Testing the waters: is it time to go back to school?

Diagnostic screening as a COVID-19 risk-mitigation strategy for reopening schools in King County, WA

Authors¹: Daniel Klein, Cliff Kerr, Dina Mistry, Niket Thakkar, and Jamie Cohen Institute for Disease Modeling, Seattle, Washington; covid@idmod.org

Results as of November 5, 2020

What do we already know?

Schools around the world and in the U.S. closed as the COVID-19 pandemic swept the globe. While schools in Florida, Texas, New York City, and elsewhere have returned to in-person learning, 95% of public K-12 schools in Washington State are conducting distance learning [1]. Our previous modeling work has demonstrated that schools are not islands; the risk of reopening schools depends on the incidence of COVID-19 infections in the community as well as school-based countermeasures. These countermeasures typically include segmenting schools into cohorts, symptom screening, contact tracing, and non-pharmaceutical interventions such as hand hygiene, physical distancing, masking, and increased ventilation. Our follow-up model-based analysis found that risks could be significantly mitigated through hybrid school schedules or via a phased-in approach that brings back K-5 first.

What does this report add?

We model various strategies to quantify the extent to which diagnostic screening could further mitigate the COVID-19 transmission risk associated with reopening K-12 schools in King County, WA. The analysis considers two types of tests: 1) gold-standard PCR tests that typically take one or more days to return results, and 2) rapid antigen-based tests that have lower sensitivity and a greater chance of false positive results. We explore the impact of testing congregate school populations either once (before the first day of in-person learning) or on a regular basis (daily, weekly, or fortnightly) on key health outcomes and in-person days lost. **Uncertainties are significant in many aspects of this work**: our sensitivity analysis highlights unknowns in the susceptibility of individuals under age 20, potential for increased mobility, and feasibility of daily screening as key programmatic components.

What are the implications for public health practice?

Frequent diagnostic screening can reduce COVID-19 infection risks associated with reopening K-12 schools; however, the impact scales with level of in-school transmission. For in-person learning strategies that mitigate risk though a combination of school-based countermeasures and hybrid or phased-in scheduling, the risk of in-school transmission is low, and therefore routine diagnostic screening has limited benefit. There may be a surveillance benefit to scenarios that screen a week or more before starting in-person learning, sample a small percentage of the school population, or screen infrequently, but these testing strategies do not directly improve outcomes. In-person days lost is dominated by scheduling, not due to keeping people home due to quarantine & isolation. Main results highlight the importance of countermeasures including symptom screening, contact tracing, non-pharmaceutical interventions, and continuing to place emphasis on reducing community transmission towards reopening K-12 schools. Diagnostic screening is a small part of the complex challenge of reopening schools. This report does not address the considerable logistical and financial challenges associated with in-person learning and the multitude of options facing school administrators and educators.

¹This work was conducted by members of the IDM COVID-19 Response Team and reviewed by Jen Schripsema, Mandy Izzo, Kate Davidson, Christopher Lorton, Guillaume Chabot-Couture, and Edward Wenger.



Executive summary

This modeling report focuses on the incremental benefits of one-time or routine diagnostic screening of congregate populations associated with K-12 schools. The analysis setting was based on King County, Washington as of early October, at which time the case detection rate was 75 per 100,000 over 2 weeks, the daily testing volume was 225 per 100,000, the test positivity was 2.5%, and prevalence was estimated at 0.2%. We assume at baseline that elementary and middle school classes are strongly cohorted (i.e., student classes do not mix, but teachers and staff can), symptom screening catches a majority of symptomatic individuals, children under 20 are less susceptible to COVID-19, and antigen tests have 97.1% sensitivity and 98.5% specificity² during the 7 days following symptom onset. Results are evaluated over the first 3 months of in-person learning for various school reopening and diagnostic screening scenarios.

Consistent with our schools are not islands report, we find that reopening schools to in-person learning without countermeasures could result in significant COVID-19 burden: up to 45% of teachers & staff and 33% of students could get infected over the first 3 months. However, **in-school countermeasures are highly effective in reducing school-based transmission** in this analysis, reducing the 3-month cumulative incidence to 2% or less for students, teachers, and staff, even with a full schedule of 5 in-person days per week. Modeled countermeasures include daily symptom screening, contact tracing, and non-pharmaceutical interventions such as face masks, hand hygiene, improved ventilation, and physical distancing.

Routine diagnostic screening with PCR or antigen tests can further reduce infections, but most of these tests will be negative, and false positives antigen tests will outnumber true positives due to the low (0.2%) prevalence modeled in this community, combined with an assumption that children are less susceptible. Simply put, with vigorous school-based countermeasures, there may be few infections for diagnostic screening tests to catch in this low-prevalence setting. Routine screening has impact on reducing transmission only when schools are a significant source of infections. With countermeasures, fortnightly screening of all students, teachers, and staff reduces the percent of teachers and staff that may acquire an infection over the first 3 months from 2.3% to 1.5% for a full schedule, and maintains a level near 1% for the hybrid and K-5 phased-in approaches. These levels are only slightly higher than if schools remain closed to in-person learning, in which 0.9% of teachers and staff are estimated to acquire a COVID-19 infection at home or in the community. Trends for students are similar, but the infection risks are about 25% lower.

School-based transmission did not significantly increase the community-wide reproduction number, R_e , in this analysis for scenarios in which school-based countermeasures were in place. We assume a constant level of infection ($R_e = 1.0$ on average over the 3-month evaluation period)³ at baseline, and observe a negligible increase for the full schedule with countermeasures reopening scenario. Diagnostic screening at fortnightly, weekly, or even daily frequencies reduces the reproduction number below 1.0 in this scenario. Only in the full schedule without countermeasures does school-based transmission cause R_e to increase dramatically above 1.0, to as high as 1.35 over the period. Without countermeasures, diagnostic screening is insufficient to bring R_e down below 1.0 unless conducted several times per week.

In-person days can be lost due to scheduling (e.g. A/B hybrid days or phasing in K-5 while keeping middle and high schools remote) or health concerns, including false positives from symptom or diagnostic screening. We find that **the number of in-person school days lost is dominated by scheduled remote learning**. This result stands despite a 1.5% chance of a false-positive result on each antigen test, and a 0.2% perindividual per-day probability of exhibiting COVID-like symptoms due to other causes. Frequent screening with an antigen test does increase in-person days lost; however, the magnitude of days lost due to all health concerns, including false-positive diagnostic screening results, is estimated to be 5% or less.

³Our previous work has modeled opening schools to in-person learning when the effective reproduction number in the broader community is $R_e = 0.9$. Having observed R_e fluctuate around 1.0 over the past few months, we assume that value as the baseline.



