and quarantining

Category	Parameter	Parameter value
If symptomatic, daily probability of recognizing symptoms	Children	75%
	Teachers, administrators, and staff	95%
If recognized symptomatic, daily probability of receiving a test	Children	75%
	Teachers, administrators, and staff	90%
Probability of reporting a test result to the school	Children	90%
Testing sensitivity	False positive rate	0.8%*
	False negative rate	3%^
Test result turnaround time	Days	Varies: 0, 2, 5, 7, or 10
Contact tracing of individual with a reported positive test result^^	Days before symptomatic individual developed symptoms	2
	Days before asymptomatic individual received the positive result	2
Quarantine duration	Days after the onset of recognized symptoms in a symptomatic individual	10
	Days after receipt of positive test result of an asymptomatic individual	10
	Days from last contact with individual that has tested positive	14

* See Cohen and Kessel, 2020.

^ See Gressman and Peck, 2020.

^^ See https://www.health.pa.gov/topics/disease/coronavirus/Pages/Guidance/Contact-Tracing-Process.aspx

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Appendix B

Outcomes for different school circumstances

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The graphs in the 12 pages that follow are intended to provide guidance for schools in specific circumstances. We provide results that distinguish three school types (elementary schools, typical secondary schools, and large secondary schools); four different levels of community infection; three strategies for responding to detected infections; and three general types of operating strategy: full-time, business-as-usual without precautions (Scenario A); full-time with masks and reduced student mixing (Scenario B); and part-time hybrid with students divided into two groups, each of which attends two days a week (Scenario E). In other words, the twelve pages of graphs provide results that encompass 108 combinations of school types, community infection levels, closing policies, and operating strategies.

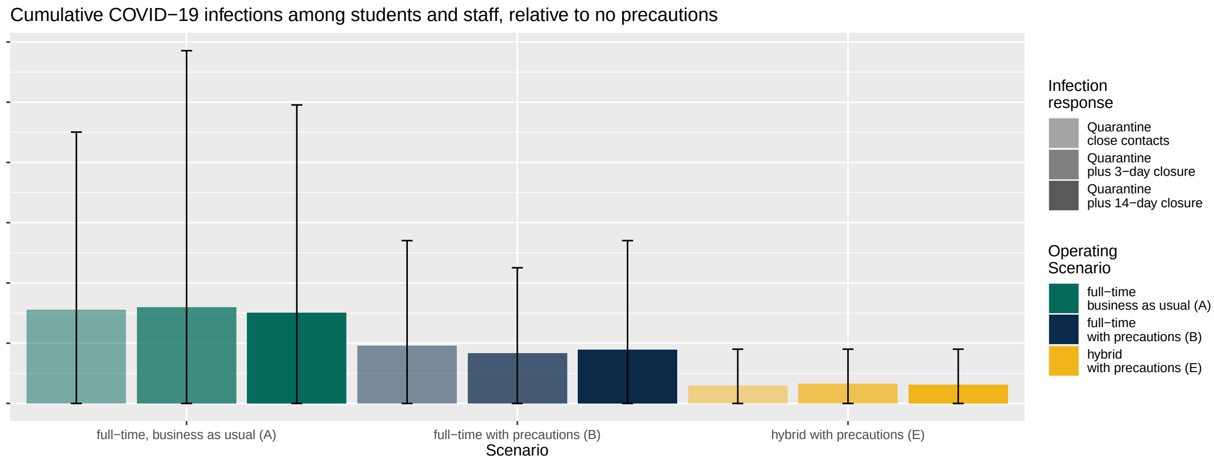
We chose to limit the number of combinations presented to avoid making the presentation overly complicated. We simplified the presentation in two ways:

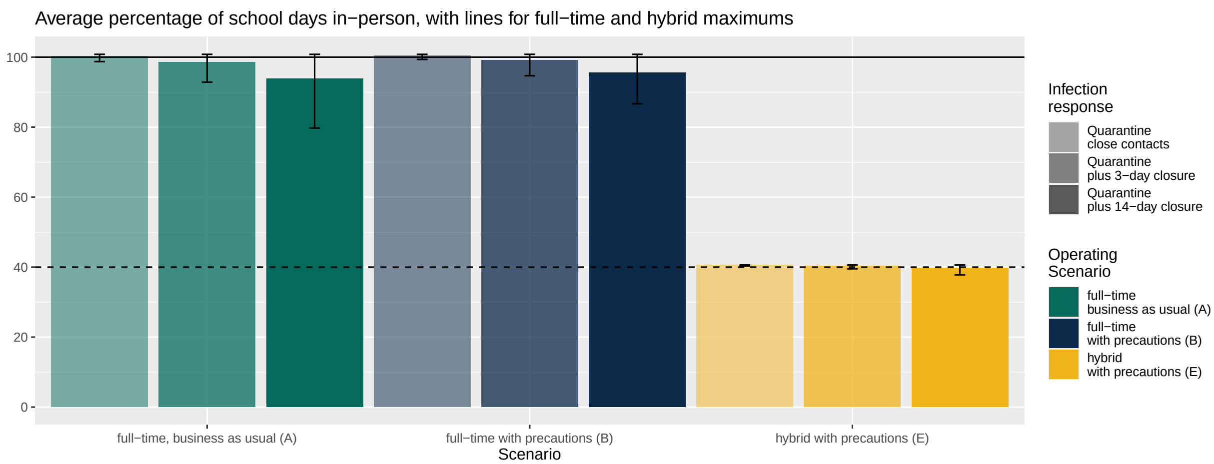
- We show only three operating scenarios rather than all seven. As discussed in the main body of the report, results for Scenarios C and D are not substantially different from Scenario B; results for Scenario F are very similar to those of Scenario E. Any schools using a one day per week hybrid approach (Scenario G) can assume that the results of Scenario F will provide a conservative estimate of their own results.
- We do not show variations in results based on differences in COVID-19 testing response time because those differences had little or no effect on results in most circumstances, as discussed in the main body of the report. All the results in this appendix are based on simulations assuming a two-day delay in receiving test results, but the results do not differ substantially for longer test response times.

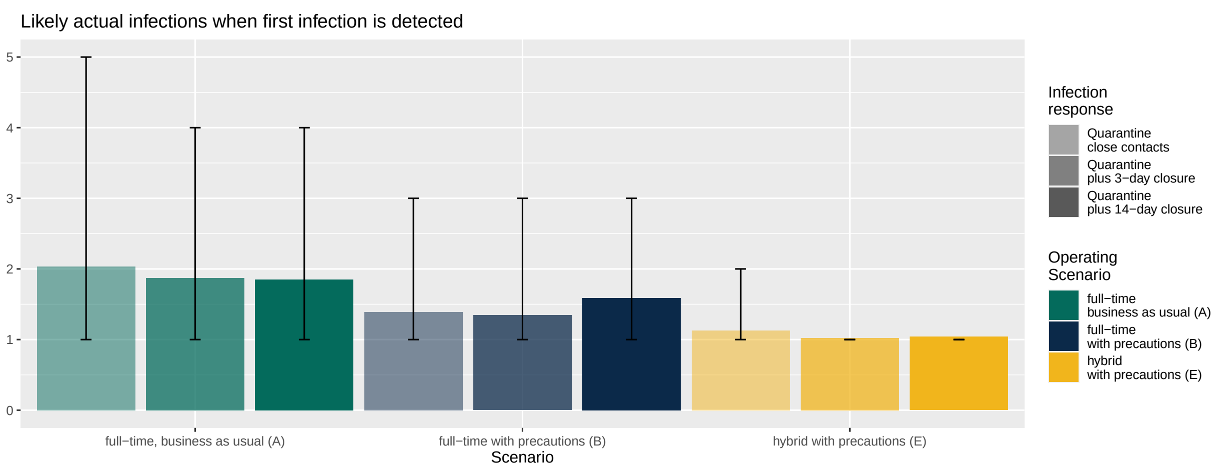
Each page that follows shows results for one of three school types (elementary, typical secondary, and large secondary) and one of four levels of community infection (10, 25, 50, and 100 per 100,000 per week)—as indicated at the top of the page. Each page shows results for Scenarios A (business as usual), B (full-time with precautions), and E (part-time hybrid), stratified by the three policies for responding to detected infections (no closure, 3-day closure, and 14-day closure). Three graphs are included on each page: the first shows relative cumulative infections in the school; the second shows the average percentage of school days that the typical student could attend in person; and the third shows the likely number of total infections (symptomatic and asymptomatic) in the school at the time the first infection is detected. Results for the first chart—cumulative infections—should not be compared across pages because the scales are different on each page.

