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

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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 42% and 80% in students, respectively, while testing with a 2-, 4- and 7-day delay results in an 88%, 79% 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 planning 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.

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,(5) and then standardized using the student and staff/faculty age-structure at our institution. [For a full list of parameter values, may be found in 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.(6) We assume that infectiousness begins on the third day after infection; this latent period is shorter than the incubation period(7) to capture 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;(8) we assume that infection incidence is ten- times that of reported cases.(6) The model runs for a typical 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 ,(9,10) 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.(11) 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. In the testing and screening analyses, we do not include the effects of social distancing, enhanced hygiene, or use of personal protective equipment given lack of data of the efficacy in a campus population, so we assume that the infectiousness (R_0) is between 2.5 and 3.5 for students and this does not change. But in a final analysis, we examined the effect of hygiene and social distancing measures to reduce transmission on campus, in the absence of testing or screening but reducing R_0 by up to 90%.

Figure 1. Schematic of A) Disease Structure and B) Student and Staff/Faculty Transmission Pathways.
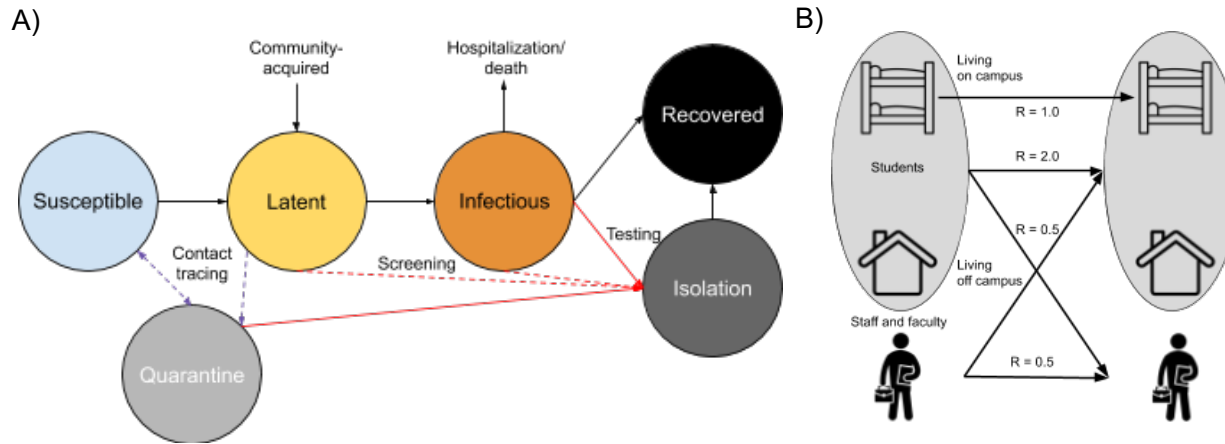
Parameterization and Analysis. In our base models, we simulated SARS-CoV-2 transmission and interventions for the Fall 2020 semester. Our main base model assumed no interventions, to project the "worst case" scenario. Counterfactual scenarios then varied the screening and testing rates, and the completeness 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 2.5th and 97.5th 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(12); 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	$1/\alpha$	(7)
Infectious period (days)	7	6 to 8	Gamma	$1/\gamma$	(13)
Proportion severe - students	0.0224	0.0133 to 0.0456	Beta		(5)
Proportion severe - staff/faculty	0.055	0.0327 to 0.1122	Beta		(5)
Proportion fatal - students	0.0006	0.0003 to 0.0014	Beta		(5)
Proportion fatal - staff/faculty	0.0052	0.0029 to 0.0105	Beta		(5)
Proportion symptomatic - students	0.35	0.27 to 0.43	Beta	$1 - p_{asy,stu}$	(14)
Proportion symptomatic - staff/faculty	0.51	0.41 to 0.59	Beta	$1 - p_{asy,saf}$	(14)
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 staff/faculty; 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	
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	(15)
Proportion of contacts reached	0.75	0.5 to 1	Uniform		
Proportion experiencing ILI symptoms per month	0.1	0.09 to 0.11			(9,10)
PCR sensitivity -- day 2 of infectiousness	0.75	0.6 to 0.83	Beta	sen_2	(11)
PCR sensitivity -- day 4 of infectiousness	0.8	0.7 to 0.85	Beta	sen_4	(11)
PCR sensitivity -- day 7 of infectiousness	0.75	0.65 to 0.8	Beta	sen_7	(11)

