Work package 2.3: Schools

Executive summary

Returning students to in-person learning and keeping schools open has been identified as a national priority. This work assesses the effectiveness of a variety of school-based surveillance, contact tracing and quarantine strategies to prevent outbreaks, reduce transmission in schools, and maximize face-to-face teaching.

Key findings

1. **Early infection detection and high vaccine coverage markedly reduce outbreak risk.**
2. **Allowing ongoing school attendance for class contacts of a case through a 'test to stay' strategy achieves equivalent outbreak containment to home quarantine and enables face to face learning.**
    - This was true for primary and secondary schools.
    - The effectiveness of test-to-stay requires at least partial compliance with testing.
    - The high frequency of testing compensates for the reduced sensitivity of rapid antigen tests.
3. **Regular screening of students in areas at risk of outbreaks can result in even fewer infections and in-person teaching days lost.**
    - By detecting cases faster, there are fewer infections present when the first diagnosis is made and a lower risk of larger outbreaks occurring.
    - Identifying and isolating cases earlier leads to fewer downstream cases requiring isolation.
    - This was true for primary and secondary schools.
4. **School based surveillance testing will have maximum utility in areas with higher-than-average transmission.**
    - The benefits of student surveillance testing for reducing infections and days of face-to-face teaching lost increase as incursion rates increase.
    - More frequent screening provides greater benefits.
5. **Surveillance of teachers had minimal benefit for reducing outbreaks in schools.**
    - Teachers only comprise a small proportion of the school community.
    - However, this analysis only considered outcomes following an incursion in a school, and does not capture potential benefits that screening teachers may have on preventing of incursions.
6. **Findings are sensitive to assumptions for the number of non-classroom contacts students have.**
    - Quarantine or test-to-stay strategies focus on classroom contacts rather than close contacts as they are more practical to identify.
    - Strategies are less effective if a greater proportion of risk comes from non-class contacts.

This analysis focuses on transmissions taking place within schools, and does not consider the benefits of community public health responses on reducing incursions into schools, nor the benefits of school closure on reducing overall community transmission.

Background and aims

Background

Returning students to in-person learning and keeping schools open has been identified as a national priority.

The current public health response to COVID-19 cases in schools involves school closure following a positive case for cleaning (often three days), as well as 7 or 14-day quarantine for all close contacts and their households. If schools reopen with high levels of COVID-19 transmission in the community, rates of incursions into schools will also be higher, and the current approach to managing cases in schools may be unsustainable and inconsistent with the national priority of maximizing face-to-face teaching. Equally, allowing infections to spread within schools and the school community can lead to adverse health outcomes for students, their households and family members (e.g., parents and grandparents). Hence, different approaches to managing cases in schools and keeping schools open may be required.

Aim and scope of work

This work assesses the effectiveness of a variety of school-based surveillance, quarantine and testing strategies to determine which are likely to be the most appropriate for preventing outbreaks, reducing transmission in schools, and maximizing in-person learning. Due to the different epidemic situations across the country, the analysis is conducted for differing levels of community transmission and school incursion rates.

The analysis does not consider the benefits of community public health responses on reducing incursions into schools, nor the benefits of school closure on reducing overall community transmission. Reduced community transmission would lead to reduced school incursions, and the impact of higher or lower incursion rates are tested in sensitivity analyses.

The modelling considers primary and secondary schools and does not consider early learning or specialized settings (e.g., specialist schools and boarding schools).

Methods

Model overview

We used an established agent-based microsimulation model, *Covasim* [1], developed by the Institute for Disease Modelling (USA) and previously adapted by the Burnet Institute to model epidemics in Australia [2-5]. The model is open-source and available online [6]. Additional model details are provided in the appendix.

For this analysis, primary and secondary schools are modelled to have different social and mixing networks within and so are reported on separately.

Primary schools

Primary schools are modelled as a collection of classrooms, aggregated into schools. Each student is assigned to a classroom with others of the same age, and each classroom has an assigned teacher (Figure 1). Primary school mixing includes student-student contacts within classrooms, student-student contacts between students in different classrooms, teacher-teacher contacts and teacher-student contacts within the classrooms that they are assigned to.

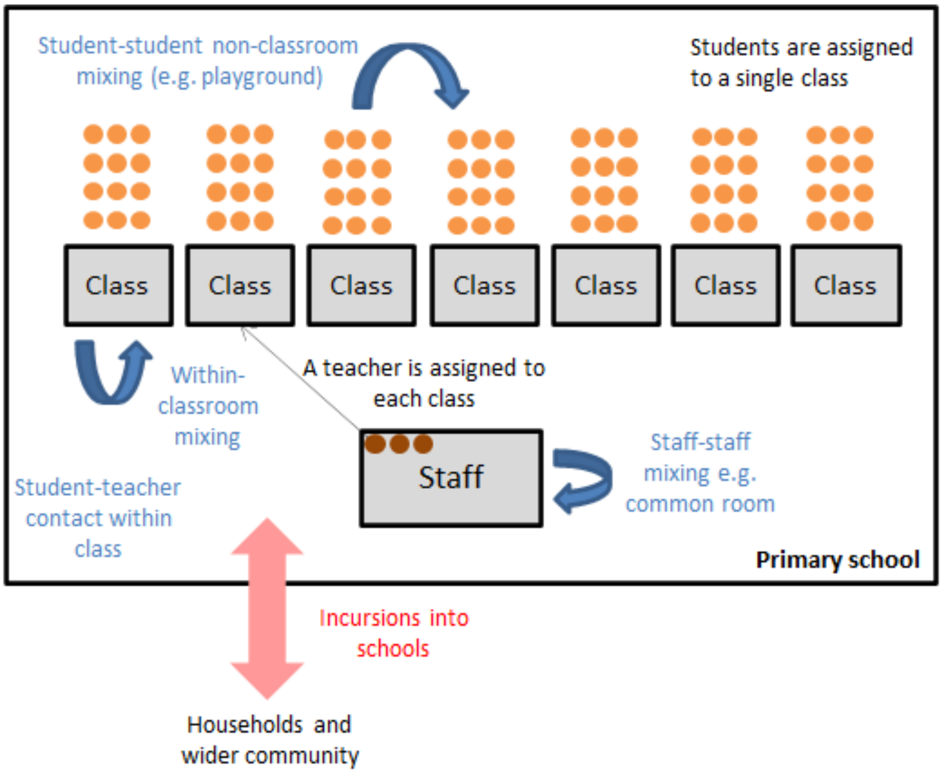


Figure 1: Contact networks within primary schools in the model. Primary schools are modelled as a collection of classrooms, where students of the same age are assigned a teacher. Primary schools include student-student classroom contacts, student-student non-classroom contacts, teacher-teacher contacts and teacher-student contacts.

Secondary schools

Secondary schools are modelled with a lower emphasis on assigned classrooms reflecting attendance at classes for multiple core and elective subjects. Hence secondary school students have a greater number of classroom contacts than primary school students. Secondary schools in the model include student-student classroom contacts, student-student non-classroom contacts, teacher-teacher contacts and teacher-student contacts (Figure 2).

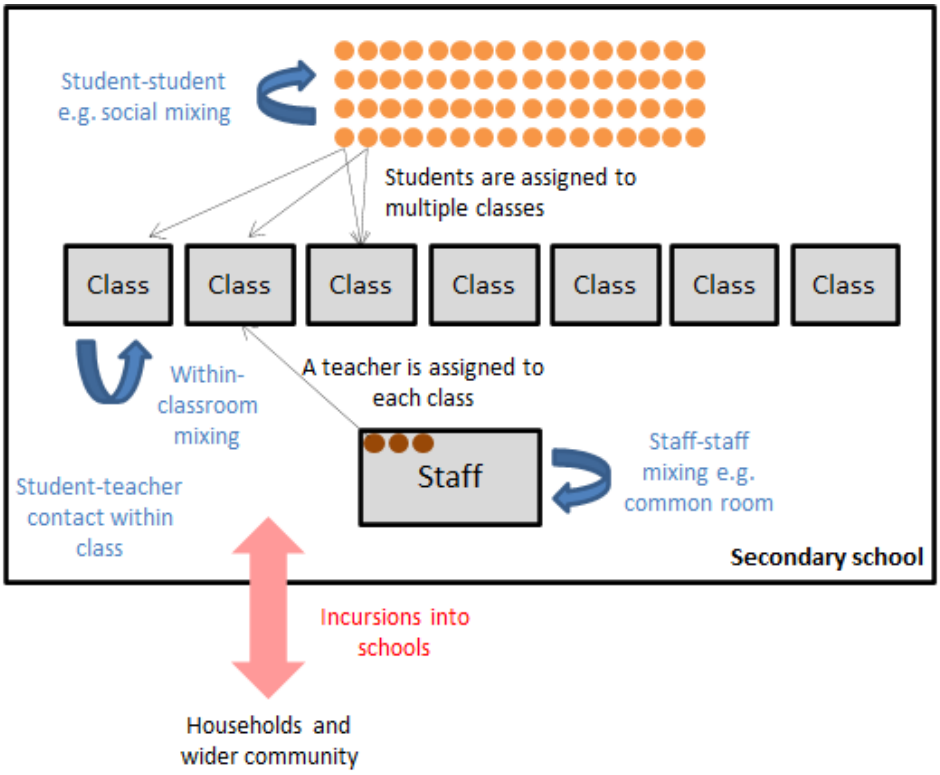


Figure 2: Contact networks within secondary schools in the model. Secondary school mixing includes student-student classroom contacts, student-student non-classroom contacts, student-teacher contacts, and teacher-teacher contacts. Secondary school students have more contacts than primary school students because they attend multiple classes.