School Type: Elementary (non-departmentalized)

Community infection (per 100,000 per week): 10





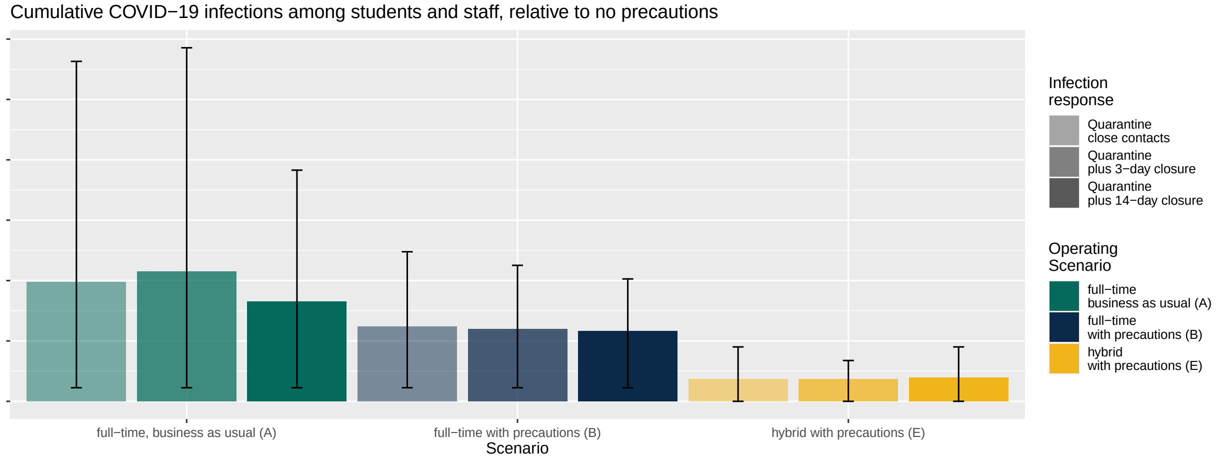


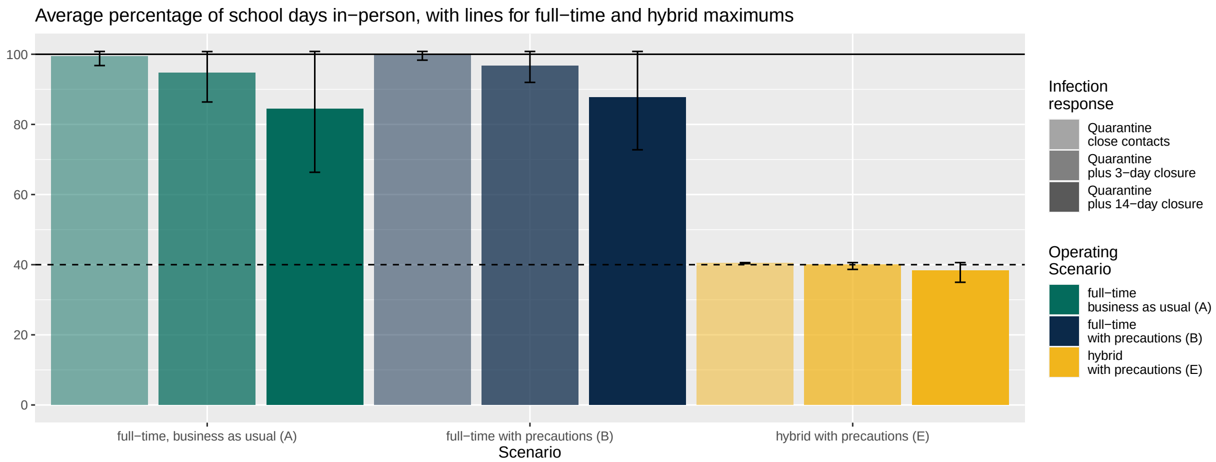
Notes:

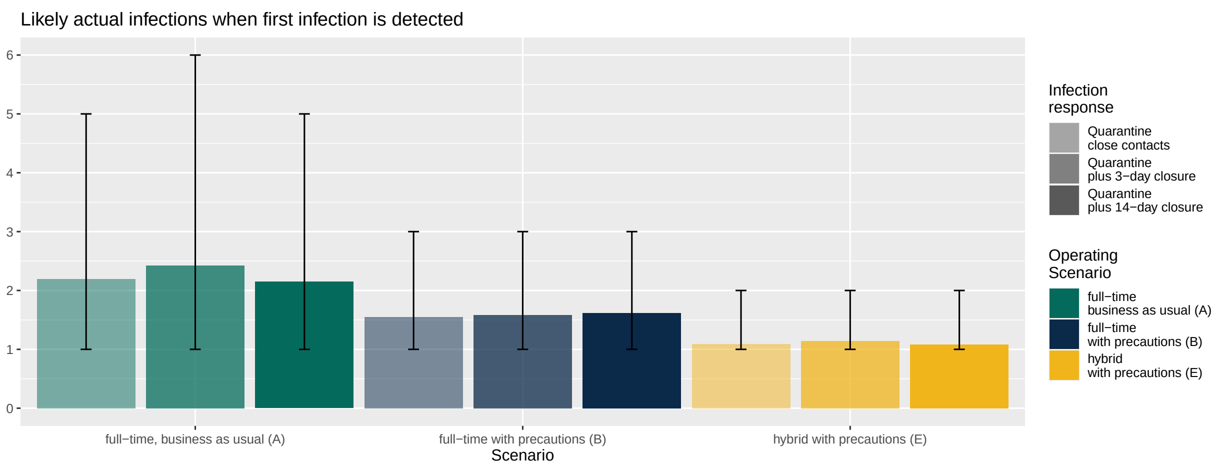
1. Whisker lines for each bar indicate the range of expected outcomes for 90 percent of schools, accounting for the random variation in infections.
2. These simulations assume that COVID-19 test results are returned in 2 days. Simulations that assume longer delays in receiving test results do not substantially change the outcomes shown.

School Type: Elementary (non-departmentalized)

Community infection (per 100,000 per week): 25







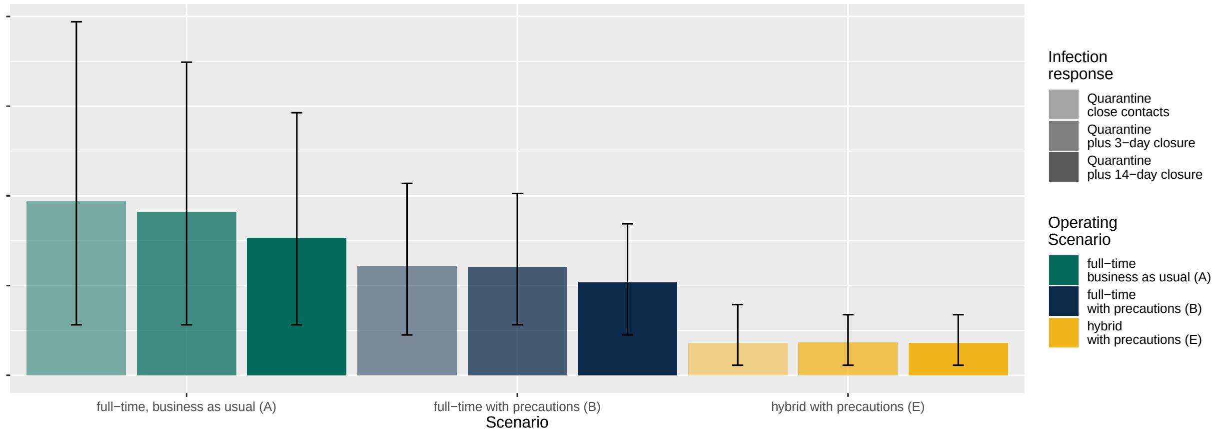
Notes:

1. Whisker lines for each bar indicate the range of expected outcomes for 90 percent of schools, accounting for the random variation in infections.
2. These simulations assume that COVID-19 test results are returned in 2 days. Simulations that assume longer delays in receiving test results do not substantially change the outcomes shown.

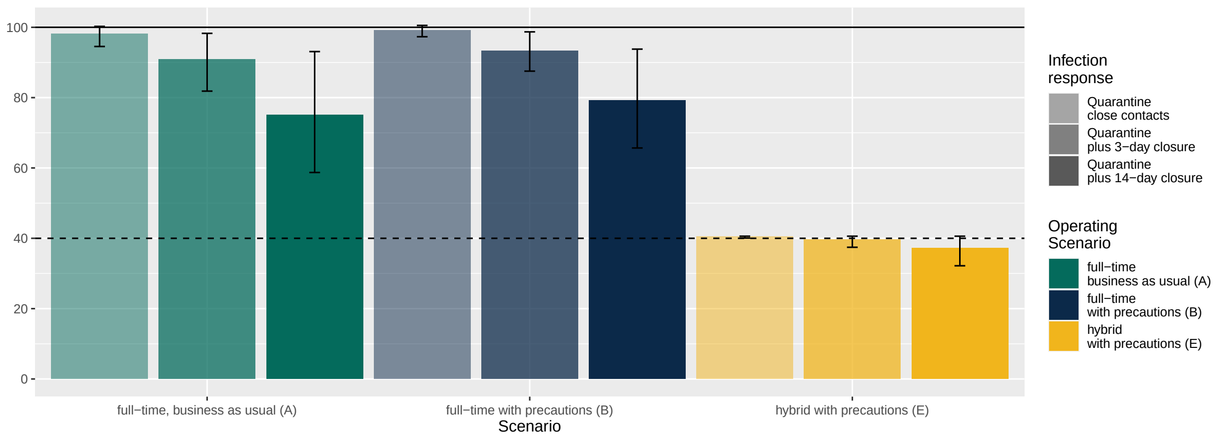
School Type: Elementary (non-departmentalized)

