**A model of COVID-19 transmission and control on university campuses**

*Ben Lopman, PhD[1];*
*Carol Y. Liu, MSc[1];*
*Adrien Le Guillou MD MPH,[1,2];*
*Timothy L. Lash, DSc[1];*
*Alexander P. Isakov MD MPH[3];*
*Samuel M. Jenness, PhD[1]*

Affiliations
[1] Emory University Rollins School of Public Health, Atlanta, GA 30322, USA
[2] Department of Research and Public Health, Reims Teaching Hospitals, Robert Debré Hospital, Reims, France
[3] Emory University School of Medicine, Atlanta, GA 30322, USA

Correspondence
Ben Lopman, Emory University, 1520 Clifton Road, Atlanta, GA 30323. Email: blopman@emory.edu.

**Abstract**
In response to the COVID-19 pandemic, institutions of higher education in almost every nation closed in the first half of 2020. University administrators are now facing decisions about how to safely return students, staff and faculty to campus. To provide a framework to evaluate various strategies, we developed a susceptible-exposed-infectious-recovered (SEIR) type of deterministic compartmental transmission model of SARS-CoV-2 among students, staff and faculty. Our goals were to support the immediate pandemic planning at our own university, and to provide a flexible modeling framework to inform the planning efforts at similar academic institutions. We parameterized the model for our institution, Emory University, a medium-size private university in Atlanta, Georgia. Control strategies of isolation and quarantine are initiated by screening (regardless of symptoms) or testing (of symptomatic individuals). We explore a range of screening and testing frequencies and perform a probabilistic sensitivity analysis of input parameters. We find that monthly and weekly screening can reduce cumulative incidence by 38% and 73% in students, respectively, while testing with a 2-, 4- and 7-day delay results in an 83%, 76% and 67% reduction in cumulative incidence in students over the semester, respectively. Similar reductions are observed among staff and faculty. A testing strategy requires far fewer diagnostic assays to be implemented than a screening assay. Our intervention model is conservative in that we assume a fairly high reproductive number that is not reduced through social distancing measures. We find that community-introduction of SARS-CoV-2 infection onto campus can be controlled with effective testing, isolation, contract tracing and quarantine, but that cases, hospitalization, and (in some scenarios) deaths may still occur. In addition to estimating health impacts, this model can help to predict the resource requirements in terms of diagnostic capacity and isolation/quarantine facilities associated with different strategies.

**Background**

In an unprecedented response to the COVID-19 pandemic, schools (including institutions of higher education) in almost every nation closed in the first half of 2020.(1) For boarding institutions like universities, this involved both transitioning classes into online teaching as well as closing dormitories by sending students off-campus. School closure as a non-pharmaceutical intervention has been aimed at reducing contact among students, family members, teachers, and school staff.(2) It is thought to be an effective means of reducing disease transmission based on the understanding that younger people are important in transmission of respiratory viruses, like influenza. Closure of schools early in a pandemic is thought to be more impactful than delayed closing.(2) According to UNESCO, approximately 70% of the global student population has been affected, with closures of pre-school, primary, secondary, and higher education institutions.(1) Since SARS-CoV-2 infections are particularity severe among older adults while younger people still get infected and transmit,(3) university populations are unique in these degree of mixing across these age groups. Prior to the emergence of SARS-CoV-2, contact data on transmission of influenza, and other respiratory virus, provided the basis of current recommendations. Universities are important and unique in that they are frequently residential, involve students traveling long distances to attend, and are assets to their regional economies.

University administrators are now facing decisions about how to safely return students, staff and faculty to campus. As of the end of May 2020, approximately two-thirds of US universities are planning for in-person instruction for Fall 2020.(4) Universities considering campus re-opening need to estimate the resources necessary to interrupt and mitigate on-campus transmission by projecting the number of possible cases, needs for screening and testing, and boarding requirements for persons needing isolation and quarantine. To provide a framework to evaluate these questions, we developed a susceptible-exposed-infectious-recovered (SEIR) type of deterministic compartmental model. This model captures the transmission process and can therefore estimate the direct and indirect (transmission-mediated) effects of control strategies. For example, through model simulations, we estimated how testing and identifying SARS-CoV-2 infected students results in them being isolated, their contacts being quarantined, as well as all the infections averted by preventing the chains of transmission that would have otherwise occurred. Our goals were to support the immediate pandemic planning at our own university, and to provide a flexible modeling framework to inform the efforts at similar academic institutions.

**Methods**

We developed a dynamic model of transmission of SARS-CoV-2 among students, staff and faculty. We parameterized the model for our institution, Emory University, which is a medium-size private university in Atlanta, Georgia. We expect the model could be applicable to other colleges and universities and therefore provide a public web-interface where key initial conditions and model parameters, such as student and staff population sizes can be varied (https://epimodel.shinyapps.io/covid-university/). The model includes the following features and assumptions.

*Population Structure and Transmission.* We modeled three distinct population groups with different degrees of interactions among them: students living on campus; students living off campus; and staff and faculty. We assume that students living on campus have a higher risk for infection than those living off campus ($R_0$ = 3.5 and 2.5 respectively), because congregate living is typical on most college campuses. Staff/faculty can be infected by students and can infect other staff/faculty. We do not track transmission in the wider community, aside from incorporating a daily rate of introduction of virus onto campus from the community.

Universities are planning an array of measures to limit transmission on campus. These may include mask-wearing; other personal protective equipment; smaller class sizes; staggered class times; enhanced cleaning protocols; enhanced hygiene; cancelling large social gatherings; fewer students living in dorms and restricting off-campus movements. We lack data on the efficacy of all these interventions, especially in this specific population, but we assume that they will have an effect on transmission. We parameterize these non-pharmaceutical controls based on a systematic review of the effect of social distancing and face coverings (5)(and assume 50% compliance), and explore a range of values around this parameter.