Transmission in schools

Transmission is modelled to occur when a susceptible individual is in contact with an infectious individual through one of their contact networks. The overall transmission probability per contact per day has been calibrated based on the delta variant epidemic wave in Melbourne over the July-September 2021 period [5]. For individual contacts this transmission risk is further weighted according to the setting of the contact (e.g., classroom, home), the time-varying viral load of the person infected, whether or not they have symptoms (based on an age-specific probability of being symptomatic), and an age-specific disease susceptibility (Table 1).

Symptomatic testing probability (COVID-19 cases)

All people with severe disease are assumed to be tested. For people with mild symptoms, the model includes a per-day probability of seeking a test, which is necessary for the first case to be diagnosed when surveillance is not in place (noting that the first case to be detected may be a household member of a student at the school, which would trigger contact tracing for the student). Symptomatic testing assumes that people who have mild symptoms and are not identified through contact tracing or exposure site notification will seek testing during their symptomatic period with a per-day testing probability of 11% (varied in a sensitivity analysis).

The rest of the community

The non-school community is included in the model, to capture dynamics such as infected students transmitting to household members. This is relevant because adult household members who become infected may be more likely to seek symptomatic testing leading to detection of the outbreak, or siblings who become infected at home can reintroduce the infection to the school (noting that the model replicates the age and household structure of Australia). For all simulations, we assume that symptomatic testing and contact tracing in the general community continues, but that no public health restrictions are in place or introduced outside of schools.

School surveillance strategies

School surveillance strategies considered were no surveillance, twice weekly teacher screening with rapid antigen tests (RAT), and twice weekly student screening with RAT. These scenarios were considered with and without contact tracing in place.

Contact tracing and quarantine strategies in schools

In all scenarios, students or teachers diagnosed with COVID-19 were assumed to be removed from the school and required to isolate until no longer infectious.

Contact tracing scenarios were based around classroom contacts, as opposed to close contacts, as classroom contacts were deemed more practical to identify and apply policies to. Options considered were no contact tracing; 7-day quarantine of classroom contacts with/without daily RAT; daily RAT of classroom contacts who remain at school ("test-to-stay"); entire school test-to-stay with daily RAT after initial case detection. The inclusion of a 7-day quarantine with RAT was to create a fairer comparison to test-to-stay by allowing equivalent likelihood of case ascertainment.

Model simulations and outcomes

The model was initialized with a single infection allocated randomly within a school. The model was run for 45 days, recording the number of cumulative infections in students or teachers attending the school. Infections were used as the primary outcome measure as opposed to diagnoses to avoid biasing strategies with lower testing rates.

For each scenario, the simulation was repeated 1000 times and reported outcomes are based on the distributions of (1) secondary infections occurring in the same school; and (2) days of face-to-face teaching lost. Days of face-to-face teaching lost are calculated for the school as the total student-days spent in isolation or quarantine as a result of a school quarantine policy over the 45 day period.

Sensitivity analyses

Sensitivity analyses were conducted to consider how outcomes varied with different assumptions or inputs for:

- School incursion rates: model initialization with 1, 2 or 3 simultaneous incursions
- Vaccination coverage:
    - 0%, 60%, 80% coverage among students 12+ years

- 0%, 60%, 80% coverage among students 5-11 years
- 60%, 80%, 100% coverage among teachers

- Non-pharmaceutical interventions (e.g. ventilation, physical distancing): efficacy at reducing transmission probability per contact of 0%, 25% or 50%
- Surveillance testing frequency (weekly or daily compared with twice weekly)
- Compliance with test-to-stay (also an equivalent sensitivity analysis for lower test sensitivity): 0-100%
- Average number of non-classroom contacts per student
- Symptomatic testing rate

Except for incursion rate and compliance with test-to-stay, these are provided in the appendix.

Table 1: Model parameters related to schools

Parameter area	Estimate	Source
Primary school		
Average school size	298	Number of primary students (2,267,564 in 2020; ABS [7] Table 42b) divided by number of Primary + Primary/secondary schools (6249+1363 in 2021; ABS [7] Table 35b).
Average class size	22	Average class size of primary schools. Victorian government [8]
Average number of student-student non-classroom contacts per day, per student	2	Assumption; tested in sensitivity analysis. This impacts the efficacy of test-to-stay of class contacts verses close contacts or entire school.
Average number of teacher-teacher contacts per day, per teacher	20	Number of FTE primary teachers (152,281 in 2020; ABS [7]) divided by number of primary schools (6249+1363)
Secondary school		
Average students per school	622	Number of secondary students (1,738,083 in 2020; ABS [7] Table 42b) divided by number of Secondary + Primary/secondary schools (1433+1363; [7] Table 35b)
Average teacher/student ratio	12	ABS data. [7] suggesting secondary schools have on average 12.1 students to one teacher.
Average number of student-student classroom contacts per day	44	Average class size in secondary school of 22 ([9]; page 354), assuming two unique classrooms of contacts per student per day.
Average number of student-student non-classroom contacts per day	5	Assumption; tested in sensitivity analysis. This impacts the efficacy of test-to-stay of class contacts verses close contacts or entire school.
Average number of teacher-teacher contacts per day	5	Assumption.
Average number of teacher-student contacts per day, per student	6	Assumes students have six classes per day
Probability of transmission per contact per day (without vaccines or NPIs)		
Student-student (primary classroom)	0.25	Delphi process; Scott et al. [2] Measured as relative to household transmission per contact - e.g. a typical day's worth of contact in school is 75% less likely to result in transmission than a typical day's worth of contact at home. Non-classroom primary school contacts equivalent to outdoor contacts; secondary school classroom contacts halved to account for shorter interactions. All transmission probabilities are scaled in sensitivity analyses when NPI efficacy is tested.
Student-student (primary non-classroom)	0.03	
Student-student (secondary class contact)	0.12	
Student-student (secondary close/social contact)	0.12	
Teacher-teacher	0.25	Assumption that transmission risks in schools are equivalent for all types of contacts. Note that the model has independent parameters to account for differences in susceptibility by age
Teacher-student (primary)	0.25	
Teacher-student (secondary)	0.12	
Age-susceptibility (relative to 20-49 year old)		
Age 0-4	0.349	Derived from Davies et al. [10]
Age 5-9	0.423	
Age 10-14	0.495	

Age 15-19	0.599	
Age 20-24	0.846	
Age 24-29	1	
Probability of being symptomatic		
Age 0-9	0.28	Davies et al. [10]
Age 10-19	0.20	
Age 20-29	0.26	
Rapid antigen testing (RAT)		
Sensitivity	0.773	Muhi et al. [11] Lower bound selected to account for inconsistent self-use. Note that PCR is modelled as having 87% sensitivity in real world use (systematic review Arevalo-Rodriguez et al. [12])

Results

Surveillance strategies, without contact tracing / quarantine

Even though secondary school students have a greater number of contacts, the chances of an incursion leading to zero secondary cases (after 45 days) was greater in secondary schools than in primary schools (

Figure 3, left green bars) – largely a result of secondary school students being vaccinated.

Twice weekly screening of teachers had minimal impact on reducing infections in primary schools, and only a marginal impact in secondary schools, since teachers make up a small percentage of the school community. However, this analysis focuses on transmission within schools, and considered outcomes given a random incursion into the school. It therefore does not capture differences between students and teachers in their probability of acquiring COVID-19 in the community. The analysis presented here likely underestimates the overall benefits of screening (and vaccinating) teachers through preventing incursions from taking place.