²Sensitivity is the probability that the test correctly identifies an infected individual as positive, whereas specificity is the probability that the test correctly identifies a healthy individuals negative.

The probability that a school will have one or more infectious individuals pass symptom screening and be present on the first in-person day increases with the size of the school. Diagnostic screening before the first day of school can reduce the risk; however, the benefit grows as the screening day approaches the first in-person day. When the screening is a full week before the first day, the probability of a 1,000-student school having an infectious individual present on day-one falls from 25% without screening to around 20%.

These results are sensitive to our assumptions. Diagnostic screening has more value if symptom screening is less effective than we have assumed. Without symptom screening, twice as many students, teachers, and staff may become infected during the first 3 months; however, fortnightly diagnostic screening compensates. We have tested each of our main assumptions and find increased risks if 1) children under 20 are as susceptible as adults, 2) community transmission increases as schools reopen, possibly due to parents and guardians returning to work, or 3) symptom screening is not implemented.

Results assume a priori that about 0.2% of the population is infected at baseline, but we know that prevalence varies geographically and by factors including essential work, race/ethnicity, and socio-economic status. Wide-scale diagnostic testing provides valuable surveillance information that is not well represented in these results. Reopening schools is a logistically complex task that requires the coordination and willingness of many parties; we have not addressed those considerations in this modeling analysis.

Key inputs and assumptions

The results presented in this report were generated using Covasim, an agent-based model of COVID-19 transmission, within-host progression, and countermeasures that was developed at the Institute for Disease Modeling. Each simulation represents a subset of all individuals from the population being modeled, King County, WA in this case. Individuals have an age, COVID-19 infection history/state, and a list of contacts from which the disease can be acquired or transmitted. The model advances in time using daily time steps until the final date is reached. Schools open for in-person learning on the 2nd of November, 2020 and the analysis concludes 3-months later, on the 31st of January, 2021. Please refer to our technical report [2] for background details about the model, or view the source code on GitHub.

Transmission takes place on a contact network composed of home, school, work, community, and eldercare layers. These networks are generated by SynthPops. For this analysis, specific attention has been given to the school layer, which represents individual elementary, middle, and high school in which classrooms consist of approximately 20 students per teacher. School size was drawn independently from school type based on enrollment statistics for the 2017 school year, see Appendix A in [3] for details. In the main analysis, elementary and middle schools are cohorted, meaning that student interactions are limited to their classroom peers, but teachers have random interactions with other teachers and staff within the same school. High schools are not similarly cohorted, due to practical considerations around flexible schedules.

Upon sufficient exposure to COVID-19, an individual will acquire an infection that begins with a noninfectious latent period. The latent period is followed by a few-day window of elevated infectivity during which symptoms may develop. Relevant to K-12 school scenarios is that the probability of ever developing symptoms increases linearly with age from 50% for those below age 10 to near 90% for older populations [4]. Even for those eventually developing symptoms, the highly-infectious pre-symptomatic period will occur before symptom onset [5]. Symptom screening in school populations will identify those individuals who are currently symptomatic with COVID-19, as well as false screen-positives due to other influenza-like illnesses (ILI). We assume the daily probability of screening positive due to other ILI in students, teachers, and staff is 0.2%, so that approximately 10-15% of the population will experience ILI over the 3-month period in consideration.

The model has been roughly calibrated to COVID-19 statistics from King County, Washington, using data and estimates available on the county's COVID dashboard in early October [6]. We have independently



estimated that the prevalence of COVID-19 in the county, see Appendix C. Specific values are presented in Table 1, and please note that transmission has increased recently as part of the "third wave". The presentday effective reproduction number is 1.2 and the case detection rate is 122 per 100,000 people over 14 days, therefore **findings in this report will under-estimate risks**. The result of model fitting is shown in Figure 9.

Indicator	Value
Case detection rate	75 per 100,000 people over 2-weeks
Number of tests conducted	225 per 100,000 people
Percent of tests that are positive	2.4%
Effective reproduction number (R_e)	1.0
Prevalence of COVID-19 in the population	0.2%, see Appendix C

This analysis considers five school reopening scenarios:

- 1. **Full schedule without countermeasures**: Students, teachers, and staff return to in-person learning 5 days per week. This is the only scenario that does not include school-based countermeasures.
- 2. Full schedule: Students, teachers, and staff return to in-person learning 5 days per week.
- 3. **Hybrid**: Students are split into "A" and "B" groups. The A group attends in-person on Monday and Tuesday whereas the B group attends on Thursday and Friday. Teachers and staff are physically present all days except Wednesday.
- 4. **K-5 in-person, others remote**: Elementary schools conduct in-person learning 5 days per week, but middle and high schools continue remote learning.
- 5. All remote: All K-12 students continue in distance learning, as they are today in most of King County.

Note that our modeling does not include a "remote option," 100% of designated students, teachers, and staff (K-12 in scenarios 1-3 and K-5 in scenario 4) return to in-person learning. For schools offering a remote learning option, risk of school-based COVID-19 transmission will be lower.

For each of the school reopening scenarios, we consider a variety of diagnostic screening scenarios based on PCR and antigen tests:

- None: Diagnostic testing continues as usual in the model, but no diagnostic screening is conducted.
- **PCR-based:** One-time diagnostic screening 7-days before school starts, or routinely at fortnightly, weekly, or daily intervals. Most scenarios assume results would be available the next day, a potentially optimistic assumption. Daily PCR is included as an extreme bounding case of diagnostic screening, and as such the delay is set to same-day. All students, teachers, and staff are included in screening, even when remote, but in the sensitivity analysis we consider if 50% are covered.
- Antigen-based: Fortnightly antigen testing is modeled either with or without PCR follow-up, denoted "f/u" in figure legends. Without follow-up, antigen-positive individuals quarantine for 14 days, but contacts are not traced. With follow-up, antigen-positive individuals quarantine until PCR diagnostic results are available, a 3-day delay. If the PCR result is negative, the individual may return to school, and if positive, they will enter isolation and contact tracing will be initiated. We also consider weekly antigen testing for just teachers & staff, with PCR follow-up and also a weekly antigen test with PCR follow-up.



Reopening scenarios 2 through 4 include the following countermeasures:

• Symptom screening: A percentage of students, teachers, or staff who are scheduled to attend school on a particular day will be screened for symptoms. For the base analysis, we have assumed coverage of symptom screening is 90% (without correlation from day-to-day). The model is agnostic to the symptom screening location, home or school. Individuals who are currently experiencing symptoms due to COVID-19 will screen positive, but note that not all COVID-19 infections will experience symptoms, and for those that do, symptoms will only develop after a brief period of elevated infectivity (as described above). The other way to screen positive is due to non-COVID causes. On each scheduled school day, each individual is assumed to have a 0.2% (without day-by-day correlation) chance of a false-positive screening to represent influenza-like illnesses that have symptoms similar to COVID-19.