Results

In the counterfactual projection (Table 2) in which no control measures are in place (no testing, isolation, contact tracing, or quarantine) for a population of 30,000 and R_0 remains at baseline levels, infection incidence peaks at 235 cases (Range, 2.5th to 97.5th centiles: 63 to 802) per day among students and 118 cases per day among staff/faculty (40 to 359), in a population of about 15,000 of each. The model estimated a total of 804 student cases (181 to 2,654) and 415 staff/faculty cases (86-1,539), 17 (3–76) student hospitalizations and 22 (3–103) staff/faculty hospitalizations, as well as deaths among faculty. Note that this number of recognized cases is substantially lower than the number of infections since we assume that only 35% of infected students and 51% of infected staff are symptomatic, given infection.(14)

We next explored a wide range of *screening* intervals, from weekly to once during the semester (Fig 2). 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 42% and 80% respectively. Similar reductions are observed among staff and faculty. For students, the cumulative incidence ranged from 159 (47-434) with weekly screening to 690 (163-2276) with one-time screening. For staff/faculty, the cumulative incidence ranged from 88 (24-246) with weekly screening to 354 (77-1305) with one-time screening.

Figure 2. Impact of Screening Frequency on Projected Covid-19 Daily and Cumulative Incidence.
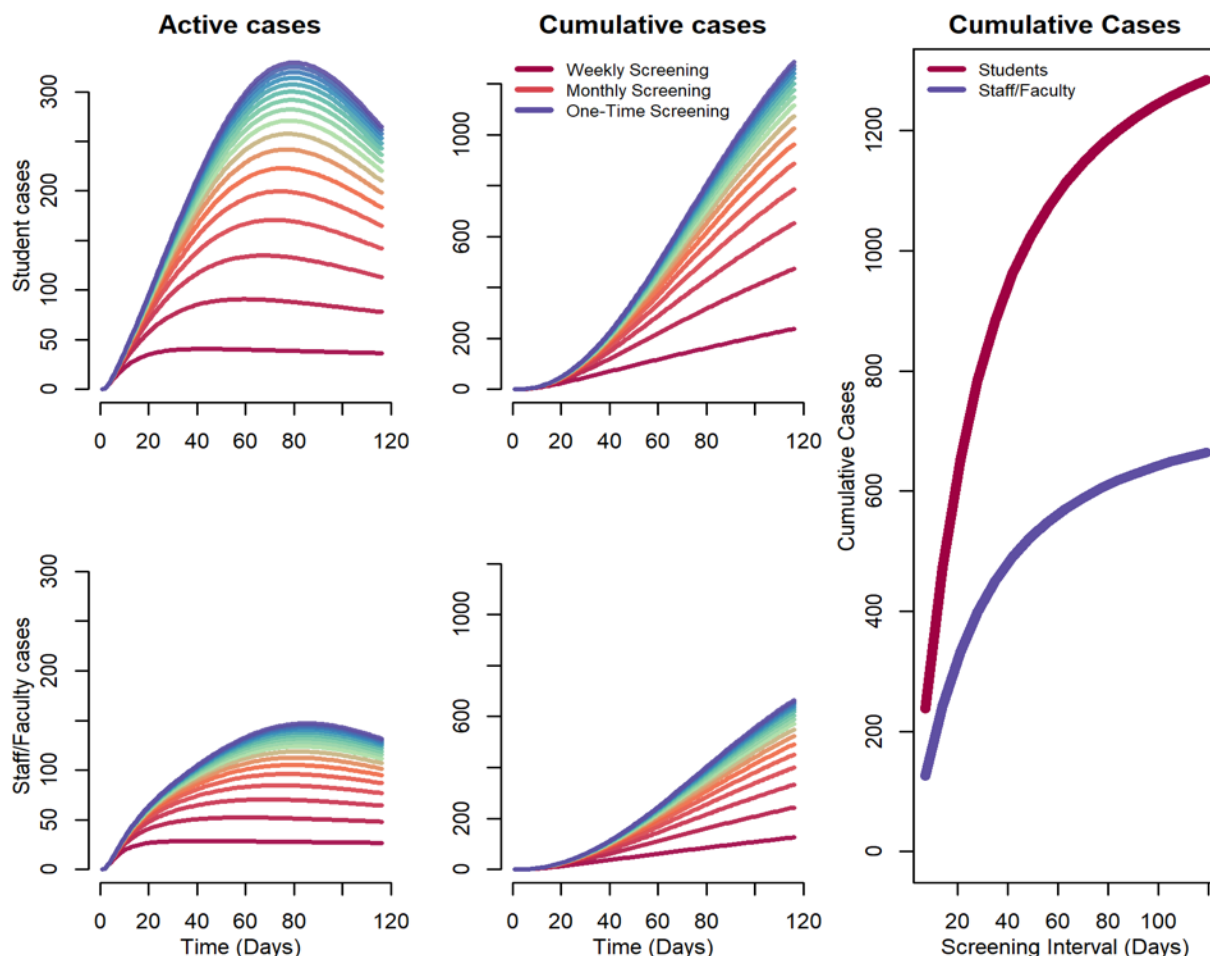