Community infection (per 100,000 per week): 50

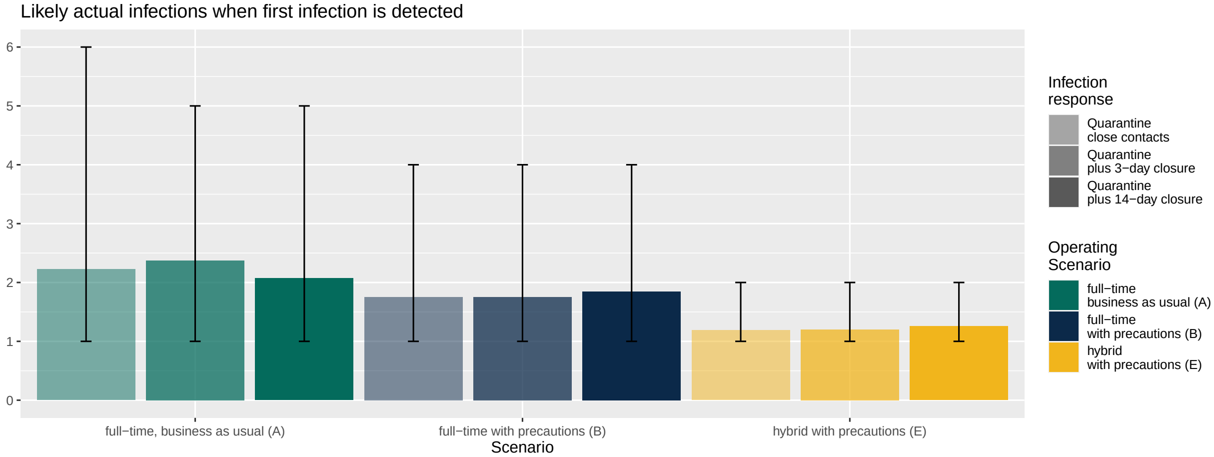
Cumulative COVID−19 infections among students and staff, relative to no precautions



Average percentage of school days in−person, with lines for full−time and hybrid maximums



Likely actual infections when first infection is detected

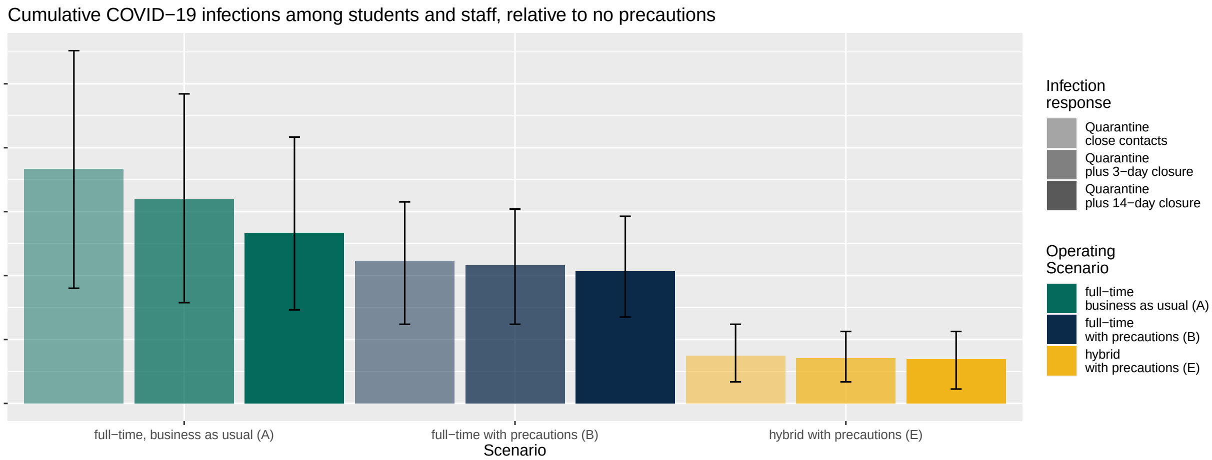


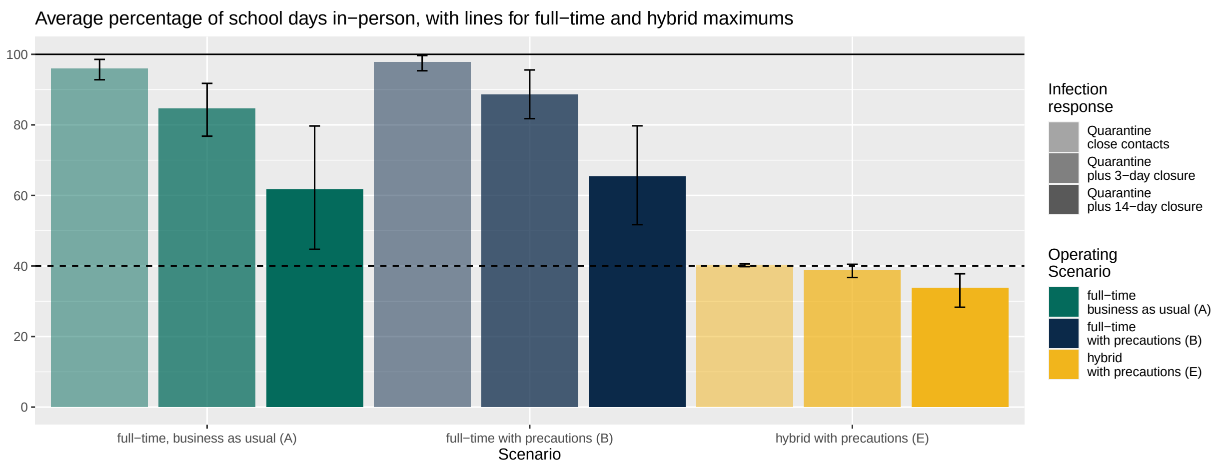
Notes:

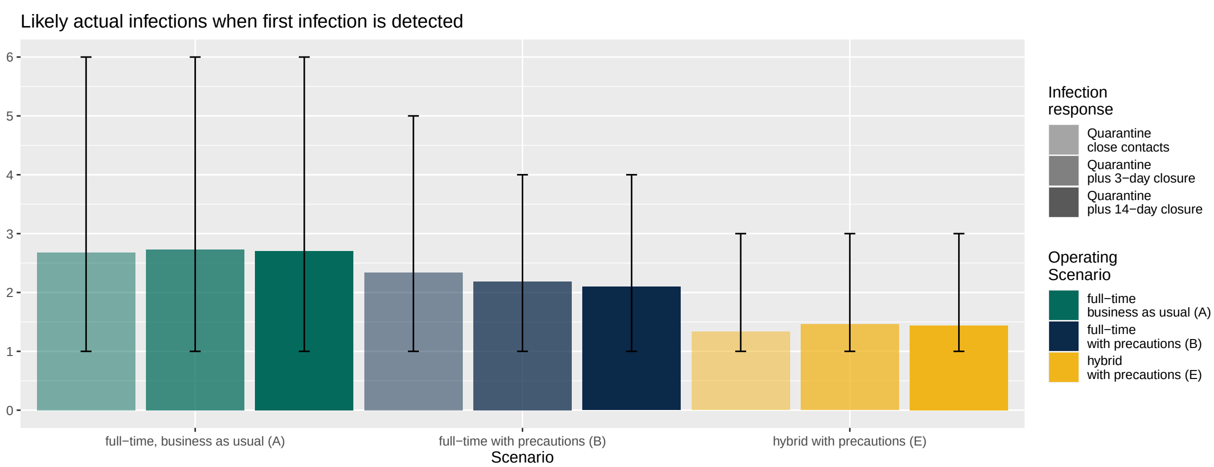
1. Whisker lines for each bar indicate the range of expected outcomes for 90 percent of schools, accounting for the random variation in infections.
2. These simulations assume that COVID-19 test results are returned in 2 days. Simulations that assume longer delays in receiving test results do not substantially change the outcomes shown.