Individuals who screen positive will begin isolation on the same day, and 50% will seek a PCR diagnostic test, which takes 3 days to return results. If the results are negative, the individual will return to school on the next in-person day. If the results are positive, contact tracing may be conducted.

• **Contact tracing:** When a student, teacher, or member of staff is diagnosed with COVID-19 by a PCR diagnostic test, there is a 75% chance that the individual will be reached by case investigators and provide a list of contacts including one or more teachers, staff, and student contacts. We assume that 75% of contacts can be reached, and begin a 14-day quarantine period starting on the same day as the index case was diagnosed (an optimistic assumption).

Outside of schools, contact tracing is a normal part of the Covasim model, and is happening in the background to school scenarios. We assume that 90% of home contacts will be notified 1 day after diagnosis and that 10% of work contacts (if any) will be notified 2 days after diagnosis. Contacts in the community layer will not be traced, as these are assumed to be informal acquaintances.

• Non-pharmaceutical interventions: We lump in-school non-pharmaceutical interventions (NPI), such as hand hygiene, masks, physical distancing, and ventilation into a single non-specific factor that reduces the per-contact daily transmission probability by 25%.

Countermeasures are influential in this analysis. In Appendix A, we find that daily symptom screening is the most influential countermeasure. The value of symptom screening has been debated, and the CDC does not currently recommend daily symptom screening be conducted by school staff [7]. However, guidance recommends that individuals who are experiencing symptoms stay home from school. Our analysis does not address the location in which symptom screening is conducted, at home or in school, but does highlight the importance of daily symptom screening. We explore a scenario without daily symptom screening in Appendix B.

This analysis focuses on the potential benefit of one-time or routine test-based screening in schools as a congregate setting. Nothing specific in this analysis requires the screening tests to be physically performed at school; however, that might be easier logistically and lead to higher coverage levels. Two types of tests are considered:

PCR: PCR tests are the clinical "gold standard" and have high sensitivity and specificity. In the Covasim model, PCR tests will return a positive result if the individual is currently in the infectious stage, and a negative result otherwise. In clinical settings, PCR tests can return positive results in the late stages, during which time individuals are potentially no longer infectious. In our model, these individuals would be the recovered stage, and the PCR test would return a negative result. Therefore, we may have under-estimated "false positive" results from PCR-based screening tests conducted in the post-infectious period. PCR tests typically take one ore more days to return results. In screening scenarios, we assume results are available on the next day, a potentially optimistic assumption. For confirmation



of screen- or antigen-positive individuals, we assume results will be available in 3 days. For routine diagnostic testing, we assume that PCR test results are available in 2 days.

Antigen: Antigen tests are less expensive than PCR and return results quickly, on the order of 15 minutes; however, they are less likely to identify true positives and more likely to generate false positives compared to PCR. There are numerous antigen-based tests, here we focus on the Abbott BinaxNOW™Ag CARD test, as these tests are broadly available within Washington State. Based on an FDA fact sheet specific to the BinaxNOW test, when applied to individuals who have experienced symptoms onset within the past 7 days, we model a sensitivity of 97.1% and a specificity of 98.5% [8]. For those not experiencing symptoms, or if symptom onset was more than 7 days in the past, we model a test sensitivity of 90% and maintain the specificity at 98.5%.

There is much uncertainty about the properties of antigen tests when used for screening⁴ the general population. The above numbers are based on just 35 positive examples. More research is needed to quantify the properties of these tests.

Additional inputs and assumptions are as follows:

- Compared to adults 20-64, children 0-9 and 10-19 are assumed to be 33% and 66% as susceptible [9].
- The probability of an infected individual becoming symptomatic increases linearly with age from 50% for 0-9 to 90% for those aged 80+ [4].
- Infectiousness is elevated during the post-latent phase, and varies between individuals, but we do not assume that asymptomatic infections are less infectious, nor do we assume that children are less infectious than adults [10].
- COVID-19 transmission within schools is highly uncertain and challenging to estimate. For this analysis, we assume that the basic reproduction number (R_0) within schools is 1.6 for the scenario in which schools were to reopen with an "as normal" 5-day schedule without countermeasures.
- The model does not include reactive school closures at this time.
- The simulation does not account for "seasonality" or other factors that may cause transmission to increase or decrease other than school reopening. We explore the potential impact of increased transmission associated with mobility in sensitivity analysis.
- Diagnostic screening scenarios reach 100% of the intended target group, e.g. students, when in reality individual consent might not be received from everyone. Therefore, results in this modeling analysis should be viewed as an upper bound on the possible impact of diagnostic screening.
- Elementary and middle school students are in tight cohorts, meaning that their only school-based contacts reside within their immediate class cohort. In sensitivity analysis, we explore implications if these "bubbles" break due to transportation, after-school care, or other logistical challenges.
- Contact tracing within a school-based setting is assumed to act on the same day as PCR confirmation. In reality, it might take a day or two to find and notify contacts, and thus we might have over-weighted the benefits of this countermeasure.
- We assume a 25% non-specific reduction due to non-pharmaceutical interventions as part of "countermeasures," and explore the impact of this assumption in sensitivity analysis.

⁴The Abbott BinaxNOW[™]Ag CARD test is authorized for use at the Point of Care (POC), i.e., in patient care settings operating under a CLIA Certificate of Waiver, Certificate of Compliance, or Certificate of Accreditation. Screening in congregate populations, such as schools, is considered off-label use.



- Symptom screening is applied to 90% of individuals attending in-person school on a given day. This screening will not identify asymptomatic or pre-symptomatic infections. In sensitivity analysis, we consider 1) lower coverage (50%) and 2) a scenario without any symptom screening.
- Opening schools for in-person learning is challenging logistically and financially. This modeling work does not address those challenges.

Main results

Attack rate in teachers, staff, and students

We first quantify the impact of countermeasures and diagnostic screening of school-based congregate populations using the attack rate. The attack rate simply measures the cumulative percentage of the specified population, either teachers and staff or students here, that acquired a COVID-19 infection during the 3-month period in consideration. All sources of infection are included in this metric, so model-based outputs will be non-zero even when all K-12 schools are remote.