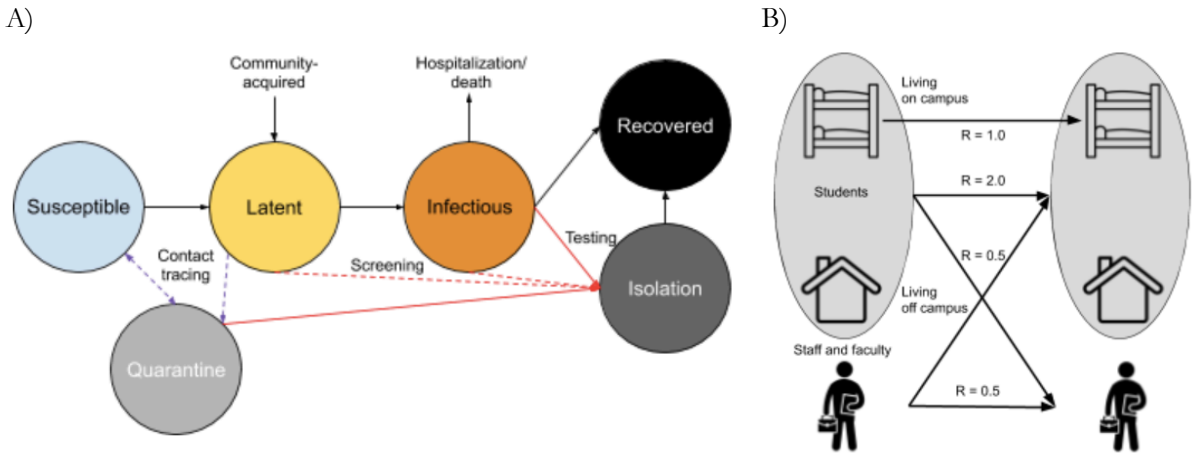
Staff and faculty had a higher risk of severe illness and death (given infection) than students, based on accumulating evidence of age-differences in the case-fatality rate,(6) and then standardized using the student and staff/faculty age-structure at our institution. [For a full list of parameter values, see Table 1.] We further assume that a fraction of cases is asymptomatic and that, the probability of symptoms is greater for staff/faculty given their older age distribution than students. We assumed that asymptomatic infected persons are as infectious as those with symptoms; this assumption may overestimate the true transmission rate in this group.(7) We assume that infectiousness begins on the third day after infection; this latent period is shorter than the incubation period(8) to represent pre-symptomatic transmission.

In order to capture external infection from non-university sources, we modeled a constant daily rate of infection being introduced on campus. In our model parameterization, this is based on confirmed COVID-19 cases in Fulton and Dekalb Counties that surround our institution;(9) we assume that infection incidence is ten-times that of reported cases.(7) The model runs for a semester from the day classes start (August 26) to the end of term (December 19). We did not assume reduced transmission over traditional Fall or Thanksgiving breaks or consider alternative schedules.

*Intervention Design.* In the model, control is initiated by SARS-CoV-2 diagnostics. Infected persons can be identified by reverse transcription polymerase chain reaction (RT-PCR) through either testing or screening, defined as follows. *Screening* is a strategy in which students, staff, and faculty are tested at a given frequency ranging from weekly to once per semester regardless of the presence of symptoms. *Testing* is a strategy whereby symptomatic students, staff, and faculty present for clinical care and are tested using RT-PCR. We assume a background level of persons with influenza-like symptoms caused by infections other than SARS-CoV-2 ,(10,11) who will test negative. Those with COVID-19 who test positive are immediately isolated. However, we assume that the diagnostic has imperfect sensitivity that varies based on what date of illness the test is performed.(12) There is evidence that PCR sensitivity varies over the course of infection, reaching a peak around day 7 of infection (or day 4 of infectiousness), then declines again. Therefore, we examined the impact of variation in the *testing* interval, defined as the average lag time between symptom onset and quarantine. Because infectiousness begins one day before symptom onset in the model, we simulated testing intervals ranging from a two -day to a one-week test delay. These testing scenarios are in the absence of any screening to isolate the causal effects of this more intensive intervention.

Following both screening and testing, those testing positive for COVID-19 were immediately isolated. Case isolation in the model mechanistically involved a complete reduction in their contact rate for the duration of infection. Positive test results also lead to contact tracing. Contact tracing is conducted by assuming public health authorities could elicit 14 contacts per case detected with 75% of those 14 successfully traced and quarantined. Quarantine, like isolation, was modeled as a complete reduction in the contact rate for the duration of infection. Some of those quarantined contacts might have been incubating but are now no longer able to infect since they are under quarantine.

**Figure 1.** Schematic of A) Disease Structure and B) Student and Staff/Faculty Transmission Pathways.




*Parameterization and Analysis.* In our base models, we simulated SARS-CoV-2 transmission and interventions for the Fall 2020 semester. Our main base model assumed no interventions, to project the "worst case" scenario. Counterfactual scenarios then varied the screening and testing rates, and the completeness of contact tracing. Our primary outcomes were both active cases per day and cumulative cases across the semester. The model tracked both total cases in each campus group (students versus staff/faculty) as well as severe cases and COVID-related mortality.

Given uncertainty in model parameters, we performed a probabilistic sensitivity analysis to determine the range of credible outcomes, given uncertainty in model parameters. In the probabilistic sensitivity analysis, we take 1,000 parameter draws using Latin Hypercube Sampling from the distributions in Table 1 and report the 2.5$^{th}$ and 97.5$^{th}$ centile of those runs (Appendix II). We use partial rank correlation coefficient to determine how much the modeled variation in cumulative incidence among students and faculty/staff depends on specific random parameters.

The model was built and simulated in the *EpiModel* package in the R statistical computing platform(13); the *LHS* package was used to perform Latin Hypercube Sampling. We also built an interactive web app for model exploration using the R Shiny framework. It can be accessed at https://epimodel.shinyapps.io/covid-university/.