Twice weekly screening of students leads to earlier detection of an incursion and reduces the number of exposure days in the school. This increases the chances of an incursion leading to no secondary infections in both primary and secondary schools, because the index cases are often detected and removed from the school before transmission occurs. Screening of students increased the average days of face-to-face teaching lost compared with no screening and no contact tracing due to the detection of asymptomatic cases; however the days of face-to-face teaching lost were entirely due to positive cases isolating.

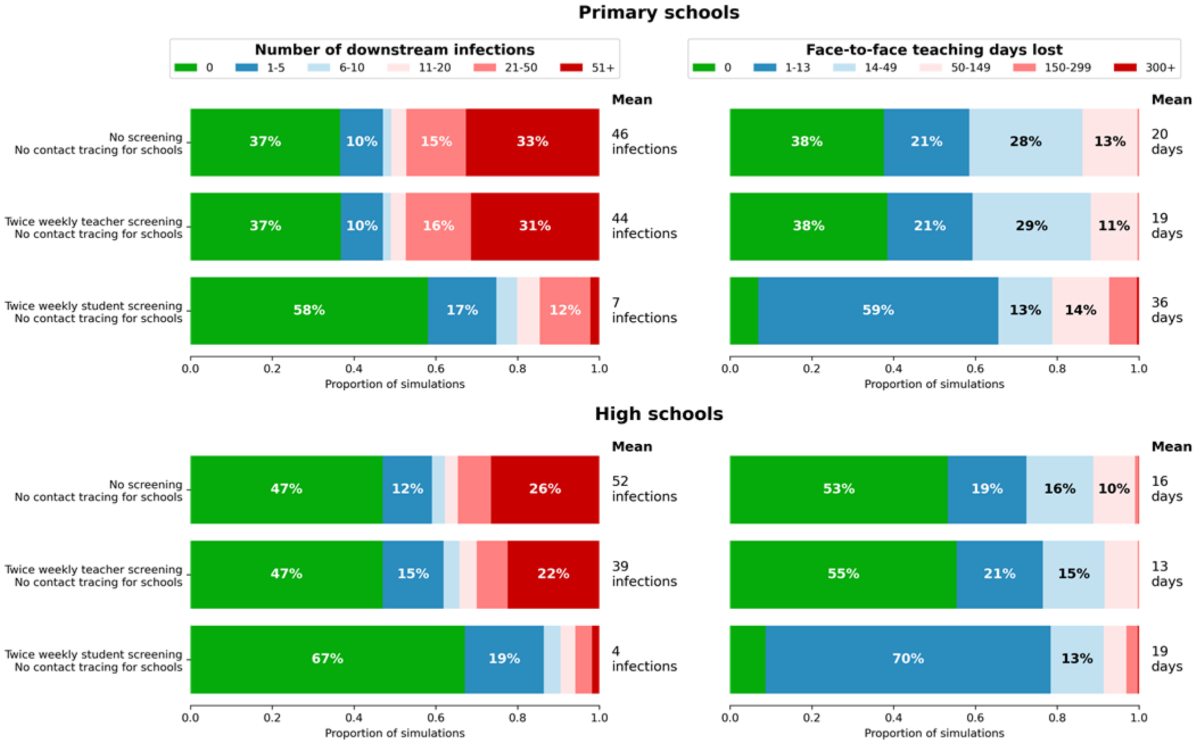


Figure 3: Impact of surveillance strategies on the distribution of outcomes for cumulative infections (left) and days of face-to-face teaching lost (right) in a single school following a single incursion. Outcomes are from 1000 model simulations run for 45 days following first diagnosis. Scenarios assume no contact tracing or quarantine (only isolation for positive cases that are detected) and from top to bottom are based on: no screening; twice weekly testing of teachers with rapid antigen tests; twice weekly testing of students with rapid antigen tests.

Contact tracing and quarantine strategies

Following detection of a case, different responses made some difference to the distribution of outcomes. Test-to-stay of classroom contacts was approximately equivalent to 7-day quarantine of classroom contacts in both primary and secondary schools, but with a significantly lower number of face-to-face teaching days lost (Figure 4). The incremental benefit of test-to-stay for the entire school, in place of just the classroom contacts, was small; however it was sensitive to assumptions about the number of non-classroom contacts that students have.

The effectiveness of test-to-stay was dependent on compliance with the daily rapid antigen testing (Figure 5), but even at partial (e.g. 50%) compliance was effective relative to no test-to-stay or quarantine.

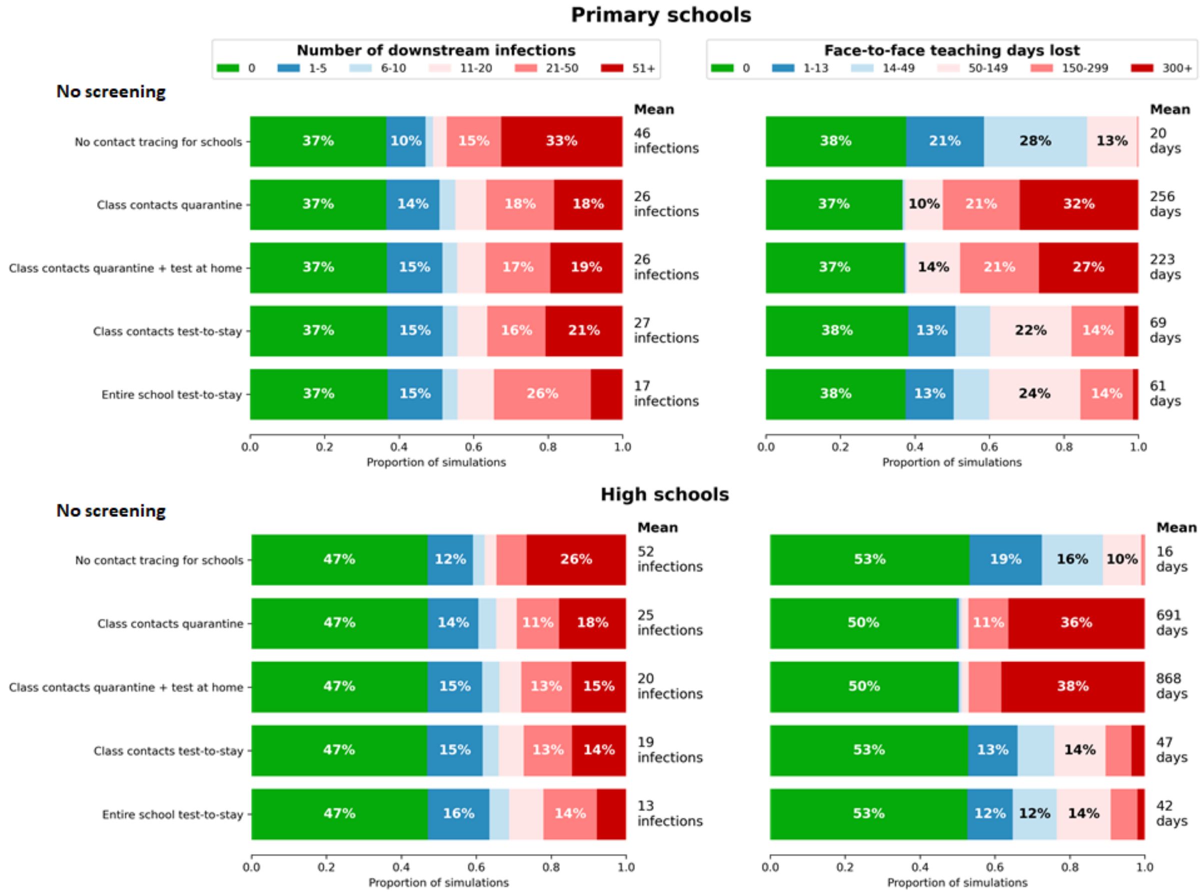


Figure 4: Impact of contact tracing and quarantine strategies on the distribution of outcomes for cumulative infections (left) and days of face-to-face teaching lost (right) in a single school following a single incursion. Outcomes are from 1000 model simulations run for 45 days following first diagnosis. Scenarios top to bottom: no contact tracing; class contacts have 7-day quarantine without / with testing; class contacts test-to-stay with rapid antigen tests; entire schools test-to-stay with rapid antigen testing. Top: Primary schools; bottom: secondary schools.