With testing and this level of contact tracing as described, the cumulative incidence for the semester ranges from 93 (32-218) among students and 57 (15-144) and staff & faculty with two-day delay testing interval, 173 (54-416) among students and 98 (26-255) among staff & faculty with a four-day delay testing interval; 264 (76-673) among students and 146 (38-396) among staff & faculty with a seven-day delay testing interval. (Fig 3) This represents an 88%, 79% and 67% reduction in cumulative incidence over the semester among students and an 86%, 76% and 65% 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 3. Impact of testing, contact tracing and quarantine at a range of testing delay intervals. Daily and cumulative Covid-19 incidence on university campus.
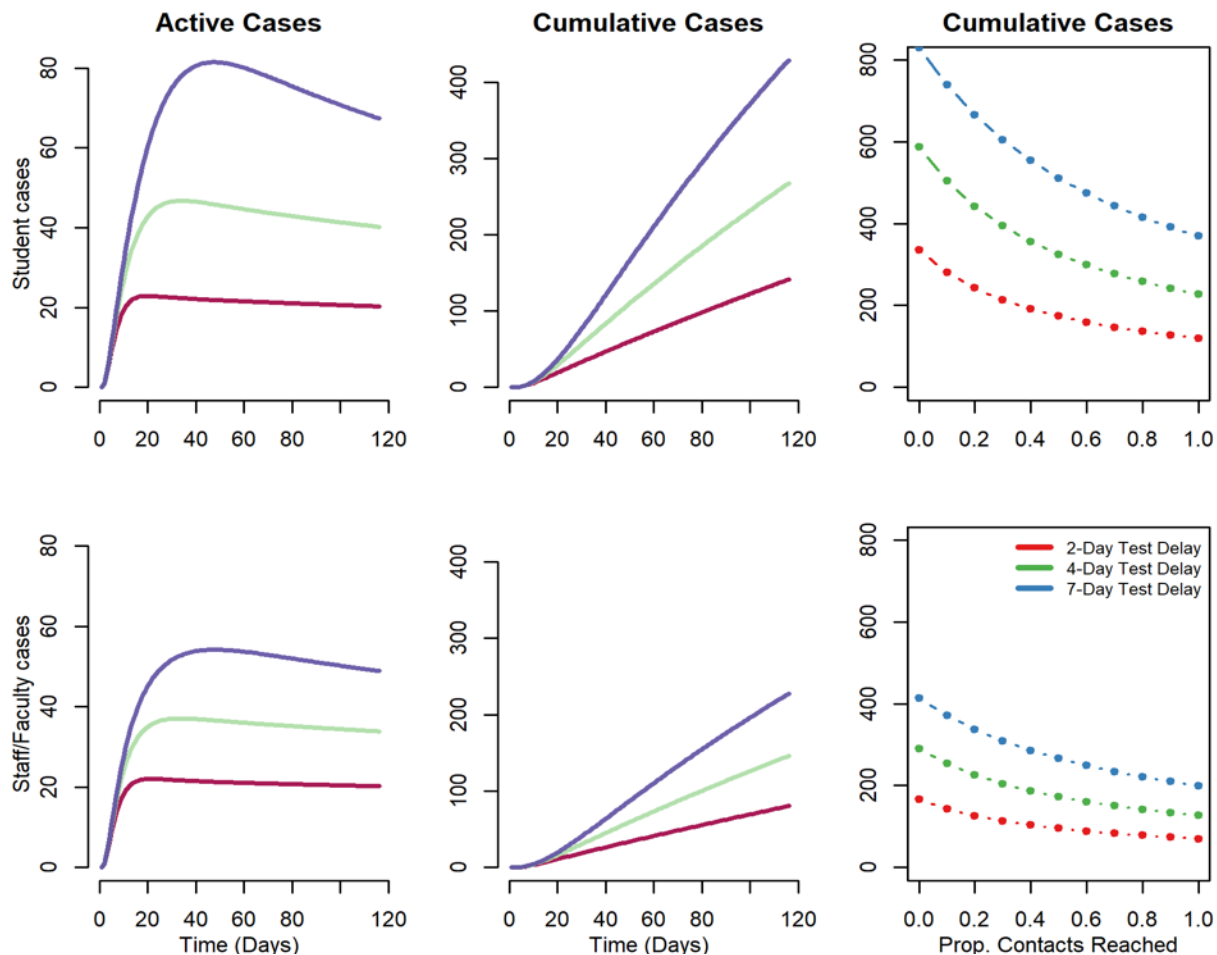
Here, with week-delayed testing (the least optimistic scenario), the expected cumulative incidence would be 264 (76-673) for students and 146 (38-396) for staff/faculty. Figure 3 shows the general relationship between "contact tracing" success and cumulative incidence assuming either a 2-day, 4-day, 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 4). Our model scenarios below varied the interval for screening between 1 week (7 days) and 1 semester (120 days) and testing between 1 and 7 days, with the number of contacts reached through tracing with values of 0, 1, and 5. These figure panels show cumulative incidence at the end