Results in Figure 1 show that the 3-month attack rate in teachers & staff and students could be as high

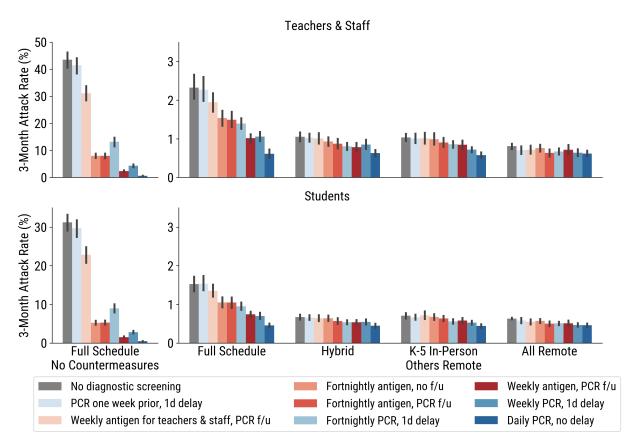


Figure 1: For each of the five school reopening scenarios considered, bar heights represent the cumulative percentage of teachers and staff (top) and students (bottom) who may acquire a COVID-19 infection over the 3-month evaluation period, from *any source* (home, community, school, etc.). Bar color indicates diagnostic screening: gray has no diagnostic screening whereas blue and red hues represent screening scenarios based primarily around PCR and antigen tests, respectively. Bar height and error bars represent the mean and 95% confidence interval based on 30 model evaluations.



as 45% and 33%. These alarming numbers come from the "Full Schedule, No Countermeasures" reopening scenario in which schools are reopened without countermeasures or diagnostic screening (gray bar). For this reopening scenario, we find that fortnightly diagnostic screening can reduce the 3-month attack rate in teachers and staff to 13% if using PCR and 8% if using an antigen test; reductions for students are proportionally similar. Even though the PCR test has high sensitivity and specificity, the antigen test results in fewer infections in this population due to the immediacy of results, see Appendix E for detail. Weekly or even daily screening frequencies perform even better, as expected.

Attack rates associated with the "Full Schedule, No Countermeasures" reopening scenario are considerably higher than in the other scenario. This qualitative difference is due to the fact that the basic reproduction in schools ($R_{0,sch}$) is 1.6, on average, in this scenario. This number represents the average number of secondary infections a single infected individual would cause in an otherwise susceptible school. Countermeasures are sufficient to reduce the reproduction number below 1.0, resulting in qualitatively different outcomes for the other four reopening scenarios considered.

Now focusing on the four scenarios that include countermeasures, the attack rate for teachers & staff and students is lowest for the all-remote scenario and increases incrementally in the K-5, hybrid, and fullschedule reopening scenarios. The impact of diagnostic screening is minimal in K-5 and hybrid scenarios, and up to 0.5% with a full schedule; the incremental benefit of adding diagnostic screening to scenarios that already include countermeasures is considerably smaller than the initial impact of adding countermeasures. Interestingly, with an assumption of one-day turnaround for the PCR tests, fortnightly PCR performs slightly better than fortnightly antigen testing in these reopening scenarios, due to the better sensitivity of PCRbased diagnostics and lower incidence rate.

One-time PCR a week before the schools open for in-person learning has near-zero impact on the 3month attack rate. The mean infectious period is not much longer than 7 days, asymptomatic and mild infections have 8 and 9 day infectious periods, respectively, so many of the infections identified by weekahead screening would have naturally cleared before the first day of school. Instead, new infections acquired at home or in the community will be present in schools on the first day, as detailed below.

We also find, but do not show here, that infrequent (monthly) or low number (10-20% monthly) testing will have little impact on the attack rate. However, results from these activities may be highly informative as surveillance.

Community-wide reproduction number

The effective reproduction number R_e measures the number of secondary infections caused by each primary infection, and we have a-priori calibrated the model to a situation in which R_e is 1.0 on average over the 3-month analysis period for the all-remote scenario without additional diagnostic screening. We assess if in-person learning might drive increases in the community-wide R_e , and the extent to which diagnostic screening reduces this measure in Fig. 2.

We find that K-5 and hybrid scenarios, combined with countermeasures, do not drive significant increases in R_e at the community level. These results mirror findings from our report on maximizing education while minimizing COVID risk. Diagnostic screening in congregate K-12 populations drives down R_e , but only when these individuals are drivers of community transmission. The notable exception is the fullschedule without countermeasures, in which R_e grows to above 1.3⁵. For this scenario, only daily PCR or antigen (not shown) testing with immediate results return is sufficient to maintain a reproduction number below 1.0 in these simulations.

For the full schedule (with countermeasures), several screening scenarios result in $R_e > 1$: no screening, PCR one week prior to starting in-person learning, and weekly antigen testing for teachers and staff

⁵This number is larger than in our maximizing education while minimizing COVID risk due in part to the fact that the baseline R_e level is 1.0 in this analysis, whereas it was 0.9 in our previous work.



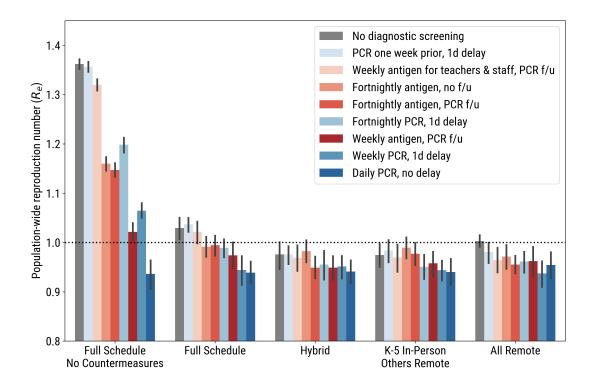


Figure 2: Impact of in-person learning on the community-wide effective reproduction number (R_e), averaged over the 3-month period in consideration. The model was calibrated to ensure that R_e is 1.0 for the "all remote" reopening scenario without diagnostic screening (rightmost gray bar). Bar color refers to diagnostic screening, if any, with blue indicating PCR-based testing and red indicating antigen-based testing. Reproduction numbers for the hybrid and K-5 phase-in scenarios are similar to the all-remote scenario, indicating that countermeasures and scheduling are sufficient to prevent schools from driving increased community transmission. Diagnostic screening is influential in the full-schedule with countermeasures, and unable to keep $R_e < 1.0$ with exception for daily immediate PCR in the no-countermeasures scenario.

with PCR follow-up amongst positives. Adding fortnightly screening with PCR or antigen testing brings the level back down to or even slightly below 1.0. More aggressive weekly or even daily testing brings the level down to match the all-remote scenario.