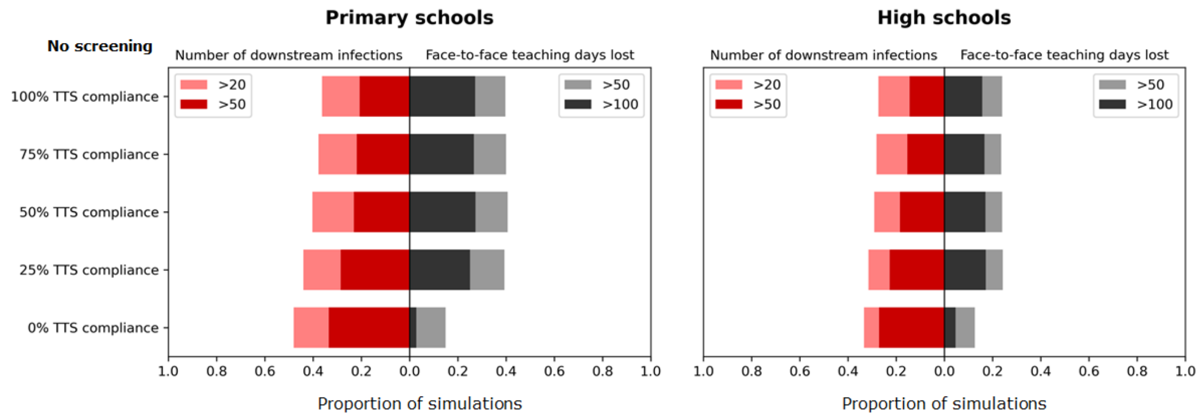


Figure 5: Impact of compliance on the effectiveness of a test-to-stay (TTS) strategy. Left bars: the percentage of simulations with more than 20 or 50 cumulative infections after 45 days of first diagnosis, for different surveillance strategies and number of initial incursions. Right bars: the percentage of simulations with more than

50 or 100 days of face-to-face teaching lost in a single school following the incursions. Outcomes are from 1000 model simulations run for 45 days following first diagnosis.

Surveillance strategies combined with contact tracing / quarantine

An additional analysis was undertaken to assess the incremental impact of surveillance strategies when contact tracing was in place. Test-to-stay strategy was used as a baseline for this analysis due to its superiority to other contact tracing and quarantine strategies in terms of minimizing infections and maximizing face-to-face teaching.

With contact tracing (test-to-stay) in place, twice weekly screening of students still had benefits in terms of reducing infections and had additional benefits in terms of reduced face-to-face teaching days lost (Figure 6). Since contact tracing is effective at detecting and isolating positive cases once an outbreak is identified, larger outbreaks in schools generate more days of face-to-face teaching lost. Therefore, by detecting and removing cases earlier, student screening combined with test-to-stay for class contacts could reduce the number of downstream infections following an incursion, reduce the likely outbreak size, and reduce the average days of face-to-face teaching lost per incursion. Despite student screening leading to fewer instances of zero days of face-to-face teaching lost – due to most incursions being detected and at least one infected student being isolated – there was also a significant reduction in the proportion of simulations where more than 150 days were lost.

With contact tracing (test-to-stay) in place, the relative benefits of twice weekly screening of students on reducing secondary infections in schools and days of face-to-face teaching lost increased as the number of incursions increased (Figure 7).

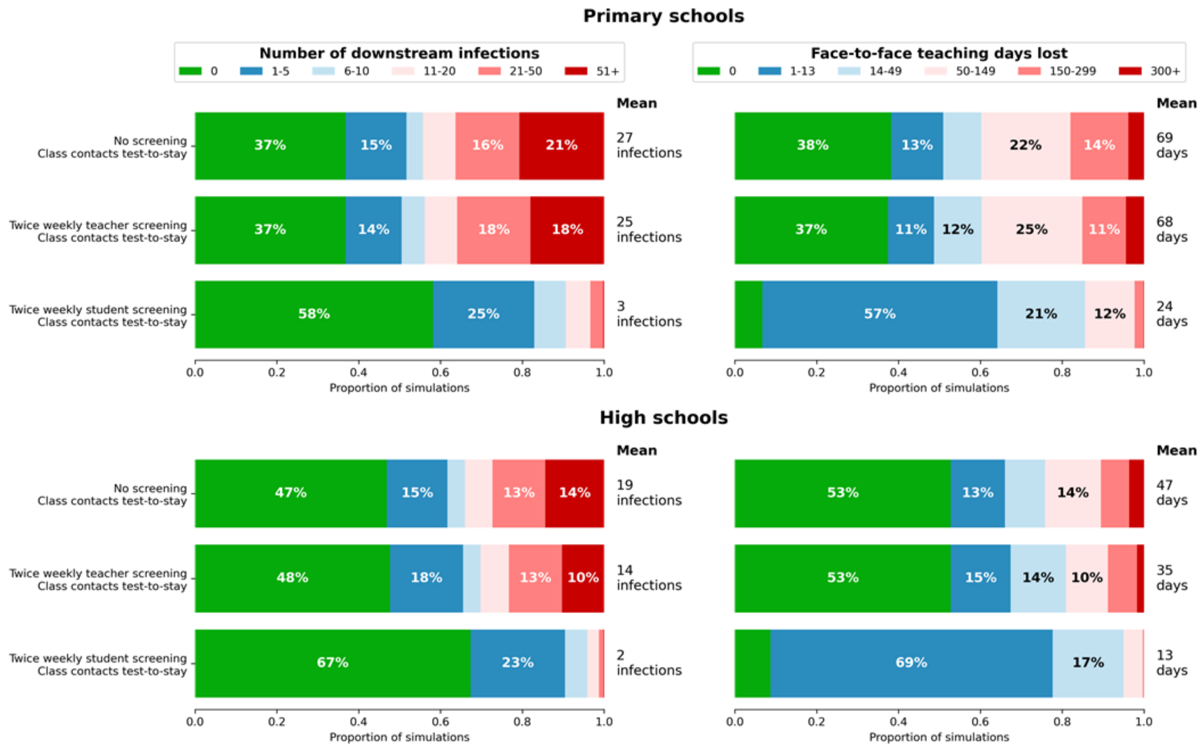


Figure 6: Impact of surveillance strategies on the distribution of outcomes for cumulative infections (left) and days of face-to-face teaching lost (right) in a single school following a single incursion. Outcomes are from

1000 model simulations run for 45 days following first diagnosis. Scenarios assume classroom contacts test-to-stay and from top to bottom are based on: no screening; twice weekly testing of teachers with rapid antigen tests; twice weekly testing of students with rapid antigen tests.

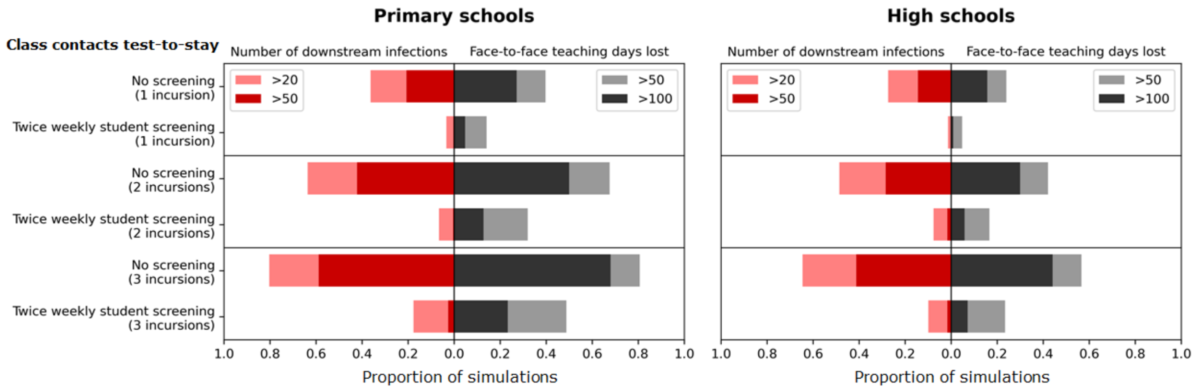


Figure 7: Impact of multiple incursions on the benefits of surveillance testing. Left bars: the percentage of simulations with more than 20 or 50 cumulative infections after 45 days of first diagnosis, for different surveillance strategies and number of initial incursions. Right bars: the percentage of simulations with more than 50 or 100 days of face-to-face teaching lost in a single school following the incursions. Outcomes are from 1000 model simulations run for 45 days following first diagnosis. Scenarios assume classroom contacts test-to-stay and from top to bottom have: no screening; twice weekly testing of teachers with rapid antigen tests; twice weekly testing of students with rapid antigen tests.