of the semester for students only. Figure 4a shows the general relationship between more frequent screening and testing, with 2-, 4-, and 7-day delayed testing. 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.
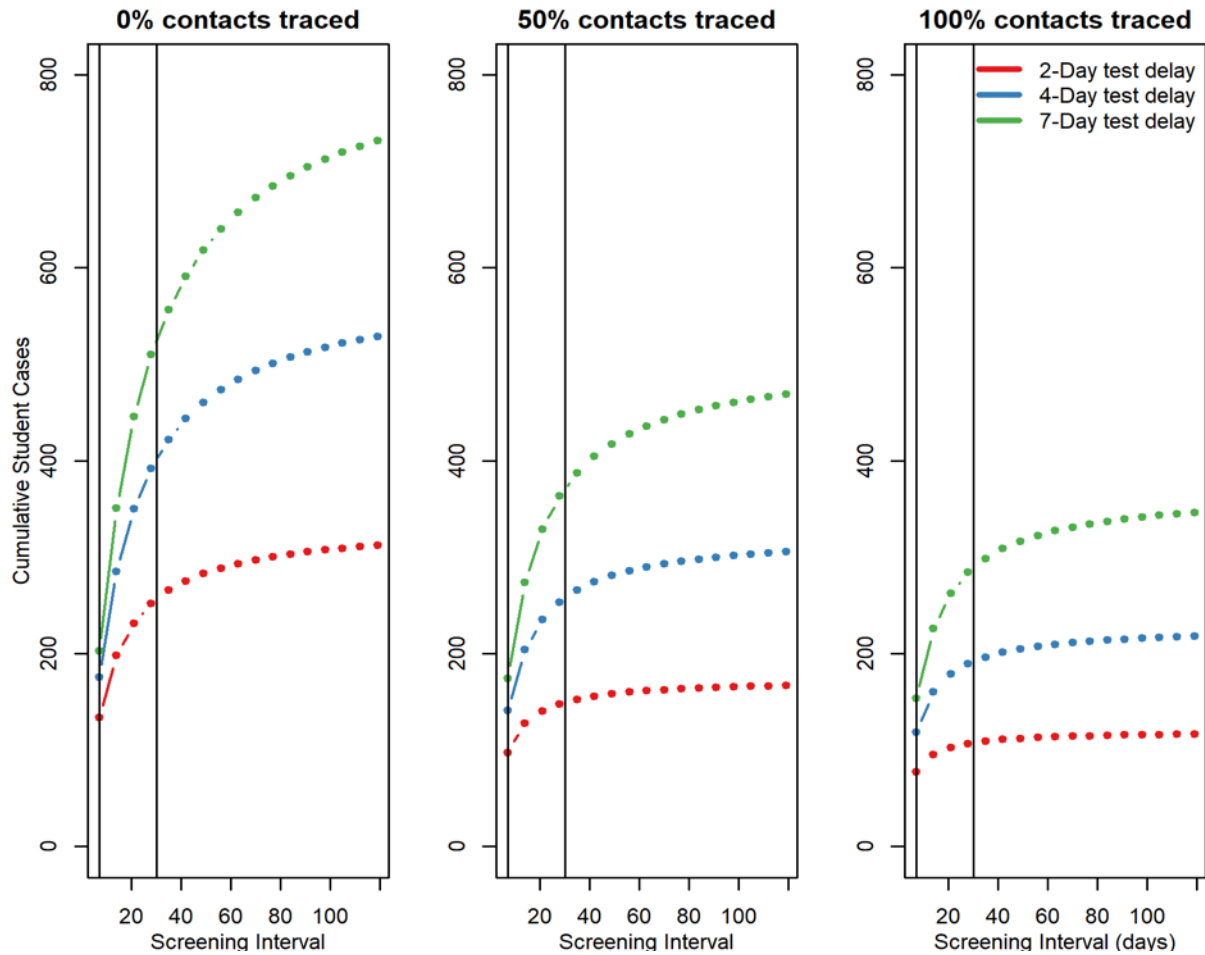
Table 2. Cumulative outcomes at end of the semester on medium size university campus (approx. 15,000 students and 15,000 staff and faculty). Values are medians and 2.5 and 97.5th percentiles of 1,000 model runs.