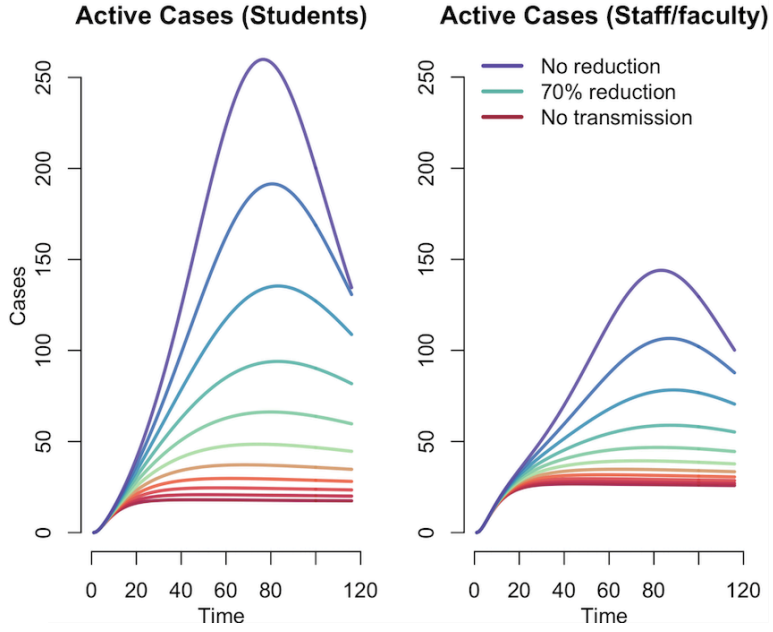
**Table 1.** Model parameters and ranges

| Parameter | Value | Range | Distribution | Symbol | Source |
|---|---|---|---|---|---|
| **Populations** | | | | | |
| Total students | 15,000 | | | | Univ. admin |
| Students living on campus | 4,500 | 1575 to 4500 | Uniform | | Univ. admin |
| Staff and faculty | 15,266 | | | | Univ. admin |
| **Natural history and clinical** | | | | | |
| Latent period (days) | 3 | 2 to 4 | Gamma | $1/\alpha$ | (8) |
| Infectious period (days) | 7 | 6 to 8 | Gamma | $1/\gamma$ | (14) |
| Proportion severe - students | 0.0224 | 0.0133 to 0.0456 | Beta | | (6) |
| Proportion severe - staff/faculty | 0.055 | 0.0327 to 0.1122 | Beta | | (6) |
| Proportion fatal - students | 0.0006 | 0.0003 to 0.0014 | Beta | | (6) |
| Proportion fatal - staff/faculty | 0.0052 | 0.0029 to 0.0105 | Beta | | (6) |
| Proportion symptomatic - students | 0.35 | 0.27 to 0.43 | Beta | $1 - p_{asy,stu}$ | (15) |
| Proportion symptomatic - staff/faculty | 0.51 | 0.41 to 0.59 | Beta | $1 - p_{asy,saf}$ | (15) |
| **Transmission** | | | | | |
| $R_0$: students to students | 2 | 0.7 to 2.5 | Uniform | $Ro_{stu,stu}$ | |
| $R_0$: on campus students to other on campus students | 1 | 0.3 to 1.4 | Uniform | $Ro_{on,on}$ | |
| $R_0$: Staff/faculty to student; staff/faculty to staff/faculty | 0.5 | 0.15 to 0.7 | Uniform | $Ro_{saf}$ | |
| Daily rate of community introduction | 0.0005 | 0.00025 to 0.001 | Beta | community | |
| Efficacy of face-coverings and social distancing | 0.7 | 0.36 to 0.86 | Beta | eff_npi | |
| **Testing and quarantine** | | | | | |
| Time from onset of infectiousness to testing (1/days) | 2 | 7 to 1 | Uniform | | |
| Screening frequency (1/days) | 30 | 120 to 1 | Uniform | | |
| Duration of quarantine (days) | 14 | | | $1/\delta$ | |
| Number of contacts per case | 14 | 12 to 16 | Uniform | contacts | (16) |
| Proportion of contacts reached | 0.75 | 0.5 to 1 | Uniform | | |
| Proportion experiencing ILI symptoms per month | 0.1 | 0.09 to 0.11 | | | (10,11) |
| PCR sensitivity -- day 2 of infectiousness | 0.75 | 0.6 to 0.83 | Beta | $sen_2$ | (12) |
| PCR sensitivity -- day 4 of infectiousness | 0.8 | 0.7 to 0.85 | Beta | $sen_4$ | (12) |
| PCR sensitivity -- day 7 of infectiousness | 0.75 | 0.65 to 0.8 | Beta | $sen_7$ | (12) |