Total days of face-to-face teaching gained

The above outputs relate to the number of face-to-face teaching days lost following a single incursion; however, schools will experience ongoing incursions, with an incursion rate influenced by transmission in the surrounding community. By early 2022, empirical data will be available to measure the actual incursion rate. In the absence of these data, we estimate the incursion rate here to outline how a cost-effectiveness analysis for screening may be performed.

Between June and October 2021 in NSW and Victoria approximately 30% of new diagnoses occurred in people aged 18 and under, and this was consistent across high and low transmission settings (regional NSW: 28.4%, Sydney: 29.9%, Victoria: 30.2%). However, 12-15 year olds only became eligible for vaccines from 13 September so this may partly explain this outcome, which may change over time.

The current relative stability in the proportion of new cases that occur in school-age children makes it possible to infer crude estimates of the total number of face-to-face teaching days gained through student screening. For a particular community, this could be simplistically estimated by multiplying:

a) New daily cases in local community (diagnoses/day not in quarantine)
b) Proportion of new cases that occur in school-age children
c) School attendance in the community (a mixture of enrollment rates and any other community restrictions modifying attendance)
d) Screening period (days) of testing in schools (e.g. to estimate the potential impact of a term of screening)
e) Average days of in-person learning gained from a single incursion in a single school due to screening (i.e. difference in average model outputs from (Figure 6).

However, caveats to this approach must be noted. Most notably, stability in the proportion of cases occurring in school-age children between June-October is an artefact of the restrictions that were in place in NSW and Victoria at that time, particularly those enforcing school closure. There is also uncertainty in the percentage of all infections that are diagnosed, which depends on community testing rates – this is likely to underestimate incursion rates. Conversely, for communities with high transmission and frequent incursions, the outcomes of each incursion may not be independent and so this may overestimate the face-to-face teaching days gained.

<u>Example: test-to-stay with/without twice weekly screening</u>

When comparing test-to-stay with or without twice weekly screening of students, the average number of face-to-face teaching days gained per school per incursion is estimated to be (Figure 6):

- 45 for twice-weekly screening of students in primary schools;
- 34 for twice-weekly screening of students in secondary schools.

Using these results, the number of days of face-to-face teaching days gained due to screening have been estimated for a population of 100,000 over a 45-day period (Figure 8).

The greatest number of face-to-face teaching days gained through screening occur when incidence is highest.

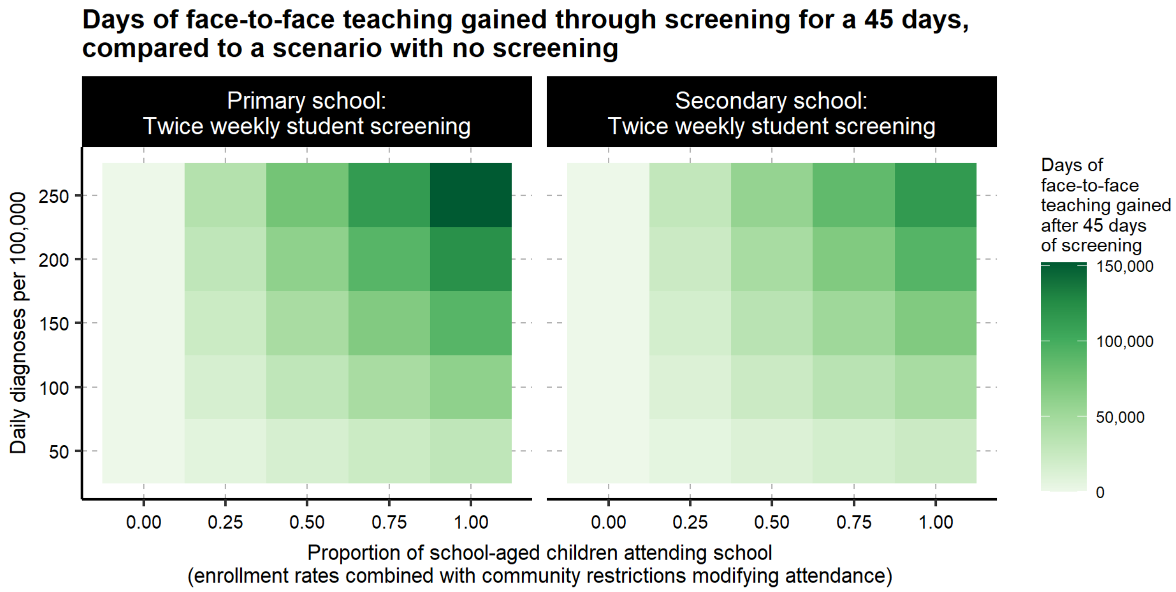


Figure 8: Estimated total days of face-to-face teaching gained through twice weekly student screening for 45 days of screening in a community with 100,000 population. Example assumes test-to-stay is in place alongside the screening. Left: Primary school. Right: secondary school. Assumes 30% of community infections are in school-aged children, an average of 45 and 34 days of face-to-face teaching are gained per incursion in primary and secondary schools respectively. Outcomes are shown for a range of community infection rates and school attendance rates (percentage of school-aged children attending school).

Limitations

The findings presented are derived from an individual-based model, which is an imperfect representation of the real world.

- Mixing within schools in the model is approximated as classroom and non-classroom contacts, where students are allocated at random to classrooms and randomly mix with other students outside of classrooms. In reality, within-school mixing is likely to include clustering due to subject selection and social mixing.
- Incursion risk was not modelled explicitly and model simulations started from a single assumed incursion. Actual incursion rates will depend on community prevalence, vaccination coverage and public health restrictions and interventions in place.
- The initial incursion that was modelled was randomly allocated to a member of the school (student or teacher); however, there may be social or other factors that make teachers or older/younger students more likely to be exposed in the community, and hence more likely to be the index case within the school.
- These results do not consider early learning or specialized settings (e.g. specialist schools and boarding schools) or small rural schools.
- Model parameters are based on best-available data at the time of writing. Results from new studies could change estimates of social mixing, contact networks, adherence to policies, quarantine advice, and disease characteristics (e.g. asymptomatic cases), and these could change these results.

References

1. Kerr CC, Stuart RM, Mistry D, Abeysuriya RG, Rosenfeld K, Hart GR, et al. Covasim: An agent-based model of COVID-19 dynamics and interventions. PLOS Computational Biology. 2021;17(7):e1009149. doi: 10.1371/journal.pcbi.1009149.
2. Scott N, Palmer A, Delport D, Abeysuriya R, Stuart R, Kerr CC, et al. Modelling the impact of relaxing COVID-19 control measures during a period of low viral transmission. Med J Aust. 2021;214(2):79-83.
3. Abeysuriya RG, Delport D, Stuart RM, Sacks-Davis R, Kerr CC, Mistry D, et al. Preventing a cluster from becoming a new wave in settings with zero community COVID-19 cases. medRxiv. 2020;https://doi.org/10.1101/2020.12.21.20248595.
4. Abeysuriya R, Delport D, Hellard M, Scott N. Estimating risks associated with early reopening in Victoria. Policy brief. Available from: https://www.burnet.edu.au/projects/467_covasim_modelling_covid_19. Sep 2020.
5. Abeysuriya R, Delport D, Sacks-Davis R, Hellard M, N. S. Modelling the Victorian roadmap. Available from: https://www.burnet.edu.au/system/asset/file/4942/Burnet_Institute_VIC_Roadmap_20210918_-FINAL.pdf. 2021.
6. Covasim model GitHub repository. https://github.com/InstituteforDiseaseModeling/covasim.
7. Australian Bureau of Statistics (ABS). Education statistics. https://www.abs.gov.au/statistics/people/education/schools/latest-release#data-download 2020.
8. Victorian Government. Government schools average class size. https://discover.data.vic.gov.au/dataset/govt-schools-average-class-size-primary-prep-to-year-2-years-3-to-year-6-total-feb-2001-2018. 2021.
9. OECD. Education at a Glance 20212021.
10. Davies NG, Klepac P, Liu Y, Prem K, Jit M, Pearson CAB, et al. Age-dependent effects in the transmission and control of COVID-19 epidemics. Nature Medicine. 2020;26(8):1205-11. doi: 10.1038/s41591-020-0962-9.