School Type: Elementary (non-departmentalized)

Community infection (per 100,000 per week): 100





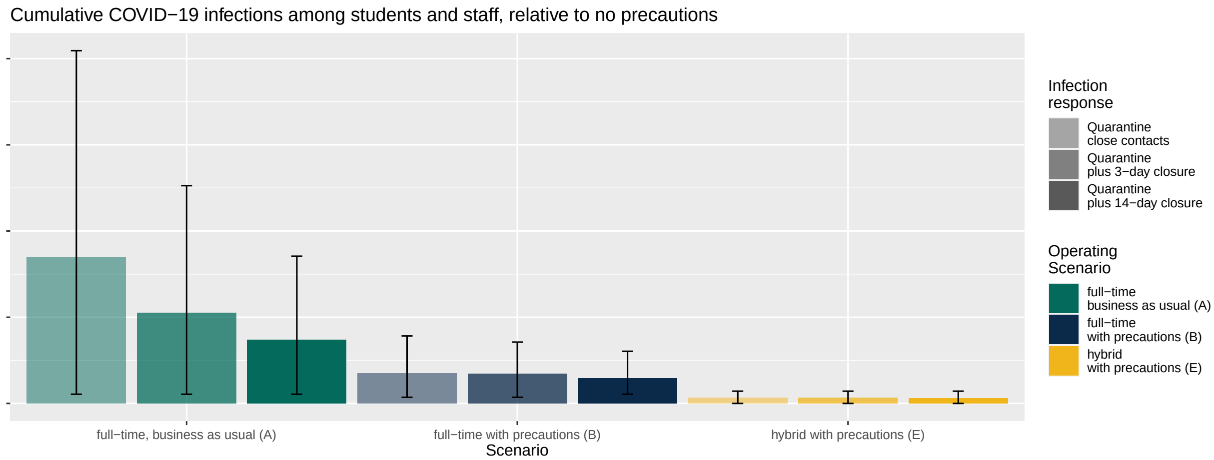


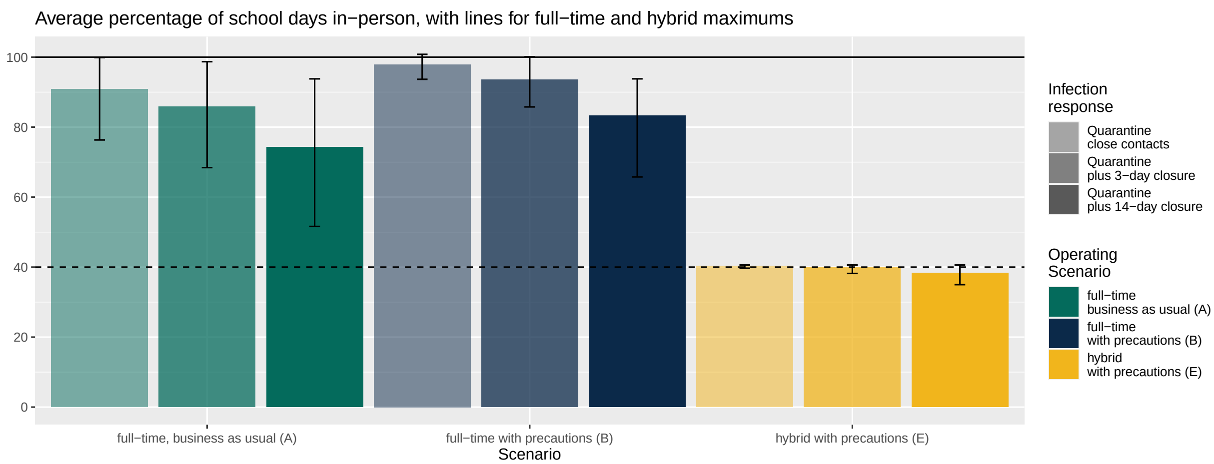
Notes:

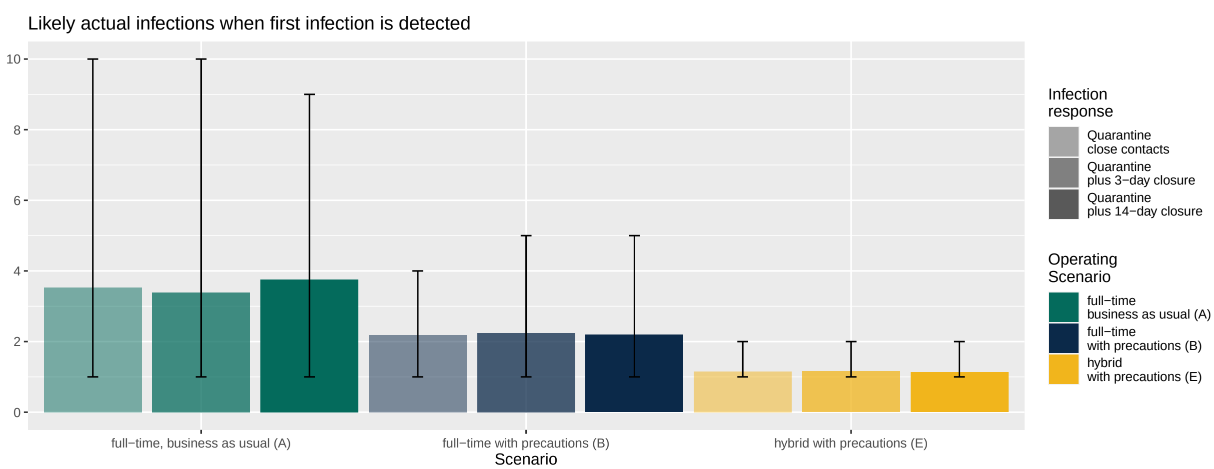
1. Whisker lines for each bar indicate the range of expected outcomes for 90 percent of schools, accounting for the random variation in infections.
2. These simulations assume that COVID-19 test results are returned in 2 days. Simulations that assume longer delays in receiving test results do not substantially change the outcomes shown.

School Type: Small secondary (~550 students and staff)

Community infection (per 100,000 per week): 10







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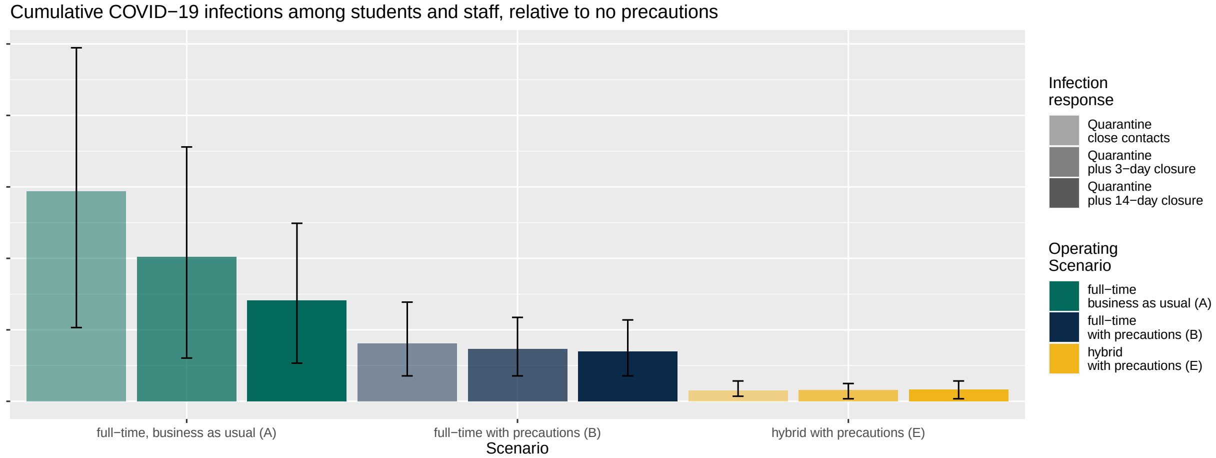
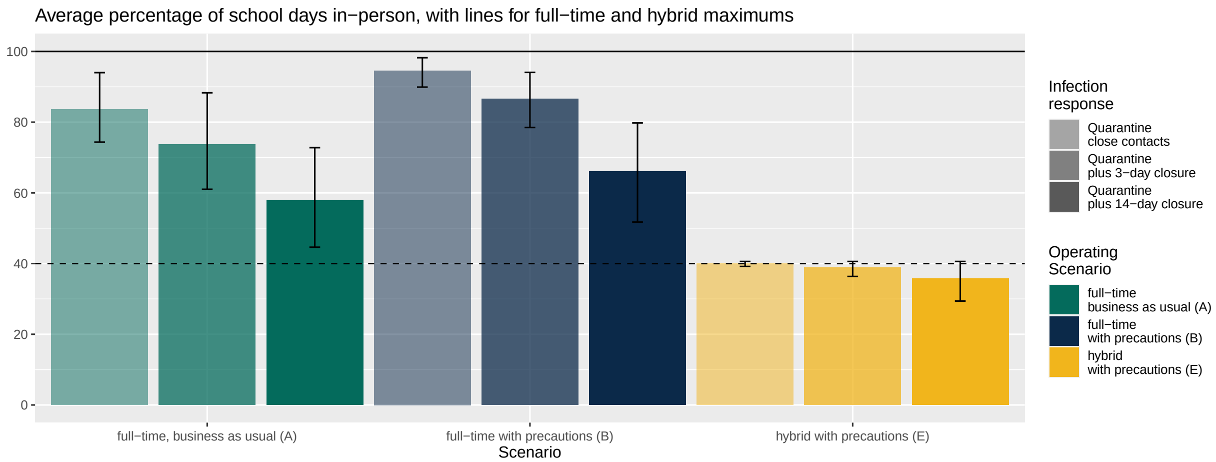
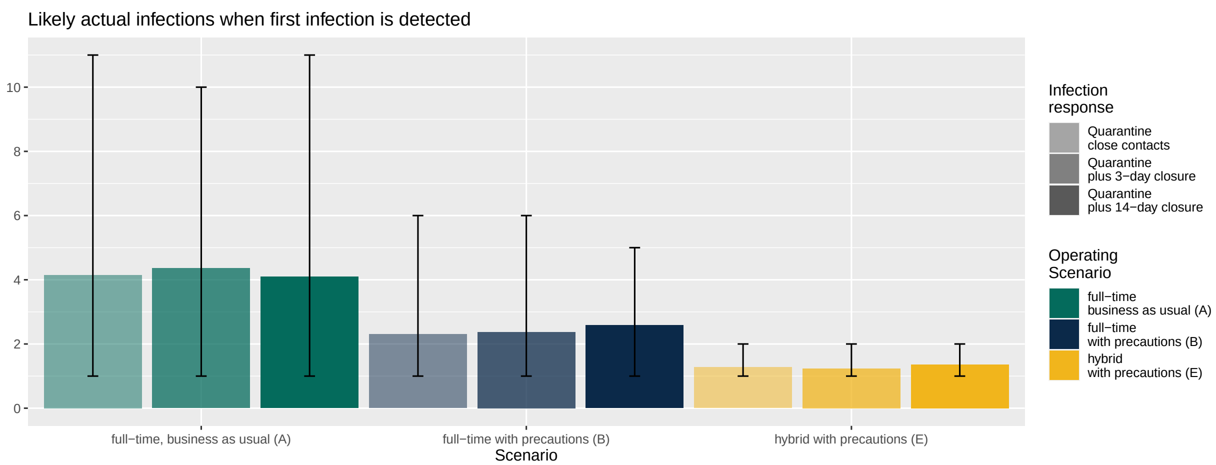
School Type: Small secondary (~550 students and staff)