One final point worth noting in these results is the impact of diagnostic screening in the all-remote scenario. While the impact on the reproduction number is small (1.0 down to about 0.95), testing drives reductions in COVID-19 transmission through isolation and contact tracing.

Schools with infections on the first day

In considering the percent of schools that may have an infectious student, teacher, or staff member physically present on the first day of in-person learning, we find that the probability increases with school size; larger schools are more likely to have one or more infectious individual present, see the black curve in Fig. 3. However, risk does not necessarily scale with school size if cohorting is effective. Note that in this analysis, we are counting only individuals who pass symptom screening, assuming screen positives would either stay home from school or would be turned away at the door.

Diagnostic screening prior to the start of in-person learning has the potential to reduce the number of schools with infectious individuals present on the first day. The impact diminishes as the number of days



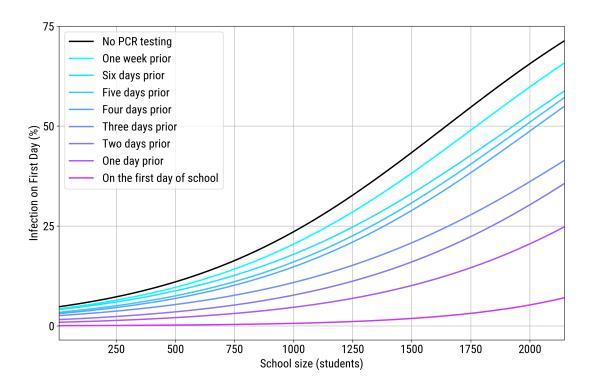


Figure 3: The percentage of schools that may have one or more infectious individual present on the first day increases with the size of the school. These individuals may not be detected, and may not transmit the infection to others. Line color denotes diagnostic screening of all students, teachers, and staff zero (pink) to seven (cyan) days in advance of the first in-person day. The black curve represents a scenario without PCR screening. While screening reduces the percent of schools with infectious individuals present on the first day, the impact diminishes as the delay between screening and the first in-person day grows.

between testing and the first day of school increases. For a school with 1,000 students, perfectly sensitive day-of testing eliminates the risk of infectious individuals attending school, and day-before testing has a probability below 10%. The probability increases to near 20% if testing is conducted one week in advance, a result that is slightly lower than the 25% that would be expected if no diagnostic screening is performed⁶.

In-person days lost

Over the 3-month analysis period, teachers & staff and students in this analysis have a possibility of 65 in-person weekdays⁷. Individuals may miss in-person school days due to isolation following COVID-19 diagnosis or quarantine following symptom or diagnostic screening. False positives are possible for both symptom screening and diagnostic screening with antigen tests. However, here we find that **scheduling losses dominate losses due to health reasons**, see Figure 4.

All possible in-person learning days are remote in the all-remote scenario. Both hybrid and K-5 scenarios schedule-in approximately 60% of days at home for students, but teachers & staff have a 20% scheduled loss in hybrid (no in-person learning on Wednesday) compared to approximately 60% scheduled loss for K-5, due to the fact that middle and high school teachers would remain remote.

⁷Schools are closed on the weekend, but this analysis does not adjust for scheduled holidays.



⁶While here we have assumed that everyone tests on the same day, testing in advance of starting in-person learning would realistically be distributed over time, thereby blending the curves shown in our results.

In-person days lost due to health concerns, including false positives from symptom and diagnostic screening, are most visible in the full-schedule scenario. This scenario has no scheduled loss, so bar heights represent health loss. Loss is highest for the antigen-based scenarios, due to false positives during diagnostic screening, but all losses are under 5%. Days lost are smallest in the full-schedule without countermeasures scenario due to the lack of symptom screening and contact tracing.

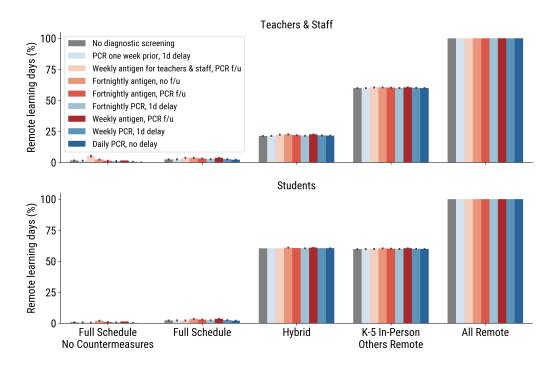


Figure 4: Out of 65 possible weekdays between Nov. 2nd and Jan. 31st, bar height indicates the percentage of in-person days lost due to scheduling and health concerns for each school reopening scenario. Bar color indicates diagnostic screening, as in previous figures. 100% of in-person days are lost for the all-remote scenario, and students miss approximately 60% of possible in-person days for both hybrid (2 in-person days per week) and K-5 (middle and high schools remote) scenarios. All teachers and staff are required on weekdays except Wednesday for the hybrid scenario, generating 1/5 (20%) loss, and teachers and staff associated with middle and high schools remote in K-5 scenario. Health-related losses from symptom and diagnostic screening are most visible in the full-schedule (with countermeasures) scenario, especially for antigen-based screening (red bars).

Sensitivity analysis

Modeling assumptions around COVID-19 transmission in general and specifically school reopening scenarios, countermeasures, and diagnostic screening drive the main results in this report. However, **there is considerable uncertainty that may impact our findings**. To address considerations, we perform a number of *one-way* sensitivity analyses to address what-if questions, see Table 2.

Due to the potentially large computational burden of simulating all variations on our baseline analysis for all school reopening and diagnostic screening scenarios, we present results exclusively for the school reopening scenario in which K-5 returns to in-person learning while middle and high schools continue remote learning. To further reduce the computational burden, we consider just four of the diagnostic screening scenarios, three of which include routine diagnostic screening and one which does not.



sis.	
naly	
a ∑	
Ĩ	
nsi	
ı se	
⊒. ס	
sse	
ě	
ad	
SUC	
ŝ	
ant	
hat	
≥	
5	
ble	
Ë	
	Table 2: What-if questions addressed in sensitivity analysis.