11. Muhi S, Tayler N, Hoang T, Ballard SA, Graham M, Rojek A, et al. Multi-site assessment of rapid, point-of-care antigen testing for the diagnosis of SARS-CoV-2 infection in a low-prevalence setting: A validation and implementation study. The Lancet Regional Health-Western Pacific. 2021;9:100115.
12. Arevalo-Rodriguez I, Buitrago-Garcia D, Simancas-Racines D, Zambrano-Achig P, Del Campo R, Ciapponi A, et al. False-negative results of initial RT-PCR assays for COVID-19: a systematic review. PloS one. 2020;15(12):e0242958.
13. Australian Bureau of Statistics (ABS). Australian Bureau of Statistics 2016, Census of Population and Housing, TableBuilder. Findings based on use of ABS TableBuilder data. https://www.abs.gov.au/ausstats/abs@.nsf/web+pages/Citing+ABS+Sources#TableBuilder i. 2020.
14. Prem K, Cook AR, Jit M. Projecting social contact matrices in 152 countries using contact surveys and demographic data. PLoS computational biology. 2017;13(9):e1005697.
15. Li B, Deng A, Li K, Hu Y, Li Z, Xiong Q, et al. Viral infection and transmission in a large well-traced outbreak caused by the Delta SARS-CoV-2 variant. MedRxiv. 2021.

Appendix: Sensitivity analyses

Non-pharmaceutical Interventions in schools

The impact of non-pharmaceutical interventions (NPIs; e.g. masks, ventilation) were tested by running scenarios where the risk of transmission per contact was reduced by either 25% or 50%. NPIs can reduce outbreak risks in schools and reduce the number of days of face-to-face teaching lost.

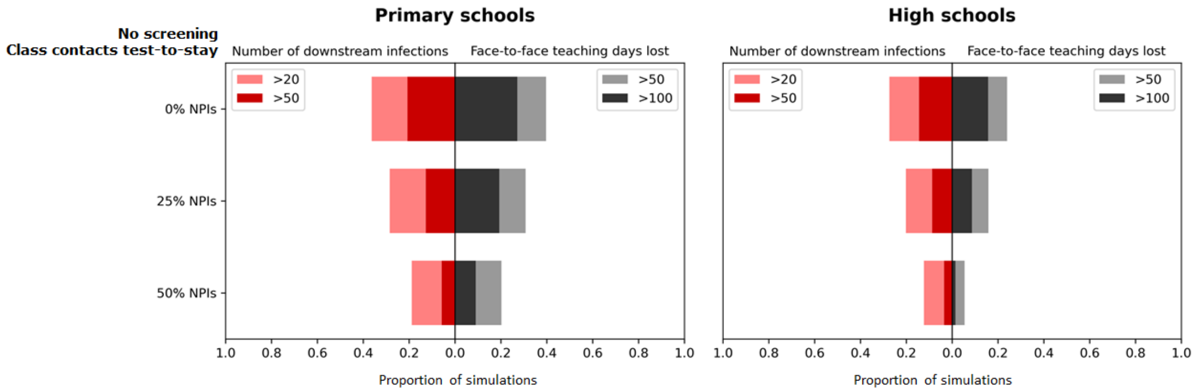


Figure 9: Impact of non-pharmaceutical interventions (NPIs) on outbreaks in schools. Red bars: the percentage of simulations with more than 20 or 50 cumulative infections after 45 days of first diagnosis. Grey bars: the percentage of simulations with more than 50 or 100 days of face-to-face teaching lost in a single school following an incursion. Scenarios assume test-to-stay is in place for class contacts and no surveillance testing.

Vaccine coverage in students

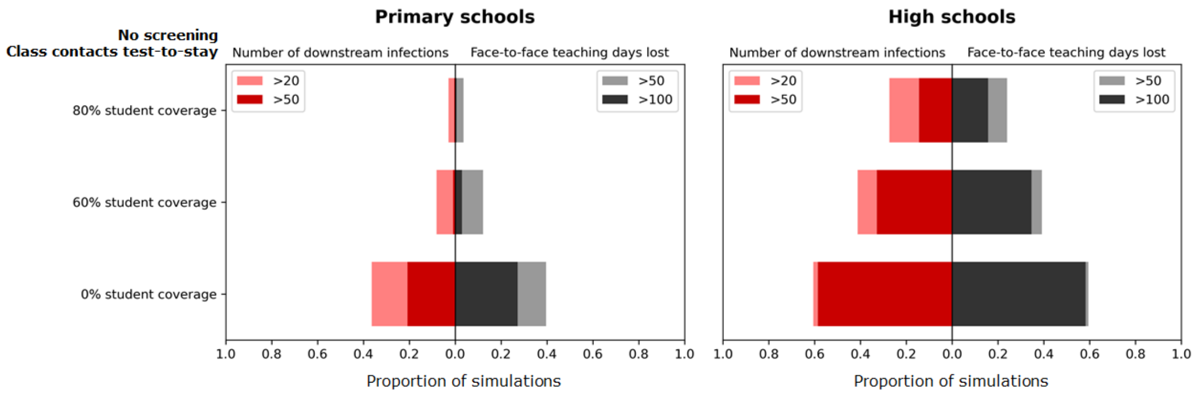


Figure 10: Impact of vaccines for students on outbreaks in schools. Red bars: the percentage of simulations with more than 20 or 50 cumulative infections after 45 days of first diagnosis. Grey bars: the percentage of simulations with more than 50 or 100 days of face-to-face teaching lost in a single school following an incursion. Scenarios assume test-to-stay is in place for class contacts and no surveillance testing.

Vaccine coverage in teachers

Note that the benefits of vaccinating teachers are not fully captured in this analysis, since the model does not account for potential reduced incursions as a result of teacher vaccination – only reduced transmission within the school once an incursion has already occurred.

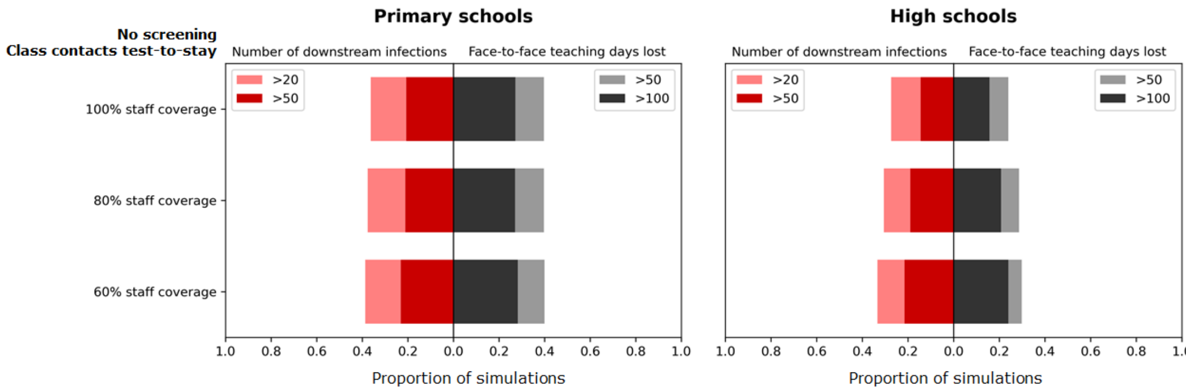


Figure 11: Impact of vaccines for teachers on outbreaks in schools. Red bars: the percentage of simulations with more than 20 or 50 cumulative infections after 45 days of first diagnosis. Grey bars: the percentage of simulations with more than 50 or 100 days of face-to-face teaching lost in a single school following an incursion. Scenarios assume test-to-stay is in place for class contacts and no surveillance testing.

Frequency of surveillance screening

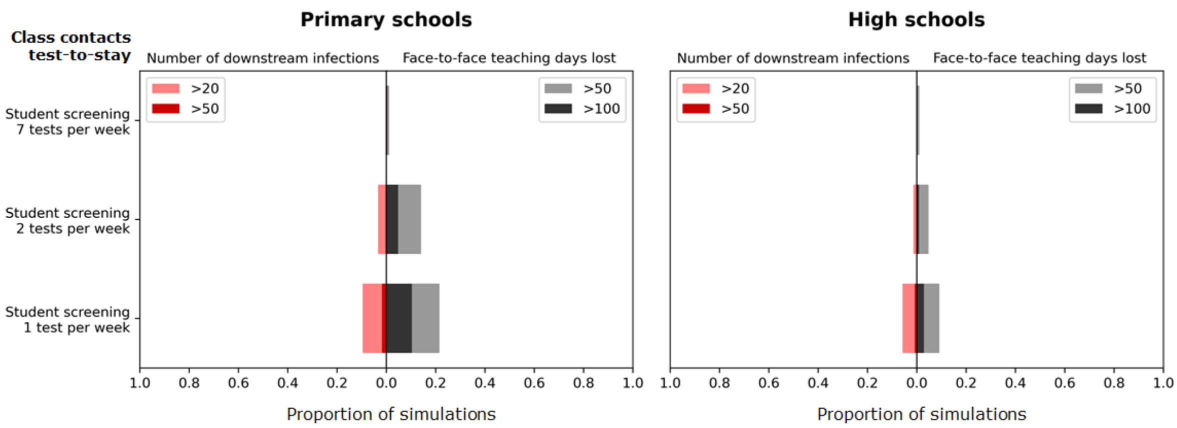


Figure 12: Impact of different frequencies of surveillance testing on outbreaks in schools. Red bars: the percentage of simulations with more than 20 or 50 cumulative infections after 45 days of first diagnosis. Grey bars: the percentage of simulations with more than 50 or 100 days of face-to-face teaching lost in a single school following an incursion. Scenarios assume test-to-stay is in place for class contacts.