**Results**

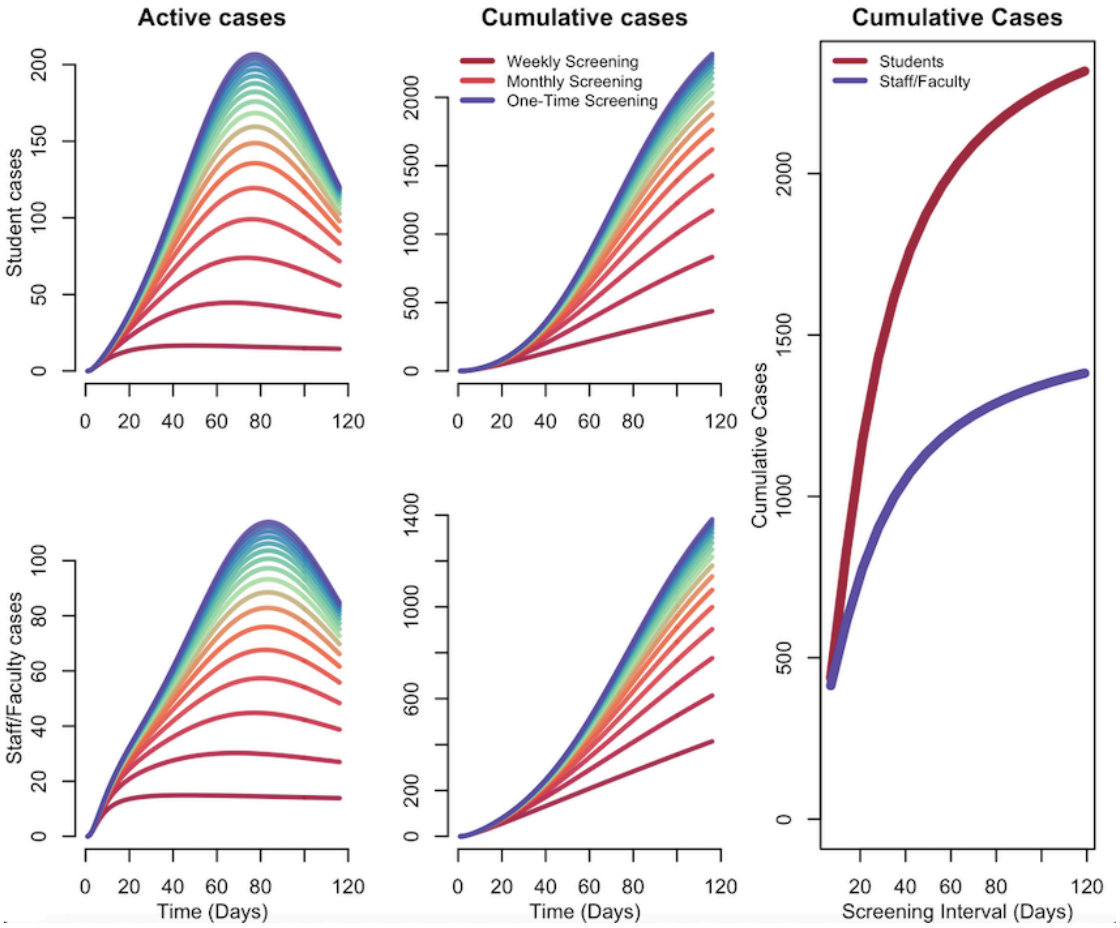
We start by simulating transmission on campus (Table 2; Figure 2) in which no diagnostic control measures are in place (no testing, isolation, contact tracing, or quarantine). With $R_0$ of 3.5 for on-campus student and 2.5 for off-campus, case prevalence peaks at 1324 cases (Range, 2.5$^{th}$ to 97.5$^{th}$ centiles: 624 to 2070) per day among students and 1061 cases per day among staff/faculty (404 to 1907), resulting in cumulative 4960 (3846 to 6264) and 5175 (2573 to 7302) cases at the end of the semester in a population of about 15,000 of each. With our baseline levels of facemask and social distancing efficacy (70%) but with no diagnostics, we estimate case prevalence peaks at 98 cases (Range, 2.5$^{th}$ to 97.5$^{th}$ centiles:15 to 1048) per day among students and 66 cases per day among staff/faculty (17 to 681), resulting in a cumulative of 1233 (231 to 5117) student cases and 888 (255 to 4210) staff cases at the end of the semester. Note that this number of symptomatic cases is substantially lower than the number of infections since we assume that 35% (27 to 43%) of infected students and 51% (41 to 59%) of infected staff are symptomatic, given infection.(15) We use this scenario as the baseline counterfactual for all subsequent comparisons.