Variation Color	Baseline assumption
ays of • Antigen sensitivity: 90% if within 7 days of Orange	What if diagnostic tests (antigen primarily, but also • Antigen sensitivity: 97.1% if within 7 days of
symptom onset and 60% otherwise	PCR) have less favorable characteristics when used in symptom onset and 90% otherwise
 Antigen specificity: 60% 	 practice? (Sensitivity and specificity are with respect Antigen specificity: 98.5%
 PCR sensitivity: 99.5% 	PCR sensitivity: 100%
PCR specificity: 100%	 PCR specificity: 100%
chools Half of all student-to-student contacts are "re-wired" Green	What if school cohort "bubbles" are broken by trans- Classroom cohorts in elementary and middle schools
20 chil- at random so that roughly 50% of contacts will be	block all contacts between one cohort (about 20 chil-
-	dren) and the next. With hybrid scheduling, cohorts
in other randomly selected cohorts.	contain half as many students.
ecceive Coverage of symptom screening lowered to 50%. Red	What if symptom screening does not catch as many Of students arriving to school each day, 90% receive
	symptom screening as described above
achers, Diagnostic screening coverage reduced to 50% Purple	What if the diagnostic screening scenarios do not Amongst the target population (students, teachers,
% are	and staff or just teachers and staff), 100% are
	screened with the diagnostic.
aability No reduction.	What if schools are not able to implement NPI reduc- Reduction in the per-contact transmission probability
	tions due to challenges around masking, ventilation, of 25% in schools.
ecceive No symptom screening. Pink	Of students arriving to school each day, 90% receive
	symptom screening as described above
creases Following Table 1 in [11], we assume lower levels of Gray	What if infections are more likely to be asymp- The probability of developing symptoms increases
e aged infections presenting with symptoms: 18% for 0-19,	with age (in 10 year buckets) from 50% for those aged
22% for 20-39, 31% for 40-59, and 35% for 60-79, and	0-9 to 90% for 80+.
66% for 80+. Because this change affects all parts of	
the model, we recalibrated to the King County base-	
line.	
	What if children under 20 are as susceptible to COVID- Compared to adults 20-64, children 0-9 and 10-19 are
-	33% and 66% as susceptible per contact per day to
intections, thereby affecting the model calibration	Intection.
(model output no longer look like King County data).	
I herefore, we have re-calibrated the model as part of this variation.	
rk and On Nov. 1 st , when schools open, work and community Turquoise	What if there are increasing levels of population mo- Compared to pre-COVID-19 levels, 65% of work and



Results for the impact of each variation on the 3-month attack rate is shown in Figure 5. We find that our baseline results are sensitive primarily to 1) increased mobility and 2) children being equally susceptible to COVID-19 infection as adults. Results are also somewhat sensitive to more asymptomatic infections.

Mobility in this analysis is a proxy for increased COVID-19 transmission in the community. The fact that increased community transmission results in a greater attack rate in schools should not be a surprise; we highlighted this finding in our schools are not islands report in mid-July. With case detection rates and R_e recently increasing in King County and much of Washington State and the country as a whole, this result should serve as a warning that our main results could under-estimate attack rates by as much as 50% due to increasing community transmission alone.

Numerous studies have evaluated the susceptibility of children relative to adults, see [12] for a review. While it is broadly accepted that children under age 10 are less susceptible, the evidence is mixed for children 10-19. Nonetheless, we take an extreme variation on our base analysis to consider if everyone under age 65 is equally susceptible. Those aged 65+ remain at elevated susceptibility in accordance with [9]. We find that this variation generates a near three-fold increase in the 3-month attack rate for the "countermeasures-only" scenario. The increased attack rate is mitigated by fortnightly diagnostic screening, but the elevated attack rate persists for students more so than teachers and staff.

In the countermeasures-only scenario, the variation in which daily symptom screening at home or

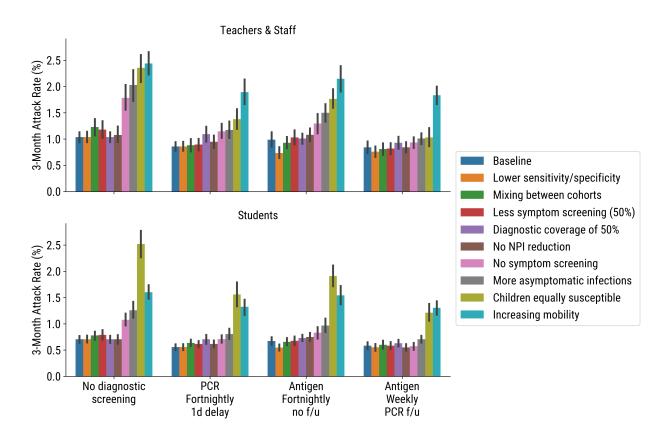


Figure 5: Results of sensitivity analysis for the school reopening scenario in which only K-5 returns in person. Results show the impact of various perturbations to baseline assumption on the 3-month attack rate. Bar groups refer to the diagnostic screening scenario, and bar color indexes the perturbation (see Table 2). Higher bars indicate a greater percentage of teachers and staff (top) or students (bottom) getting infected over the 3-month period in consideration.

& IDM

school is eliminated has a near two-fold increase in the 3-month attack rate. Adding fortnightly diagnostic screening captures symptomatic and asymptomatic infections that may be present in school populations, and therefore serves as a backstop to symptom screening. However, at fortnightly frequency, diagnostic screening is insufficient to return risk to the baseline level. Similar trends are observed for the scenario in which more infections are asymptomatic.

In considering in-person days lost (not shown), the only significant deviation is due to the assumption around the specificity of antigen testing. The reduction of antigen test specificity from 98.5% to 60% creates a near-20% increase in days lost for the screening scenario without PCR follow-up. With PCR follow-up, false positives will quarantine for three days while awaiting diagnostic results before being allowed to return to school.

Beyond these noted exceptions, results are generally robust to the variations considered. However, these one-way variations do not capture possible interactions in which several of our baseline assumptions may be violated simultaneously.

Appendix

A Understanding the impact of countermeasures

Countermeasures in this analysis include three core components: 1) symptom screening, 2) contact tracing, and 3) non-pharmaceutical interventions (NPI) such as masks, physical distancing, ventilation, and hand hygiene. Results presented in Figure 1 show that the combination of these three countermeasures is essential in reducing the 3-month attack rate in teachers and staff as well as in students. To learn how each countermeasure influences outcomes independently or in combination with other countermeasures, here we run full-schedule scenarios varying which of the three countermeasure components are enabled. We present results for two diagnostic screening scenarios: 1) no diagnostic screening and 2) fortnightly antigen screening with PCR follow-up.

We find that the most influential single countermeasures in this analysis is symptom screening, see Figure 6. Symptom screening explains most of the difference between the "no countermeasures" and "with countermeasures" full-schedule scenarios. NPI and tracing independently reduce the attack rate by over 50% compared to no countermeasures, but have a lesser effect when combined with symptom screening. The relative trends are the same when screening fortnightly with an antigen-based test, including PCR follow-up, but the attack rates are lowered by the screening intervention.