Symptomatic testing rate

The model has an underlying parameter for the per-day probability that an individual with mild COVID-19 symptoms will have a test. This parameter plays an important role in determining how long it takes to detect an outbreak in scenarios where regular testing of students or teachers are not in place. Hence a sensitivity analysis was run to understand what influence this parameter had on key outcomes. Figure 13 shows that maintaining symptomatic testing is important for earlier detection of outbreaks and reduced outbreak size.

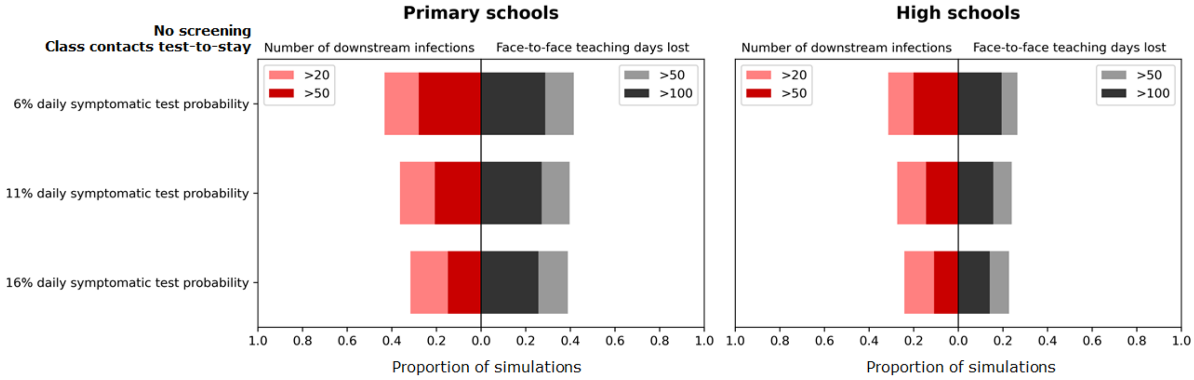


Figure 13: Impact of symptomatic testing probability on outbreaks in schools. Red bars: the percentage of simulations with more than 20 or 50 cumulative infections after 45 days of first diagnosis. Grey bars: the percentage of simulations with more than 50 or 100 days of face-to-face teaching lost in a single school following an incursion. Scenarios assume test-to-stay is in place for class contacts and no surveillance testing.

Sensitivity to number of non-classroom contacts

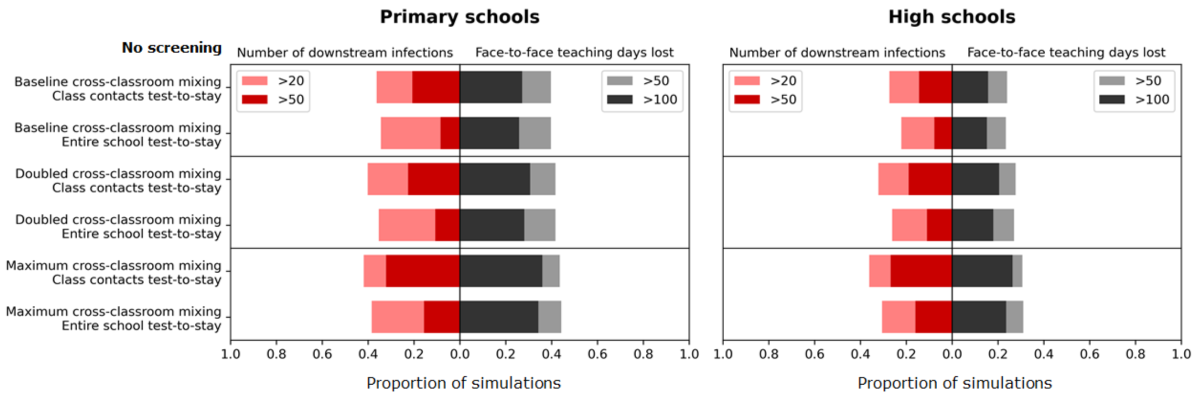


Figure 14: Impact of assumptions around number of non-classroom contacts per student. Doubled cross-classroom mixing assumes 4 and 10 non-classroom contacts for primary and secondary school students respectively. Maximum cross-classroom mixing assumes 11 and 22 non-classroom contacts for primary and secondary school students respectively. Red bars: the percentage of simulations with more than 20 or 50 cumulative infections after 45 days of first diagnosis. Grey bars: the percentage of simulations with more than 50 or 100 days of face-to-face teaching lost in a single school following an incursion. Scenarios assume no surveillance testing.

Appendix: Additional methodological details

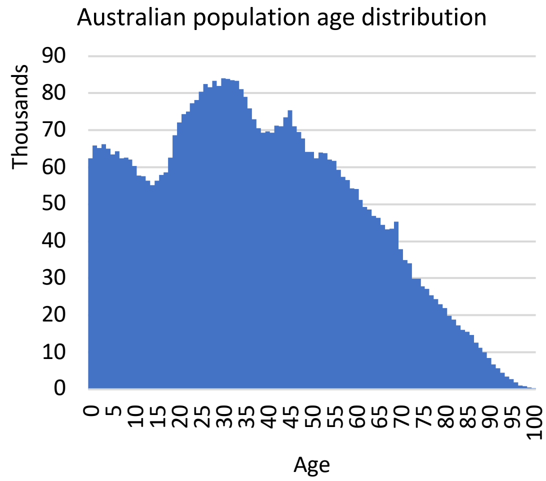
The agent-based model Covasim models the spread of COVID-19 by simulating a collection of agents representing people. Each agent is characterised by a set of demographic and disease properties:

- Demographics:
  - Age (one-year brackets)
  - Household size, and uniquely identified household members
  - Uniquely identified school contacts (for people aged 5-18)
  - Uniquely identified work contacts (for people aged 18-65)
  - Average number of daily community contacts (multiple settings / contact networks modelled, described below)
- Disease properties:
  - Infection status (susceptible, exposed, recovered or dead)
  - Whether they are infectious (no, yes)
  - Whether they are symptomatic (no, mild, severe, critical; with probability of being symptomatic increasing with age, and the probability of symptoms being more severe increasing with age)
  - Diagnostic status (untested vs tested)

Transmission is modelled to occur when a susceptible individual is in contact with an infectious individual through one of their contact networks. The probability of transmission per contact is calibrated to match the epidemic dynamics observed and is weighted according to whether the infectious individual has symptoms, and the type of contact (e.g. household contacts are more likely to result in transmission than community contacts). Transmission dynamics depend on the structure of these contact networks, which are randomly generated but statistically resemble the specific setting being modelled. The layers included are described below, and the model parameters values are provided for each layer that was included.

Model population

For this analysis a synthetic model population was initialized comprising of 100,000 people. The age and household size structure of the model population was based on the Australian population.



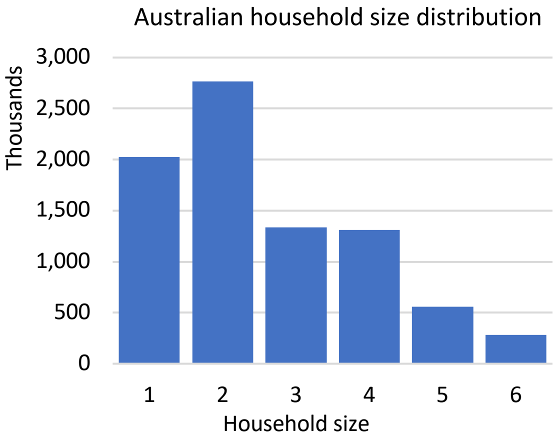


Figure 15: Population age structure and household size distribution [13].