**Figure 2.** Effect of non-pharmaceutical interventions (with no testing and screening) on daily COVID-19 prevalence.



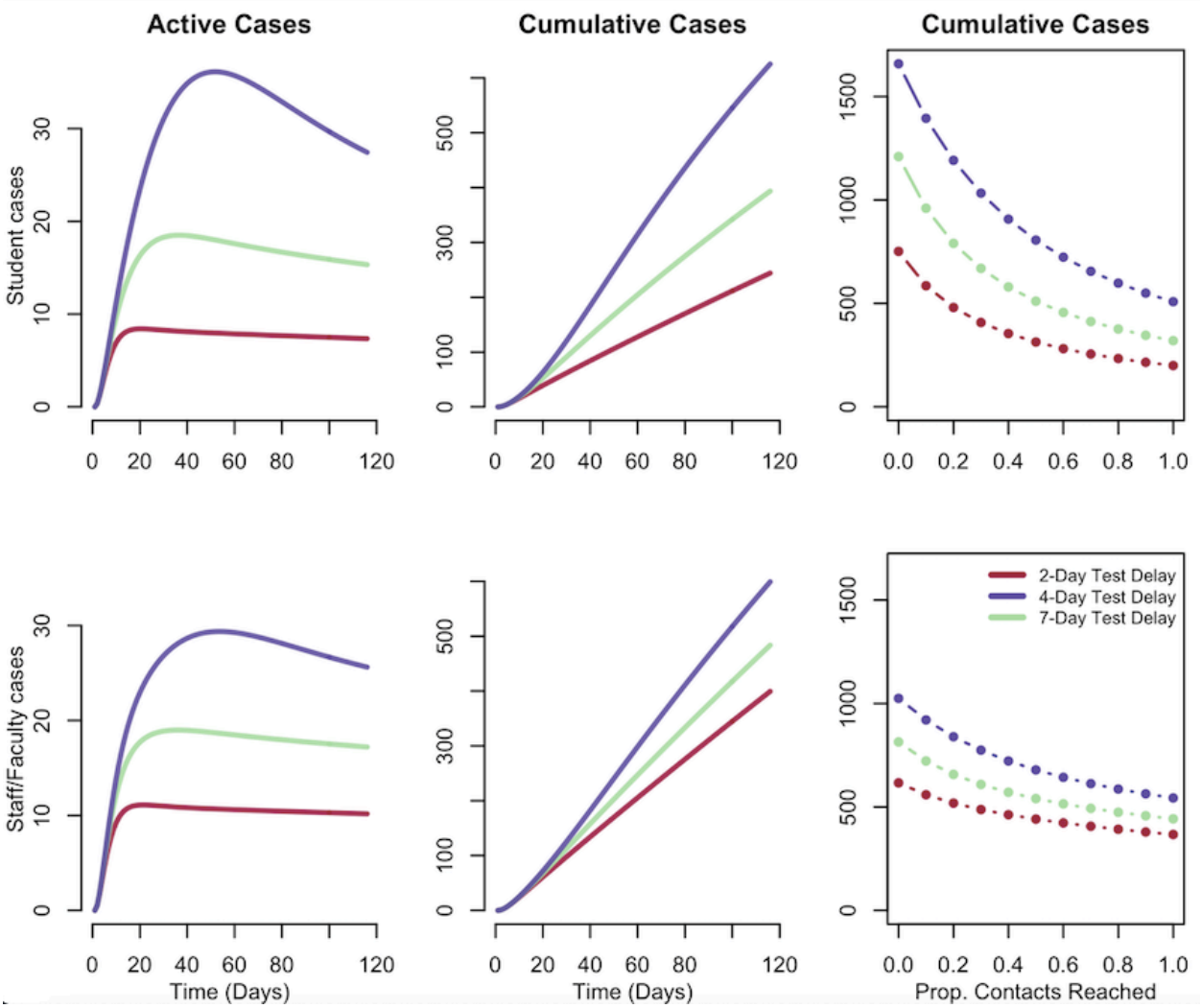
We next explored a wide range of *screening* intervals, from weekly to once during the semester (Fig 3). One-time screening, whereby the population is tested on average once during the 4-month semester, reduced cumulative student incidence overall by 14%; monthly and weekly screening reduced cumulative student incidence by 38% and 73% respectively. For staff and faculty, one-time screening reduced cumulative incidence by 10%; monthly and weekly screening reduce cumulative incidence by 27% and 58% respectively. For students, the cumulative incidence ranged from 336 (115-1536)with weekly screening to 1060 (219 -4839) with one-time screening. For staff/faculty, the cumulative incidence ranged from 371 (142-751)) with weekly screening to 804 (242-3850) with one-time screening.

**Figure 3.** Impact of Screening Frequency on Projected Covid-19 Daily and Cumulative Incidence.




With testing and this level of contact tracing as described, the cumulative incidence for the semester ranges from 207 (78-507) among students and 364 (148-751)57 (15-144) and staff & faculty with two-day delay testing interval, 296 (106-1055) among students and 426 (165-1023) among staff & faculty with a four-day delay testing interval; 412 (136-1851) among students and 498 (184-1405) among staff & faculty with a seven-day delay testing interval. (Fig 3) This represents an 83%, 76% and 67% reduction in cumulative incidence over the semester among students and an 59%, 52% and 44% reduction in cumulative incidence among staff & faculty. The impact of testing is highly sensitive to the success of contact tracing, which can overwhelm the impact of quarantine of the tested and isolation of the cases themselves.

**Figure 4**. Impact of testing, contact tracing and quarantine at a range of testing delay intervals. Daily and cumulative Covid-19 incidence on university campus.




Here, with week-delayed testing (the least optimistic scenario), the expected cumulative incidence would be 412 (136-1851) for students and 498 (184-1405) for staff/faculty. Figure 3 shows the general relationship between "contact tracing" success and cumulative incidence assuming either a 2-day, 4-day, or 7-day delay in testing/quarantine following symptoms. Although the testing interval can reduce the cumulative incidence, the greater impact of this testing scenario is achieved by the number of contacts reached.

In the final scenarios, we combined the testing and screening rates under different assumptions of contact tracing related to testing (Figure 5). Our model scenarios below varied the interval for screening between 1 week (7 days) and 1 semester (120 days) and testing at2-, 4- and 7-day delay, with the efficacy of contact tracing ranging from 0, 50% and 100%. These figure panels show cumulative incidence at the end of the semester for students only. When combined with testing, screening generally has little effect unless it is performed at least monthly.

**Figure 4.** Impact of combined screening and testing of covid-19 cases among students. Vertical lines represent weekly and monthly screening.

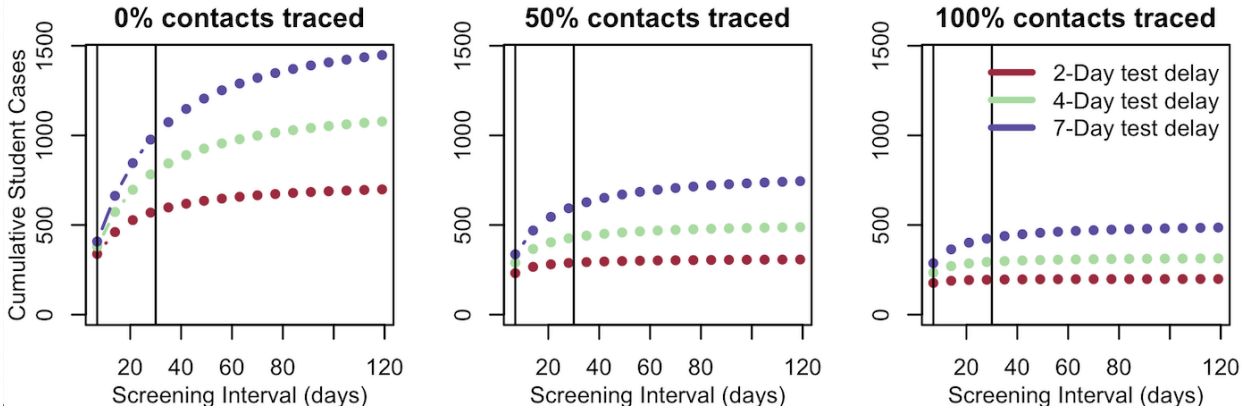


**Table 2.** Cumulative outcomes at end of the semester on medium size university campus (approx. 15,000 students and 15,000 staff and faculty). Values are medians and 2.5 and 97.5th percentiles of 1,000 model runs.