Community infection (per 100,000 per week): 25







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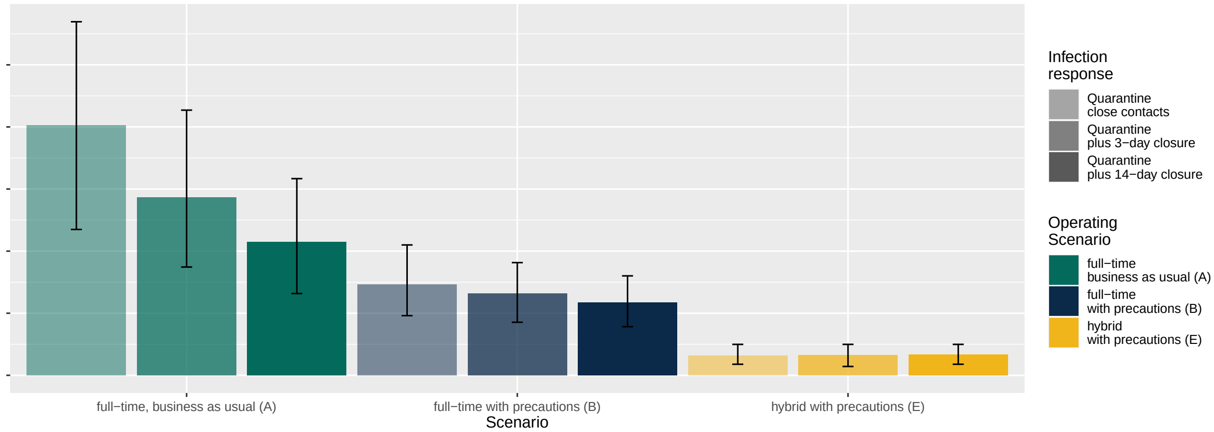
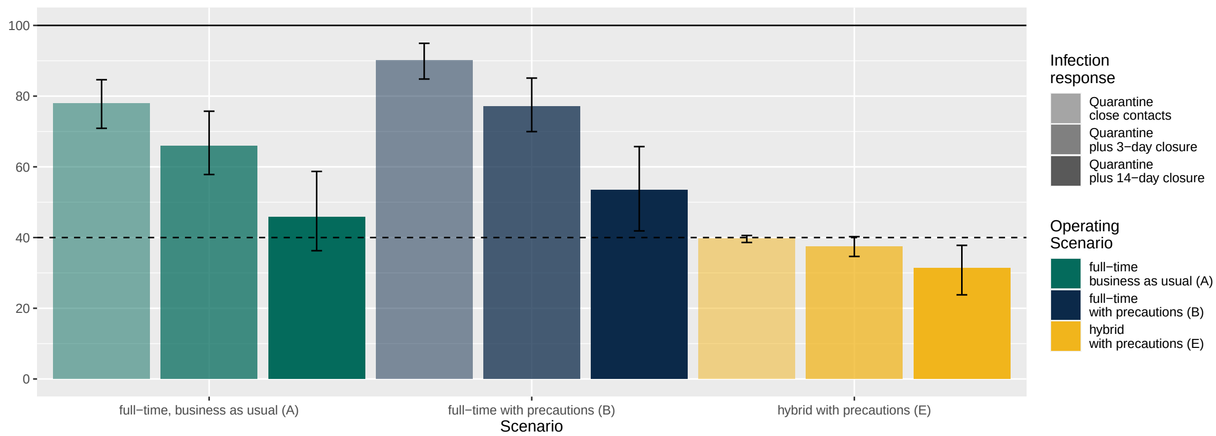
School Type: Small secondary (~550 students and staff)

Community infection (per 100,000 per week): 50

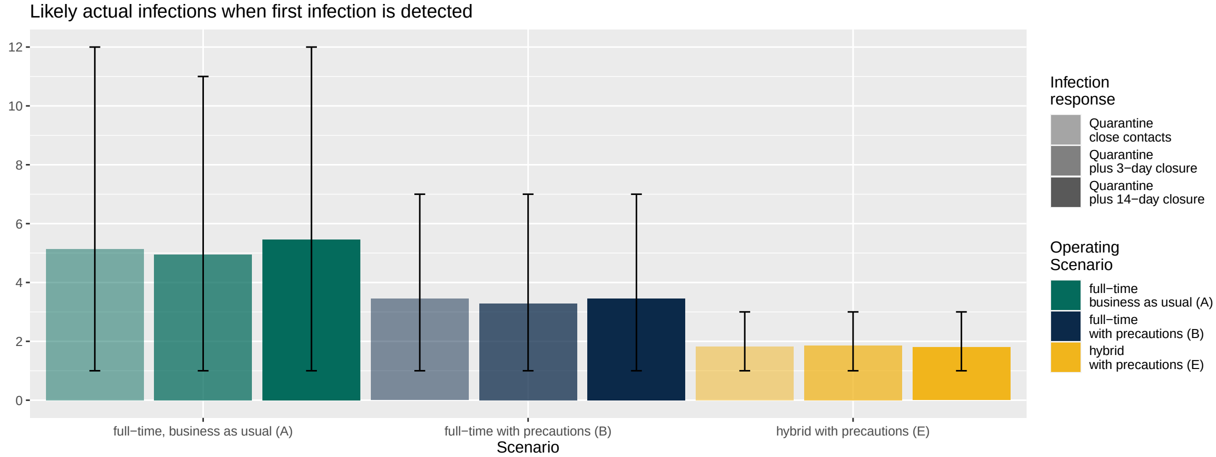
Cumulative COVID−19 infections among students and staff, relative to no precautions



Average percentage of school days in−person, with lines for full−time and hybrid maximums