In the model, the probability of an individual developing symptoms increases linearly with age from 50% in those aged 0-9 to 90% for those aged 80+, in 10-year increments. For those eventually developing symptoms, the delay between the beginning of infectiousness and the onset of symptoms is distributed log-normally, resulting in an average delay of one day⁸. We assume at baseline that 90% of students, teachers, and staff are screened before each school day.

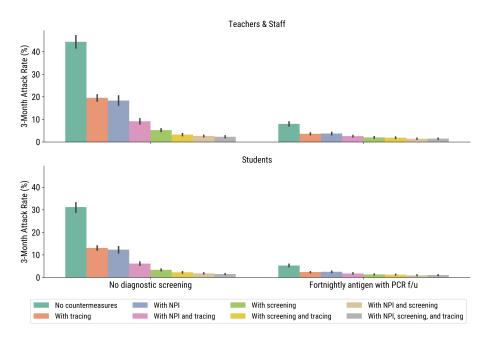


Figure 6: The impact of countermeasure components, independently or in combination, for the fullschedule scenario. Diagnostic screening scenarios are none (left) or fortnightly antigen screening with PCR follow-up (right).

⁸We quantize the log-normal distribution due to the one-day time step of the simulation. Approximately 30% develop symptoms concurrently with becoming infectious, 50% develop symptoms on the next day, and the remaining 20% develop symptoms 2+ days after becoming infectious.



B What if symptom screening is not possible?

Sensitivity analysis revealed that symptom screening was the most significant independent component of the countermeasures considered in this analysis. The efficacy of symptom screening has been debated, it may be logistically challenging for schools to implement, and parents may not take home-based symptom screening seriously. To explore the impact of symptom screening beyond the sensitivity analysis, we repeated the main analysis with daily symptom screening disabled. This is a pessimistic scenario because it allows highly symptomatic individuals to attend in-person learning. Nonetheless, we believe this is a useful bookend to our main analysis.

We find that attack rates are increased across all scenarios that had countermeasures, particularly for the full-schedule scenario. Hybrid scheduling and K-5 in-person scenarios are more robust to symptom screening. This finding is reassuring in the sense that symptom screening is not singularly driving our main results, but nonetheless supports daily symptom screening to the extent possible.

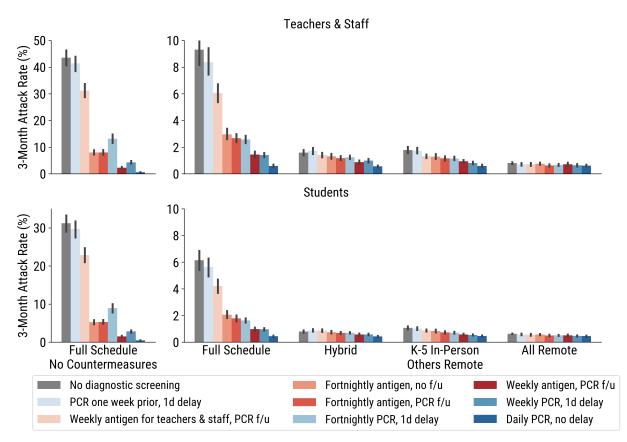


Figure 7: Variation on the main analysis in which the daily symptom screening countermeasure is disabled. Bar groups and colors are as in previous figures. These results show elevated risk compared to main results, particularly for the full schedule scenario. Hybrid scheduling and the phased-in approach scenarios also have elevated risk, but the difference is smaller.

🔅 IDM

C Estimating prevalence in King County

The agent-based model's rough calibration to King County's COVID-19 epidemiology was facilitated by an estimate of recent population prevalence using data from the Washington Disease Reporting System up to October 9. Prevalence was estimated using a compartmental disease transmission model which tracks susceptible, exposed, and infected populations at county-scale and assumes that susceptible and infected individuals are well-mixed in the community. At a high level, this transmission model estimates the time course of population prevalence, R_e , and case ascertainment rates consistent with daily testing, hospitalization, and mortality data. For the technical details of this approach, see our corresponding report.

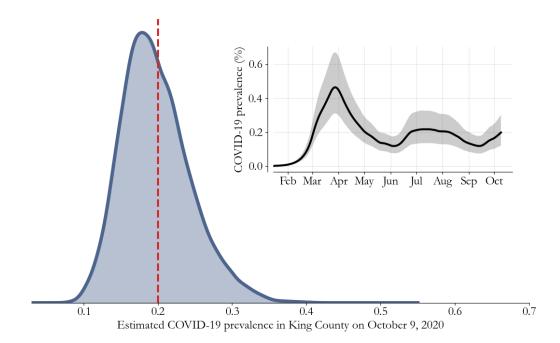


Figure 8: COVID-19 prevalence in King County as estimated by our compartmental transmission model. 10,000 model runs generate a distribution of daily prevalence estimates (inset, 95% interval in grey) showing a pronounced first and second COVID transmission wave in King County consistent with observed case, hospitalization, and mortality data. Recently, we estimate that on October 9, 0.20% of King County's population (0.12 to 0.30 95% interval) was actively infected with COVID-19 (inferred distribution in blue). This estimate (red dashed line) is used as a calibration target for the agent-based model used throughout this report.

In King County, we estimate in Figure 8 that prevalence began increasing most recently in mid September (inset) and is roughly consistent with levels from July and August. On October 9, we estimate that between 0.12 and 0.30% of King County's population was actively infected with COVID-19. Our best estimate, 0.20%, is used as a calibration target for the agent-based model used throughout this report.

🔅 IDM

D Model fitting

The model was fit to the data listed in Table 1 using a python-based global optimization algorithm [13]. The algorithm seeks to minimize a mean-absolute-error objective function,

$$J(\theta) = \sum_{i=1}^{5} w_i \frac{|\text{simulated } \text{target}_i(\theta, r) - \text{target}_i|}{\text{target}_i}, \tag{1}$$

where target_i is the i^{th} target value in Table 1, θ is a vector of three model parameters (described below), and r is a random number selected to seed the random number generator of the stochastic simulation. The weighting factor w_i is 5 for prevalence and 1 for the other four targets.

Three parameters identified during this calibration are described in Table 3.

Table 3:	Calibration	targets
----------	-------------	---------

Parameter	Significance	Range
seed_infections	The model is initialized on Sept. first with this many infections	100-300 in a population of
		225,000 particles
beta	Scalar multiplier on the per-contact transmission probability	0.35-0.65
symp_prob	The probability that a COVID-symptomatic individual seeks test-	5-20%
	ing, per day while symptomatic	

The calibration algorithm identifies a ranked list of parameter combinations, θ , along with the random number generator seed, r, that achieved the low value of the objective function, J.