| | Base scenario | 4-day test delay | 30-day screen interval | Combined test and screen |
|---|---|---|---|---|
| **Students** | | | | |
| Cumulative cases (n) | 1233 (231-5117) | 296 (106-1055) | 759 (195-4231) | 273 (101-872) |
| Peak daily cases (n) | 98 (15-1048) | 13 (5-69) | 46 (10-639) | 11 (4-44) |
| Hospitalizations (n) | 56 (3-399) | 10 (1-93) | 32 (2-322) | 8 (1-72) |
| Deaths (n) | 1 (0-12) | 0 (0-3) | 1 (0-10) | 0 (0-2) |
| Isolated (n) | 0 (0-0) | 266 (98-966) | 486 (127-2766) | 367 (135-1168) |
| Isolated (max) | 0 (0-0) | 35 (12-176) | 72 (17-773) | 47 (17-183) |
| Isolated (days) | 0 (0-0) | 3283 (1201-12378) | 5928 (1545-38031) | 4528 (1659-14830) |
| Quarantined (n) | 0 (0-0) | 3742 (1285-13673) | 0 (0-0) | 3077 (1089-9712) |
| Quarantined (max) | 0 (0-0) | 359 (120-1781) | 0 (0-0) | 291 (101-1206) |
| Quarantined (days) | 0 (0-0) | 33784 (11520-129763) | 0 (0-0) | 27834 (9751-93101) |
| **Staff and Faculty** | | | | |
| Cumulative cases (n) | 888 (255-4210) | 426 (165-1023) | 644 (204-2959) | 389 (154-895) |
| Peak daily cases (n) | 66 (17-681) | 16 (6-43) | 38 (11-357) | 13 (5-32) |
| Hospitalizations (n) | 46 (2-430) | 8 (1-64) | 25 (2-295) | 7 (1-49) |
| Deaths (n) | 4 (0-47) | 1 (0-7) | 2 (0-33) | 0 (0-5) |
| **Testing** | | | | |
| Total performed (n) | 0 (0-0) | 13561 (11663-17181) | 116020 (116020-116020) | 129214 (127535-131997) |
| Per capita | 0 (0-0) | 0 (0-1) | 4 (4-4) | 4 (4-4) |

**Discussion**

We find that unmitigated transmission of Covid-19 in a population of 30,000 staff, faculty and students would lead to thousands of illnesses, many hospitalizations and likely deaths in this population, which is clearly an unacceptable outcome by administrators and the university community. Combined with measures to reduce transmission, a testing strategy whereby symptomatic students, staff and faculty are identified, administered viral testing, and isolated is largely effective at controlling transmission. We find that the success of this strategy relies on contact tracing and quarantining most contacts of infected individuals. Screening would have to be performed at least monthly to have much of an impact on the course of the outbreak on campus and increases the sample collection and assay requirements considerably. However, because we assume the campus community is not a closed population and that there is an ongoing risk of importation of virus, there are considerable numbers of cases even under the most optimistic scenario, which therefore requires substantial resources. Overall, we recommend that these results be interpreted qualitatively, since there is considerable uncertainty in these projections stemming from lack of precision of parameter inputs (e.g. true $R_0$ in this population).

There are a number of limitations to this modeling analysis, which we outline here. First, we lack empirical data about the efficacy of any prevention and control measures aside from testing that are implemented on campus. Smaller class sizes, staggered class times, use of face coverings, use of other protective equipment and general behavior change are not separately accommodated in this model.(5) If such data become available in campus population or ones that can serve as a good proxy, model parameters can be refined. Moving more students to off-campus housing has little effect on our projections because we make the assumption that transmission on-campus ($R_0$ = 3.5) is only moderately higher than off campus ($R_0$ = 2.5). This assumption is based on risk factor data on influenza-like illness among students during the 2009 H1N1 outbreak, but if more data become available, we could revisit this assumption.(17) In our model, the campus outbreak cannot go extinct because we assume a constant rate of introduction from the community. Depending on levels of student, staff and faculty behavior off-campus and the general prevalence in the surrounding community (Atlanta metro area in our model), this could be an under- or overestimate of risk. We have not explicitly included a scenario in which all or a subset of students (e.g., those residing on campus) are screened upon return to campus. Given our assumptions that student prevalence is the same as among the general population, screening on return would have limited effect, but would increase requirements by ~4,500 to 15,000 tests, depending on the breadth of testing of the student body. Finally, we have not included seasonal effects whereby virus becomes more transmissible in Fall or alternative semester dates (e.g.., end of classes at Thanksgiving break) whereby the period of campus transmission is reduced.

In conclusion, we present a model of SARS-CoV-2 transmission and control to assist universities in planning potential impacts and resource needs. Our model is conservative in that we assume a high reproductive number that is not reduced through non-pharmaceutical interventions. Despite this, we find that community-introduction of SARS-CoV-2 infection onto campus can be controlled with effective testing, isolation, contract tracing and quarantine, consistent with observations that this strategy has been successful in the general population where implemented properly (e.g. South Korea).(18) The results of this model simulation approach have been influential in Emory University's decision to open in Fall 2020. The University will implement a comprehensive testing strategy and will shorten the semester with an early start, with no breaks in order to end by Thanksgiving, amongst a number of other strategies to suppress transmission.(19)

**Refences**


1. https://plus.google.com/+UNESCO. Education: From disruption to recovery [Internet]. UNESCO. 2020 [cited 2020 Jun 5]. Available from: https://en.unesco.org/covid19/educationresponse

2. Cauchemez S, Ferguson NM, Wachtel C, Tegnell A, Saour G, Duncan B, et al. Closure of schools during an influenza pandemic. Lancet Infect Dis. 2009 Aug;9(8):473–81.