Likely actual infections when first infection is detected



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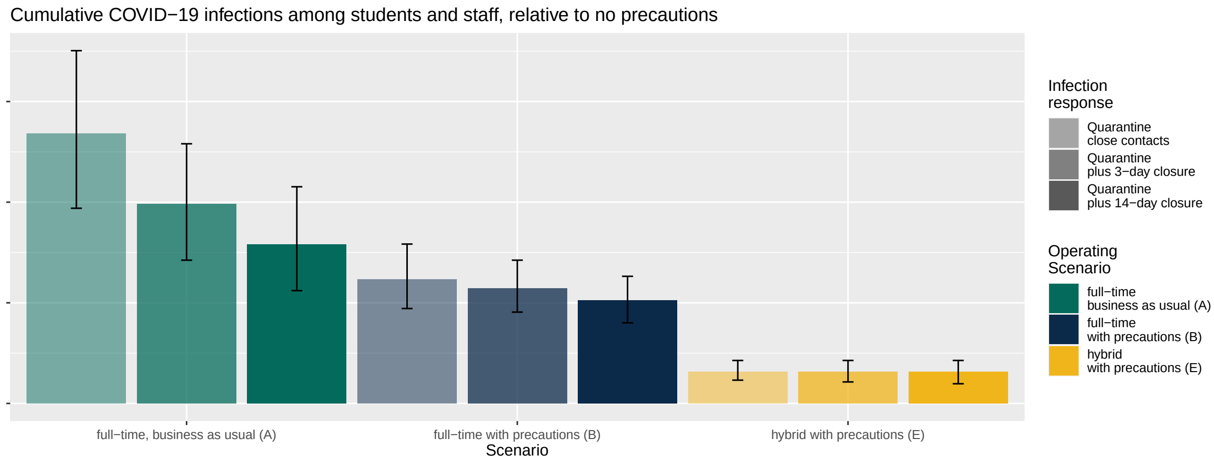
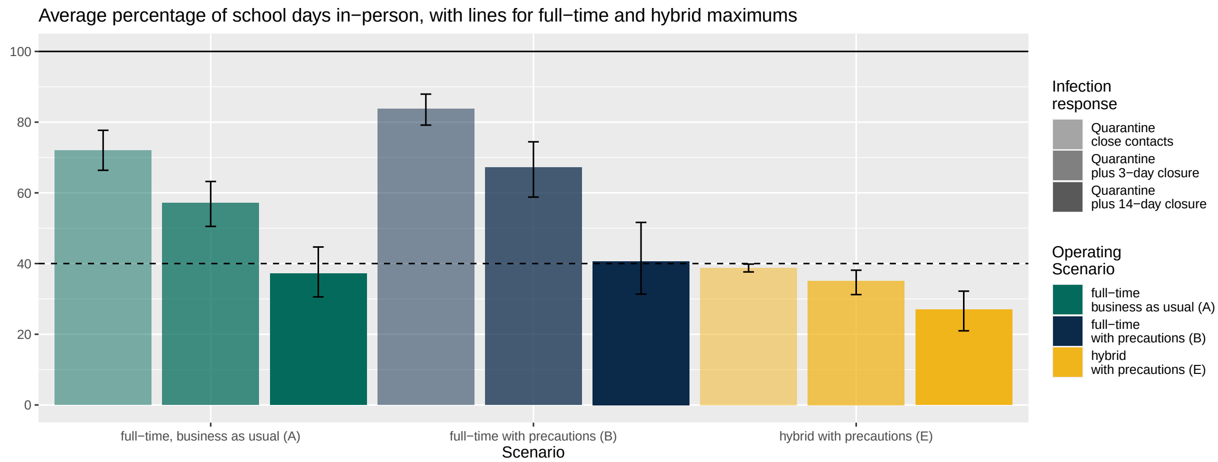
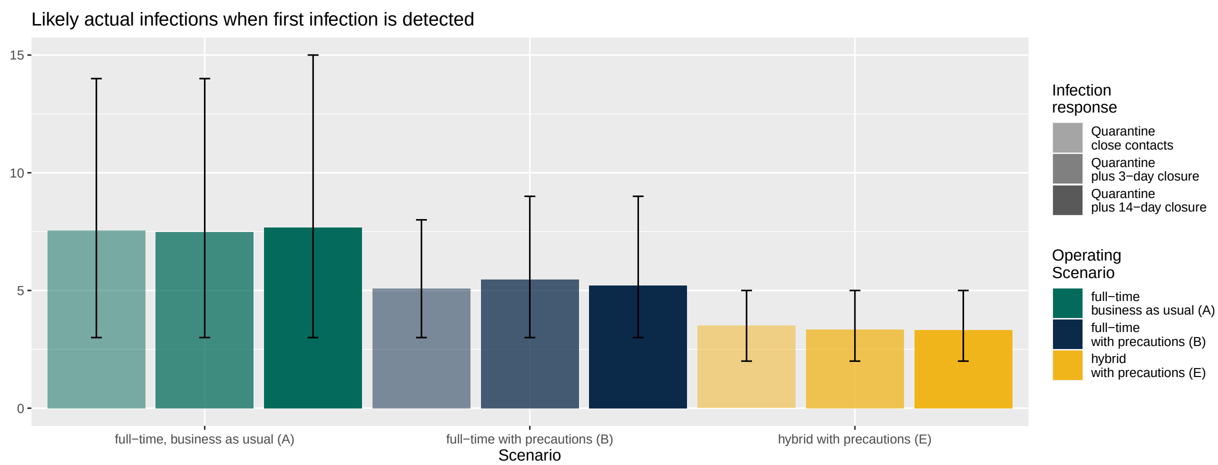
School Type: Small secondary (~550 students and staff)

Community infection (per 100,000 per week): 100







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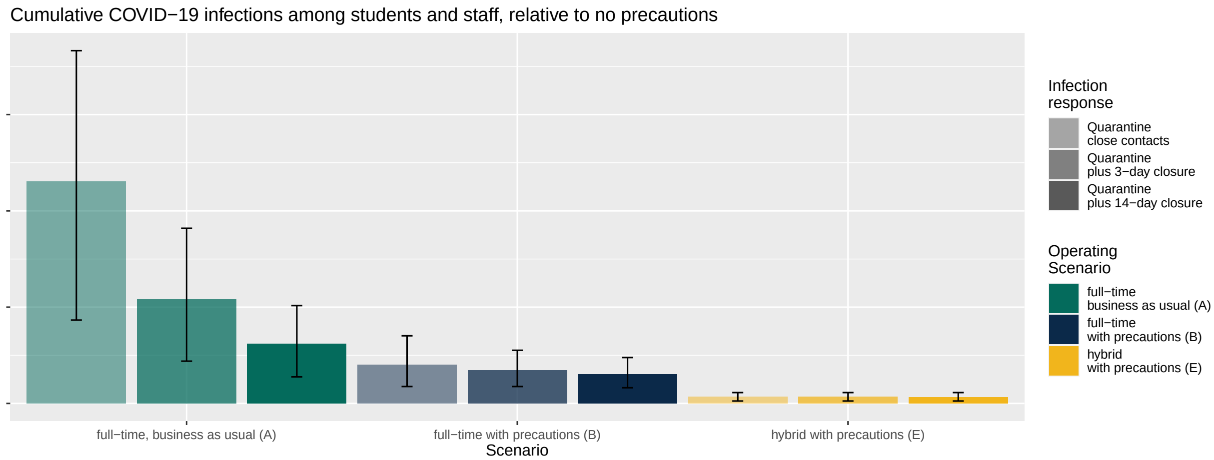
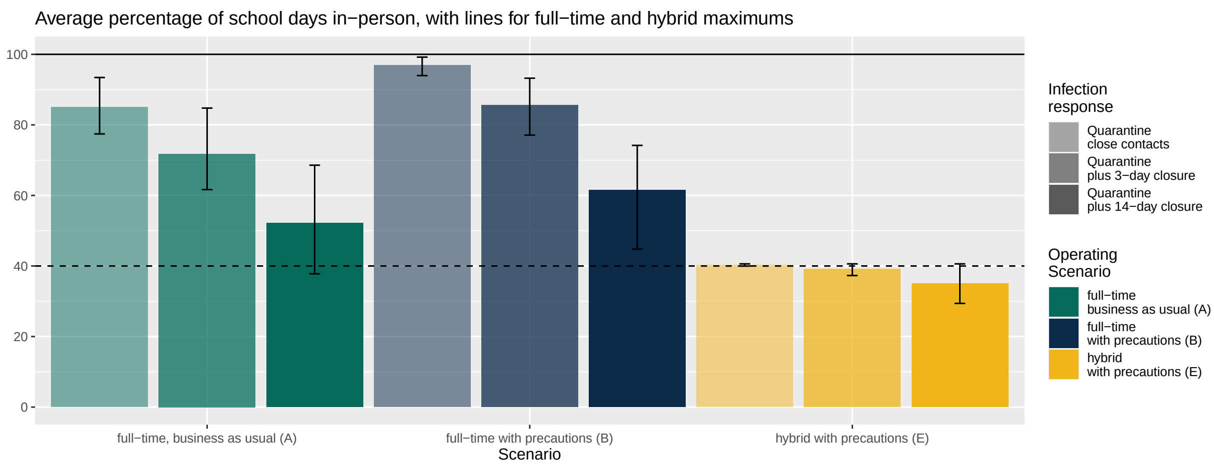
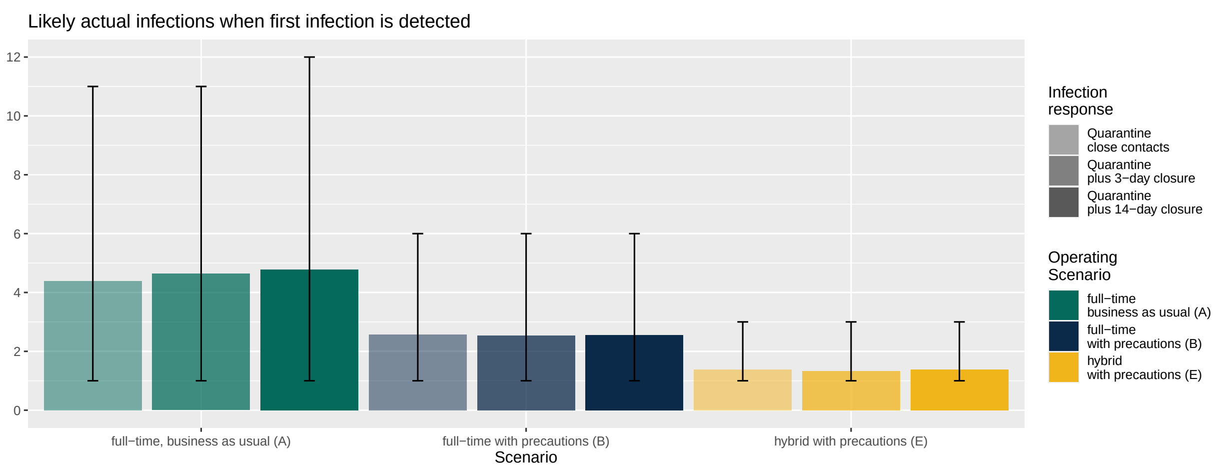
School Type: Large secondary (~1600 students and staff)