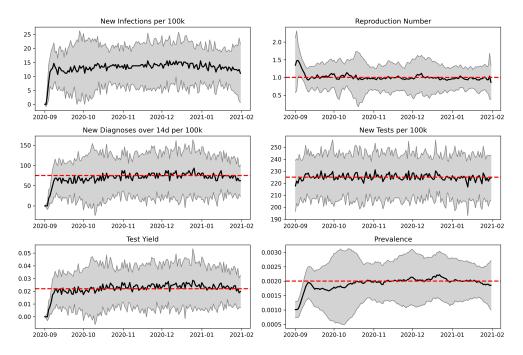


Figure 9: Model calibration results are show in black (median) with 95% confidence interval from the top 30 parameter configurations. Calibration targets are drawn as red dashed lines.

E PCR and antigen diagnostics

A surprising result in Figure 1 was that fortnightly antigen testing resulted in a lower 3-month attack rate than PCR testing with 1-day delay for the full schedule *without countermeasures* scenario, despite the fact that the PCR test is more sensitive. In this case, the speed of antigen tests in returning results is more important than sensitivity in this high incidence scenario (recall this is for the full-schedule *without* countermeasures scenario). Results sweeping the PCR results delay from 3 days down to same-day are shown in Figure 10. The 3-month attack rate for students and teachers & staff is highest for fortnightly screening with a PCR diagnostic that takes 3-days to return results. The attack rate decreases as the PCR screening returns results more quickly, to the point where same-day PCR is better than the antigen test (with immediate quarantine an PCR-follow-up). The lower sensitivity of the antigen test is represented by the slightly higher attack rate seen in the light red bar compared to a hypothetical antigen test with perfect sensitivity (dark red bar).

The other potential reason screening with an antigen test may out-perform PCR-based screening is due to false positive results. False positives result in fewer people physically present in school, and therefore a lower attack rate. In other words, healthy individuals kept at home due to a false positive antigen result are "shielded" from school-based infections. However, the magnitude of this effect is small compared to the impact of delays.

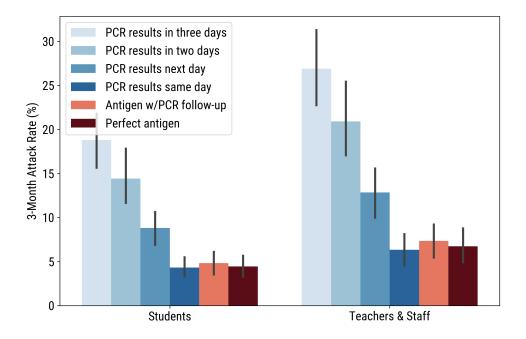


Figure 10: Three-month attack rate for students (left) and teachers & staff (right) for the full-schedule without countermeasures scenario. Screening is conducted fortnightly amongst all students, teachers, and staff. PCR tests with various delays to return results are shown in blue bars for comparison with an antigen test with PCR follow-up (light red) or a hypothetical antigen test with 100% sensitivity and specificity (dark red). In this high-incidence countermeasure-free setting, the same-day speed of antigen screening out-performs the higher-sensitivity of PCR-based screening.

References

- [1] "How are districts serving students to start the 2020-21 school year?." https://tableau.ospi.k12. wa.us/t/Public/views/AESDRe-Opening/Dashboard1?:isGuestRedirectFromVizportal= y&:embed=y. Accessed: 2020-10-26.
- [2] C. C. Kerr, R. M. Stuart, D. Mistry, R. G. Abeysuriya, G. Hart, K. Rosenfeld, P. Selvaraj, R. C. Nunez, B. Hagedorn, L. George, *et al.*, "Covasim: an agent-based model of covid-19 dynamics and interventions," *medRxiv*, 2020.
- [3] J. Cohen, D. Mistry, C. Kerr, D. Klein, M. Izzo, and J. Schripsema, "Maximizing education while minimizing covid risk: priorities and pitfalls for reopening schools," *covid.idmod.org*, 2020.
- [4] N. G. Davies, P. Klepac, Y. Liu, K. Prem, M. Jit, R. M. Eggo, C. C.-. working group, *et al.*, "Age-dependent effects in the transmission and control of covid-19 epidemics," *MedRxiv*, 2020.
- [5] A. E. Benefield, L. A. Skrip, A. Clement, R. A. Althouse, S. Chang, and B. M. Althouse, "Sars-cov-2 viral load peaks prior to symptom onset: a systematic review and individual-pooled analysis of coronavirus viral load from 66 studies," *medRxiv*, 2020.
- [6] "Key indicators of COVID-19 activity in King County." https://www.kingcounty.gov/depts/ health/covid-19/data/key-indicators.aspx. Accessed: 2020-10-15.
- [7] "Screening k-12 students for symptoms of COVID-19: Limitations and considerations." https://www.cdc.gov/coronavirus/2019-ncov/community/schools-childcare/ symptom-screening.html. Accessed: 2020-10-26.
- [8] "Binaxnow covid-19 ag card." https://www.fda.gov/media/141570/download. Accessed: 2020-10-26.
- [9] J. Zhang, M. Litvinova, Y. Liang, Y. Wang, W. Wang, S. Zhao, Q. Wu, S. Merler, C. Viboud, A. Vespignani, et al., "Changes in contact patterns shape the dynamics of the covid-19 outbreak in china," Science, 2020.
- [10] T. Heald-Sargent, W. J. Muller, X. Zheng, J. Rippe, A. B. Patel, and L. K. Kociolek, "Age-related differences in nasopharyngeal severe acute respiratory syndrome coronavirus 2 (sars-cov-2) levels in patients with mild to moderate coronavirus disease 2019 (covid-19)," JAMA pediatrics, vol. 174, no. 9, pp. 902–903, 2020.
- P. Poletti, M. Tirani, D. Cereda, F. Trentini, G. Guzzetta, G. Sabatino, V. Marziano, A. Castrofino, F. Grosso,
 G. Del Castillo, *et al.*, "Probability of symptoms and critical disease after sars-cov-2 infection," *arXiv* preprint arXiv:2006.08471, 2020.
- [12] R. Viner, O. Mytton, C. Bonell, *et al.*, "Susceptibility to sars-cov-2 infection amongst children and adolescents compared with adults: a systematic review and meta-analysis. medrxiv. 2020."
- [13] T. Akiba, S. Sano, T. Yanase, T. Ohta, and M. Koyama, "Optuna: A next-generation hyperparameter optimization framework," in *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pp. 2623–2631, 2019.