3. Davies NG, Klepac P, Liu Y, Prem K, Jit M, CMMID COVID-19 working group, et al. Age-dependent effects in the transmission and control of COVID-19 epidemics. Nat Med. 2020 Jun 16;

4. Staff C. Here's a List of Colleges' Plans for Reopening in the Fall. The Chronicle of Higher Education [Internet]. 2020 Apr 23 [cited 2020 Jun 5]; Available from: https://www.chronicle.com/article/Here-s-a-List-of-Colleges-/248626

5. Chu DK, Akl EA, Duda S, Solo K, Yaacoub S, Schünemann HJ, et al. Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and COVID-19: a systematic review and meta-analysis. The Lancet. 2020 Jun;S0140673620311429.

6. Verity R, Okell LC, Dorigatti I, Winskill P, Whittaker C, Imai N, et al. Estimates of the severity of coronavirus disease 2019: a model-based analysis. Lancet Infect Dis. 2020 Jun 1;20(6):669–77.

7. Li R, Pei S, Chen B, Song Y, Zhang T, Yang W, et al. Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV2). Science [Internet]. 2020 Mar 16 [cited 2020 Mar 26]; Available from: https://science.sciencemag.org/content/early/2020/03/24/science.abb3221

8. Lauer SA, Grantz KH, Bi Q, Jones FK, Zheng Q, Meredith HR, et al. The Incubation Period of Coronavirus Disease 2019 (COVID-19) From Publicly Reported Confirmed Cases: Estimation and Application. Ann Intern Med. 2020 Mar 10;172(9):577–82.

9. COVID-19 Status Report [Internet]. Georgia Department of Public Health. [cited 2020 Jun 5]. Available from: https://dph.georgia.gov/covid-19-daily-status-report

10. Nichol KL, D'Heilly SJ, Greenberg ME, Ehlinger E. Burden of Influenza-Like Illness and Effectiveness of Influenza Vaccination among Working Adults Aged 50–64 Years. Clin Infect Dis. 2009 Feb;48(3):292–8.

11. Iuliano AD, Reed C, Guh A, Desai M, Dee DL, Kutty P, et al. Notes from the Field: Outbreak of 2009 Pandemic Influenza A (H1N1) Virus at a Large Public University in Delaware, April–May 2009. Clin Infect Dis. 2009 Dec 15;49(12):1811–20.

12. Kucirka LM, Lauer SA, Laeyendecker O, Boon D, Lessler J. Variation in False-Negative Rate of Reverse Transcriptase Polymerase Chain Reaction–Based SARS-CoV-2 Tests by Time Since Exposure. Ann Intern Med [Internet]. 2020 May 13 [cited 2020 Jun 5]; Available from: https://www.acpjournals.org/doi/10.7326/M20-1495

13. Jenness SM, Goodreau SM, Morris M. EpiModel: An R Package for Mathematical Modeling of Infectious Disease over Networks. J Stat Softw. 2018 Apr;84.

14. Kissler SM, Tedijanto C, Goldstein E, Grad YH, Lipsitch M. Projecting the transmission dynamics of SARS-CoV-2 through the post-pandemic period. medRxiv. 2020 Mar 6;2020.03.04.20031112.

15. Davies NG, Klepac P, Liu Y, Prem K, Jit M, CMMID COVID-19 working group, et al. Age-dependent effects in the transmission and control of COVID-19 epidemics [Internet]. Epidemiology; 2020 Mar [cited 2020 Jun 5]. Available from: http://medrxiv.org/lookup/doi/10.1101/2020.03.24.20043018

16. Mossong J, Hens N, Jit M, Beutels P, Auranen K, Mikolajczyk R, et al. Social Contacts and Mixing Patterns Relevant to the Spread of Infectious Diseases. PLOS Med. 2008 Mar 25;5(3):e74.

17. Guh A, Reed C, Gould LH, Kutty P, Iuliano D, Mitchell T, et al. Transmission of 2009 Pandemic Influenza A (H1N1) at a Public University--Delaware, April-May 2009. Clin Infect Dis. 2011 Jan 1;52(Supplement 1):S131–7.

18. Flattening the curve on COVID-19: How Korea responded to a pandemic using ICT 상세보기 | Bilateral RelationsEmbassy of the Republic of Korea to the Hellenic Republic [Internet]. [cited 2020 Jun 23]. Available from: http://overseas.mofa.go.kr/gr-en/brd/m_6940/view.do?seq=761548

19. Fall 2020 Return to Campus | Emory University | Atlanta GA [Internet]. [cited 2020 Jun 21]. Available from: http://emory.edu/forward/index.html