Community infection (per 100,000 per week): 10







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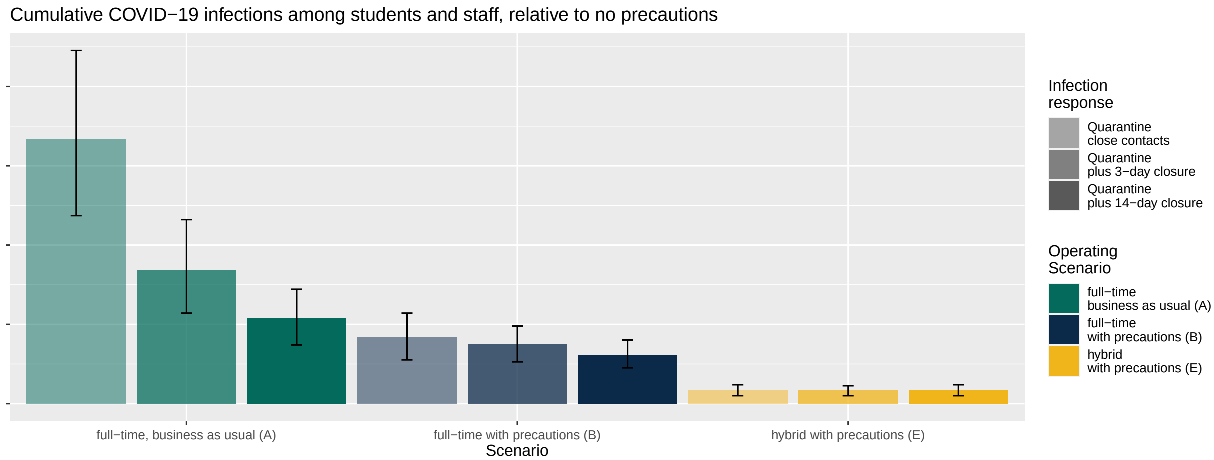
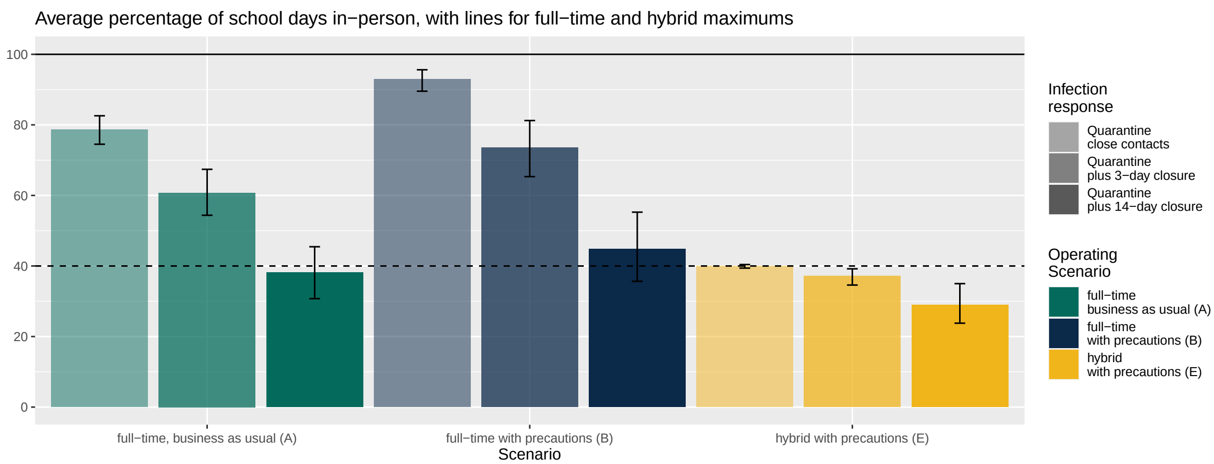
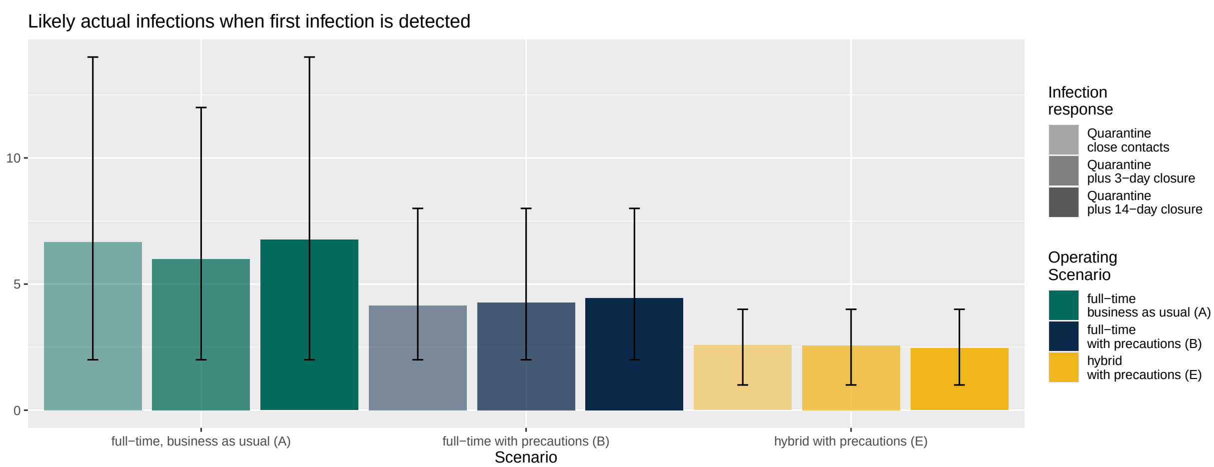
School Type: Large secondary (~1600 students and staff)