Household contact network: household size and age structure

The household contact network was set up by explicitly modelling households. The households size distribution for Australia [13] was scaled to the number required for the number of agents in the simulation. Each person in the model was uniquely allocated to a household. To assign ages, a single person was selected from each household as an index, whose age was randomly sampled from the distribution of ages of the Household Reference Person Indicator in the 2016 Census [13]. The age of additional household members were then assigned according to Australian age-specific household contact estimates from Prem et al. [14], by drawing the age of the remaining members from a probability distribution based on the row corresponding to the age of the index member.

School contact networks

Schools and school contact networks were set up as described in the main report.

Work contact networks

Two different workplace types are included: public facing (e.g. retail, hospitality) and non-public facing. Contact networks for non-public facing workplaces were created as a collection of disjoint, completely connected clusters for the percentage of people aged 18-65 who worked in those settings. The mean size of each cluster was equal to the estimated average number of daily work contacts (Table S1). For the percentage of people aged 18-65 who worked in public facing workplaces, their workplace networks consisted of a completely connected cluster with other work colleagues, as well as each day having a number of random contacts with the community.

Additional contact networks

An arbitrary number of additional networks can be added. Each network layer requires inputs for: the proportion of the population who undertake these activities; the average number of contacts per day associated with these activities; the risk of transmission relative to a household contact (scaled to account for (in)frequency of some activities such as pubs/bars once per week); relevant age range; type of network structure (random, clustered, or specialized [as per schools/workplaces]); and effectiveness of quarantine and contact tracing interventions. Parameters for the networks currently in the model are in Tables S1 and S2.

Parameter values for each contact network

Tables S1 and S2 show the parameters that define each contact network in the model. Unless otherwise noted, parameters are derived in [2] from a mix of published and grey literature and a Delphi parameter estimation process. The columns refer to:

- **Network structure type:** Clustered refers to a network structure comprised of disjoint, completely connected groups of contacts. Random refers to individuals being allocated connections to anyone else in the network. Random networks are also dynamic and regenerated each day. Public facing networks are a combination of completely connected clusters for staff, who are then connected to random community members

- **Mean contacts:** The average number of contacts per person in each network. Each person in the model has their individual number of contacts draw at random from a Poisson distribution with these values as the mean. For the social network layer, a negative binomial distribution was used with dispersion parameter 2 to account for a longer tail to the distribution.
- **Mean public-public contacts:** For the percentage of people who participate in an activity, the average number of contacts they have with other members of the public (draw at random from a Poisson distribution with these values as the mean)
- **Mean public-staff contacts:** For the percentage of people who participate in an activity, the average number of contacts they have with staff (draw at random from a Poisson distribution with these values as the mean)
- **Relative transmission risk:** The transmission probability per contact is expressed relative to household contacts, and reflects the risk of transmission depending on behaviour. For example, a casual contact in a public park is less likely to result in a transmission event compared to a contact on public transport. Similarly, the relative transmission risks between staff-staff, public-public and staff-public are characterised for public-facing workplaces.
- **Quarantine effect:** If a person is quarantined, the transmission probability is reduced by this factor. For example, an individual on quarantine at home would likely not work or use public transport, but they may still maintain their household contacts.
- **Population proportion:** Each network will only include a subset of the population e.g. every person has a household, but not every person regularly uses public transport.
- **Age bound:** Each network will only include agents whose age is within this range.
- **Contact tracing probability:** Probability that each contact can be notified in order to quarantine
- **Effectiveness of quarantine and isolation:** When a close contact is asked to quarantine for 14 days, or a confirmed case asked to isolate while they are infected, these parameters represent he effectiveness of at reducing transmission through the specific networks. For example quarantine is assumed to have no impact on household transmission and greater impact on other contacts, reflecting compliance.

Table S1: Contact parameters for each of the networks in the model.

Contact network	Network structure type*	Mean contacts	Mean public-public contacts	Mean public-staff contacts	% of workforce	Relative transmission risk	Relative transmission risk (staff-staff)	Relative transmission risk (public-public)	Relative transmissio n risk (staff-public)	% of population	Age bound
House	Specialized	4				1.00					
School	Specialized										5-17
Non-retail work	Specialized	5			0.80	0.28					
Retail work	Public facing	5	8	2	0.11		0.28	0.04	0.04	0.70	12+
Community (general)	Random	1				0.10				1.00	
Places of worship	Clustered	20				0.04				0.11	
Community sport	Clustered	30				0.07				0.34	4-30
Entertainment	Public facing	25	8	2	0.02		0.28	0.01	0.01	0.30	15+
Cafe/restaurant	Public facing	5	8	2	0.02		0.28	0.04	0.04	0.60	12+
Pub/bar	Public facing	5	8	2	0.03		0.28	0.06	0.06	0.40	18+
Public transport	Random	25				0.16				0.11	15+
Public parks	Random	10				0.03				0.60	
Child care	Clustered	20				0.25#				0.55	1-6
Social	Random	6 (disp=2)				0.12				1.00	15+
Aged care	Clustered	12				0.58				0.07	65+

Table S2: Contact tracing parameters for each of the networks in the model.

Contact network	Assumed contact tracing probability	Assumed effectiveness of quarantine on network	Assumed effectiveness of isolation on network
House	1	0.00	0.80
School	0.95	0.99	0.99
Non-retail work	0.95	0.90	0.90
Retail work	0.95	0.90	0.90
Community (general)	0.1	0.80	0.80
Places of worship	0.5	0.99	0.99
Community sport	0.5	1.00	1.00
Entertainment	0.5	1.00	1.00
Cafe/restaurant	0.5	1.00	1.00
Pub/bar	0.5	1.00	1.00
Public transport	0.1	0.99	0.99
Public parks	0.1	1.00	1.00
Child care	0.95	0.99	0.99
Social	0.75	0.50	0.80
Aged care	0.95	0.80	0.80

<u>Contact tracing: non-school contacts</u>

Following detection of a positive case, the model initiates a contact tracing algorithm. *For cases detected in schools, this is described in the main report*. For cases in the community, the testing/contact tracing system was approximated as follows:

1. Day 0: Test is taken by index case
2. Day 1 (24 hours following test): Positive test results are returned, index case is notified and enters isolation.
3. Day 2 (48 hours following test being taken^): Contact tracing completed, with contacts having a setting-specific probability of being detected (Table S2), reflecting differences in the level of difficult in identifying contacts in that network (e.g. households vs public transport contacts). Identified contacts are tested and quarantined for 14 days regardless of test results, along with their entire households. Contacts are additionally tested on day 11 of quarantine, regardless of symptoms.
4. Day 3 (72 hours following test): Test results for contacts become available, and any contacts who returned a positive initial test would then have their contacts traced within the next 24 hours, in the same manner as the index case.

It was assumed that contact tracing deteriorated as case numbers increased. Caps on contact tracing assumed: at 0, 25, 75, 150 and 500+ cases per day, 100%, 80%, 50%, 30% or 20% of detected cases are subject to the above algorithm. The cap does not apply to household, school or childcare contacts who are assumed able to conduct their own tracing.

<u>Virus strain</u>

The model was based on transmission of the delta variant, with infectiousness calibrated to outcomes of the 2021 Victorian epidemic wave. The incubation period was shortened to a mean time from exposure to becoming infectious of 3.71 days, compared to 4.50 days for the wild type virus [15].

Vaccine properties

In the model, vaccination acts to reduce the probability of acquiring an infection when a contact occurs with an infectious case, as well as the probability of developing symptoms (both mild and severe) for people who are vaccinated and become infected. The assumed efficacy values used in this modelling are as per the main report.

The vaccine's prevention of infection is approximated as "leaky", meaning that each person vaccinated has reduced but non-zero risk of becoming infected based on the vaccine efficacy (as opposed to an "all or nothing" vaccine, where 80% efficacy means that 80% of people have perfect protection and 20% have no protection).

Model calibration

Model parameters for transmission and testing were calibrated to data on daily new detected cases, hospitalisations and ICU from the delta COVID-19 epidemic wave in Melbourne over the July-September 2021 period [5]. The model was initialised with a population of 100,000 agents, and the overall transmission risk per contact (which multiplies the transmission probabilities in Table S1 for each layer), the per-day probability of a symptomatic individual seeking testing were varied such that the distribution of model outcomes for diagnoses, hospitalizations and number of tests was centred near the actual epidemic trajectory. For additional details see [5].

For this analysis, the model was initialized with only a single case in a school, as described in the main report, however the transmission and testing parameters were based on this previous calibration.