**Appendix I. Model equations**

$$\frac{\mathrm{d}S_\mathrm{i}}{\mathrm{dt}} = \lambda_i S_i - community * S_i - testing * \left(1 - p_{asym_i}\right) I_i * sens * \ (contacts - Ro_i) * p.contacts + \frac{1}{isol.} Q_i (contacts - \frac{Ro_i}{contacts})$$

$$\frac{\mathrm{d}E_\mathrm{i}}{\mathrm{dt}} = \lambda_i S_i + community * S_i - \alpha E_i - screening * sensitivity_t * E_i - testing * sensitivity_t * \left(1 - p_{asy.i}\right) * p.contacts * (Ro_i) \ * I_i$$

$$\frac{dI_i}{dt} = \alpha E_i - \gamma I_i - screening * sensitivity_t * I_i - testing * sensitivity_t \left(1 - p_{asy,i}\right) * I_i$$

$$\frac{dP_i}{dt} = testing * sensitivity_t * \left(1 - p_{asy.i}\right) * I_i + screening * sensitivity_t * \ (E_i + I_i) \ - \ \delta P_i$$

$$\frac{dQ_i}{dt} = testing * sensitivity_t * \left(1 - p_{asy.i}\right) * contacts * p.contacts * I_i - \delta Q_i$$

$$\frac{dR_i}{dt} = \gamma I_i + \ \delta P_i + \delta Q_i * (Ro_i)/contacts$$

where

*i* = on (students living on campus); off (students living off campus); saf (staff and faculty)

$$\lambda_{on} = (1 - eff_{npi})(\beta_{stu,stu} \left(\frac{I_{on}}{Non} + \frac{I_{off}}{Noff}\right) + \ \beta_{on,on} \left(\frac{I_{on}}{N_{on}}\right) + \beta_{stu,saf} (\frac{I_{saf}}{N_{saf}}))$$

$$\lambda_{off} = \left(1 - eff_{npi}\right) (\beta_{stu,stu} \left(\frac{I_{on}}{Non} + \frac{I_{off}}{Noff}\right) + \ \beta_{stu,saf} (\frac{I_{saf}}{N_{saf}}))$$

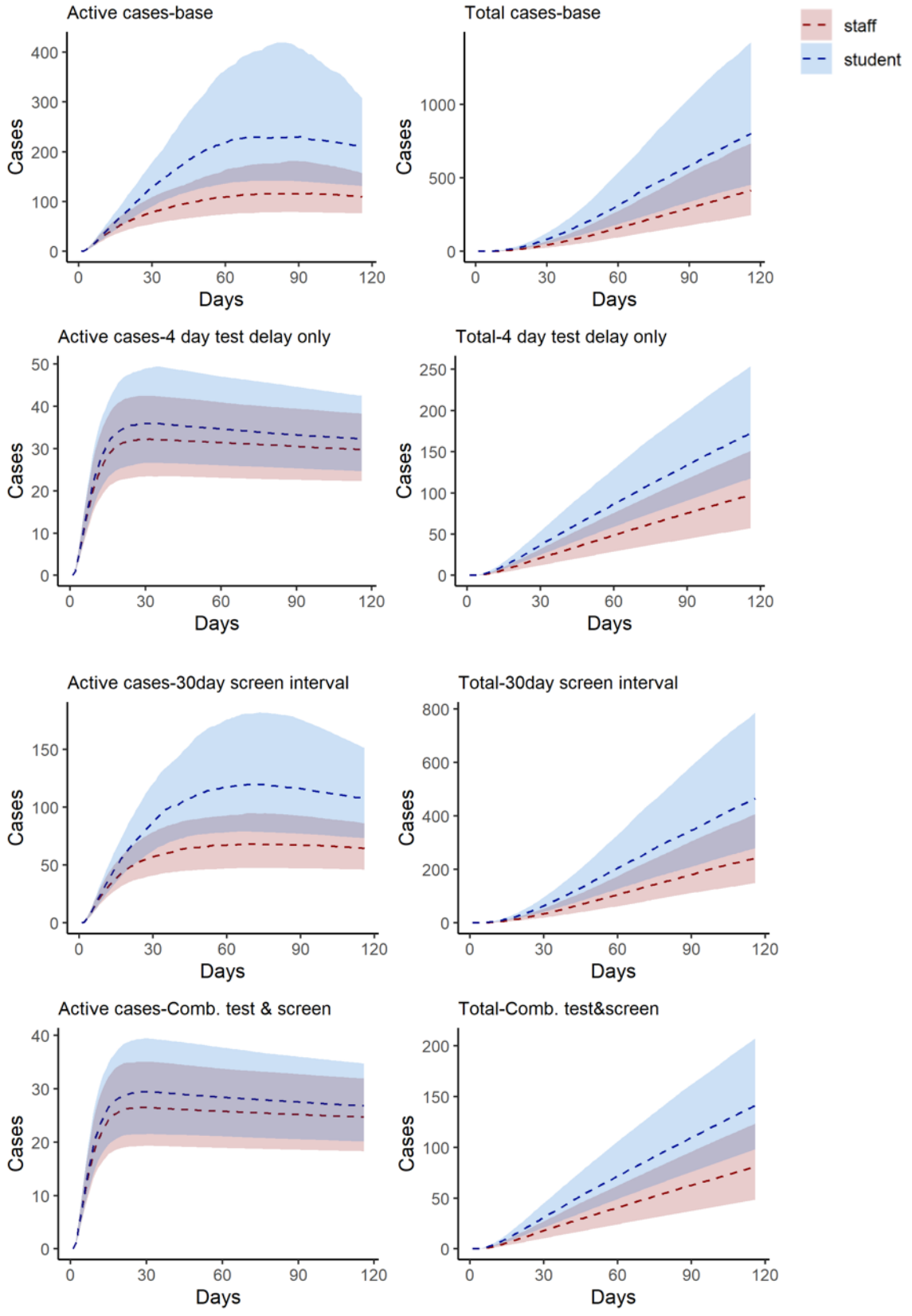
$$\lambda_{saf} = \left(1 - eff_{npi}\right)(\beta_{saf,stu} \left(\frac{I_{on}}{N_{on}} + \frac{I_{off}}{N_{off}} + \frac{I_{saf}}{N_{saf}}\right))$$

$$Ro_{on} = \ Ro_{on,on} + \ Ro_{stu,stu}$$

$$Ro_{off} = \ Ro_{stu,stu}$$

$$Ro_{saf} = \ Ro_{saf}$$

**Appendix II. Estimated active and cumulative cases under intervention scenarios with 25th and 75th centile range**



**Appendix III.** Partial rank correlation coefficient of key model inputs.