Community infection (per 100,000 per week): 25







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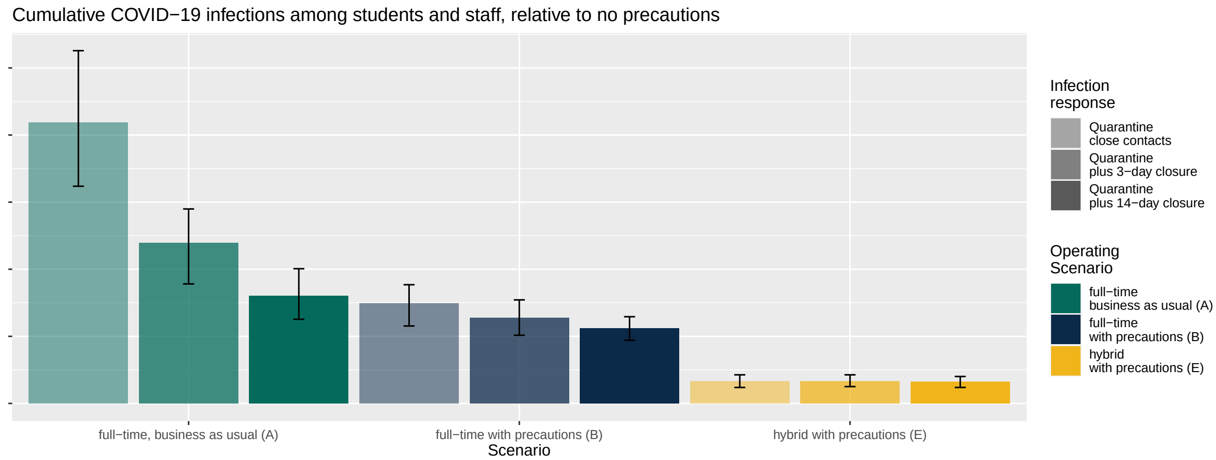
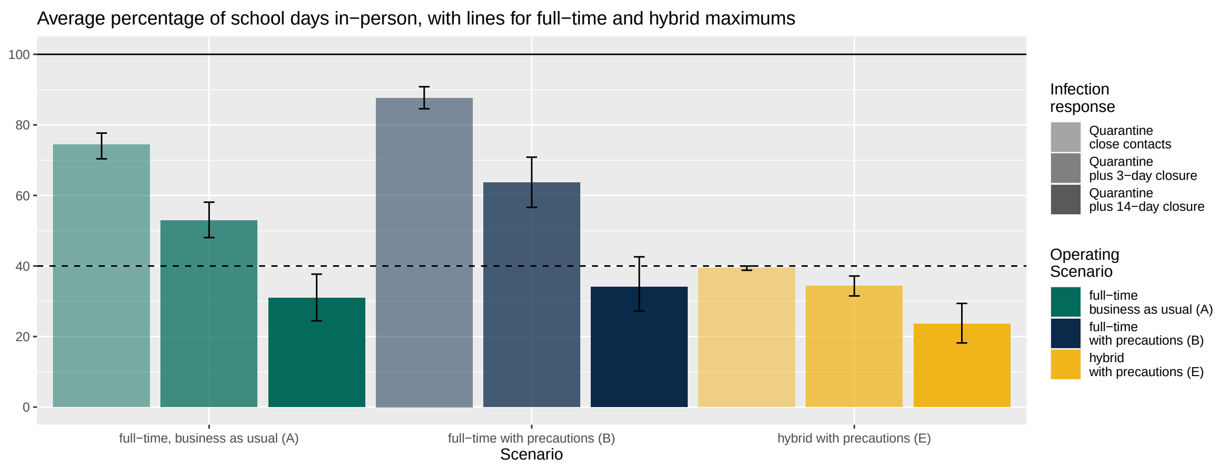
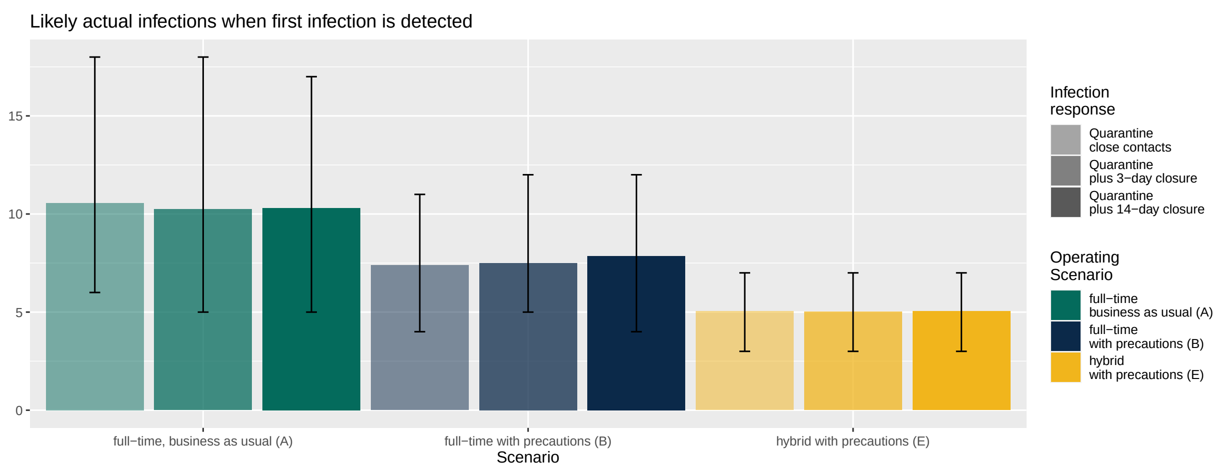
School Type: Large secondary (~1600 students and staff)

Community infection (per 100,000 per week): 50







Notes:

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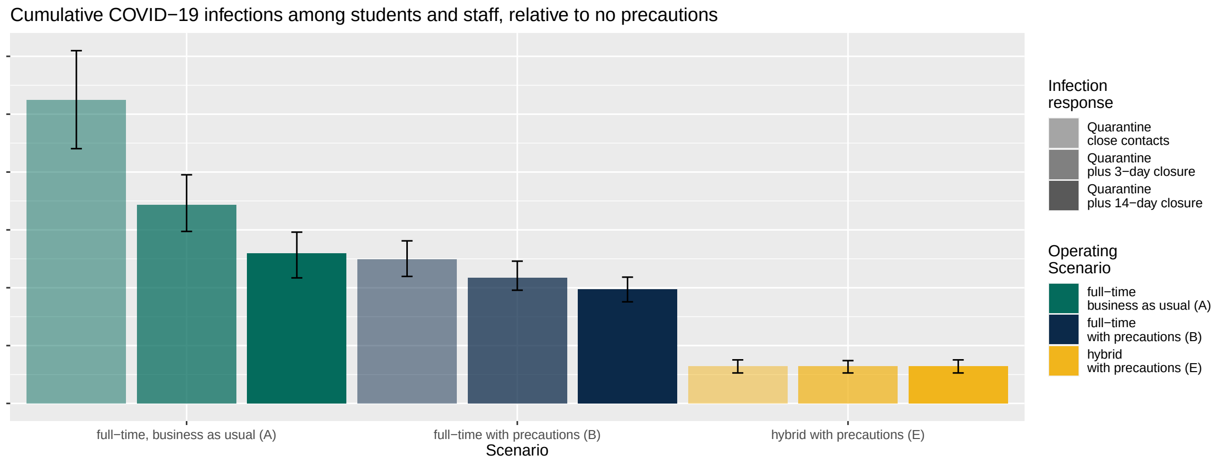
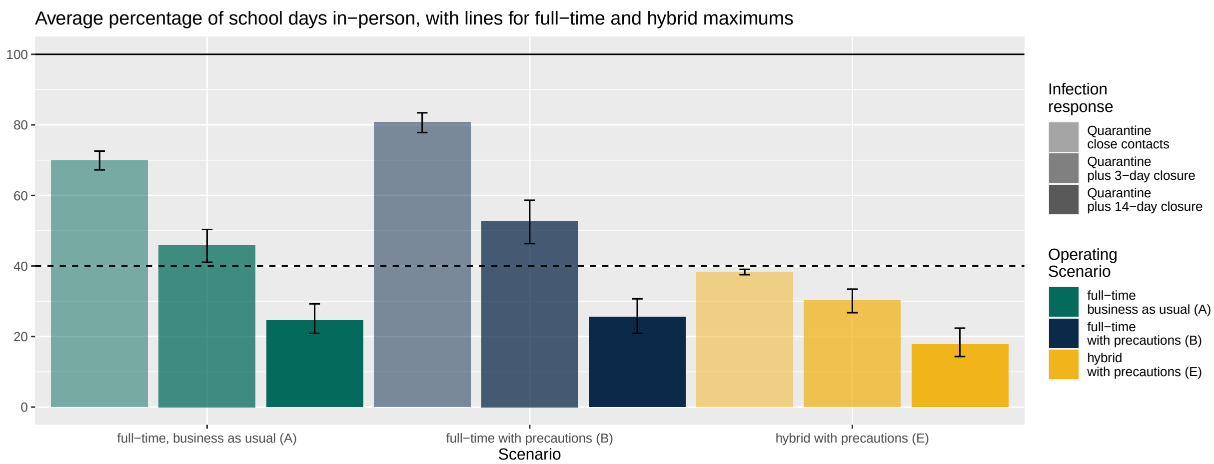
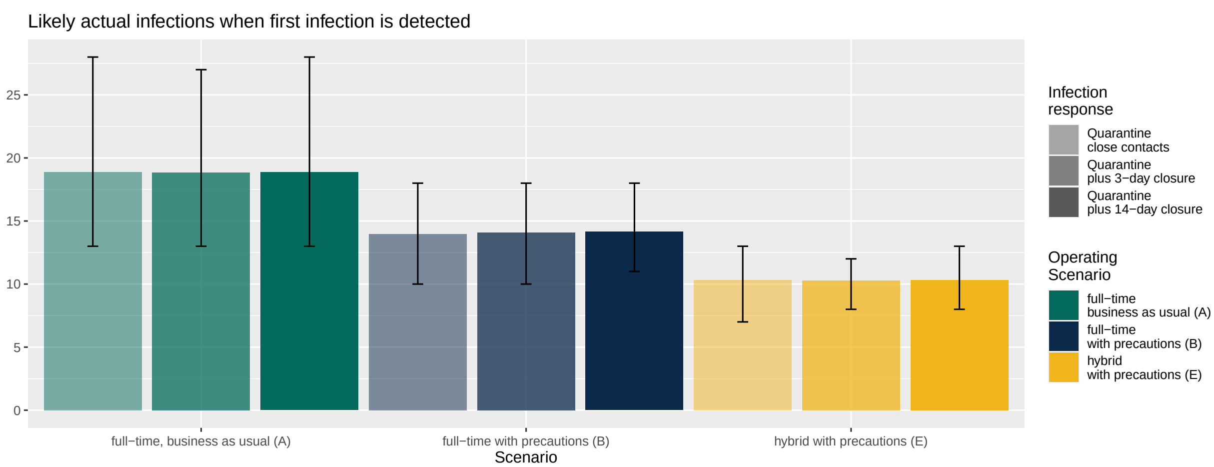
School Type: Large secondary (~1600 students and staff)

Community infection (per 100,000 per week): 100







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