	Base scenario	4-day test delay	30-day screen interval	Combined test and screen
Students				
Cumulative cases (n)	804 (181-2654)	173 (54-416)	466 (117-1475)	142 (46-337)
Peak daily cases (n)	235 (63-802)	36 (13-83)	121 (37-321)	29 (10-64)
Hospitalizations (n)	17 (3-76)	4 (1-12)	10 (2-43)	3 (1-10)
Deaths (n)	0 (0-2)	0 (0-0)	0 (0-1)	0 (0-0)
Isolated (n)	0 (0-0)	260 (99-511)	457 (156-1072)	356 (134-703)
Isolated (max)	0 (0-0)	34 (13-69)	67 (21-174)	46 (17-91)
Isolated (days)	0 (0-0)	3209 (1220-6350)	5505 (1902-13185)	4397 (1644-8739)
Quarantined (n)	0 (0-0)	3626 (1393-7332)	0 (0-0)	2991 (1155-5910)
Quarantined (max)	0 (0-0)	344 (134-732)	0 (0-0)	281 (111-602)
Quarantined (days)	0 (0-0)	32594 (12759-68822)	0 (0-0)	26770 (10570-56617)
Staff and Faculty				
Cumulative cases (n)	415 (86-1539)	98 (26-255)	242 (59-809)	81 (22-208)
Peak daily cases (n)	118 (40-359)	32 (12-65)	69 (25-167)	27 (10-53)
Hospitalizations (n)	22 (3-103)	5 (1-18)	12 (2-55)	4 (1-15)
Deaths (n)	2 (0-9)	0 (0-2)	1 (0-5)	0 (0-1)
Testing				
Total performed (n)	0 (0-0)	13398 (11679-15495)	116020 (116020-116020)	129100 (127527-131000)
Per capita	0 (0-0)	0 (0-1)	4 (4-4)	4 (4-4)

Finally, we examined the effect of hygiene and social distancing measures to reduce transmission on campus, in the absence of testing or screening (Fig 5). The 'no reduction' in transmission scenario equated to our base case scenario; while in the 'no transmission' scenario all cases are imported from community transmission. In terms of impact on cumulative cases, 4-day test delay is roughly equivalent to the impact of reducing R_0 by between 40-50%.

Figure 5. Effect of other non-pharmaceutical interventions (with no testing and screening) on daily Covid-19 incidence.
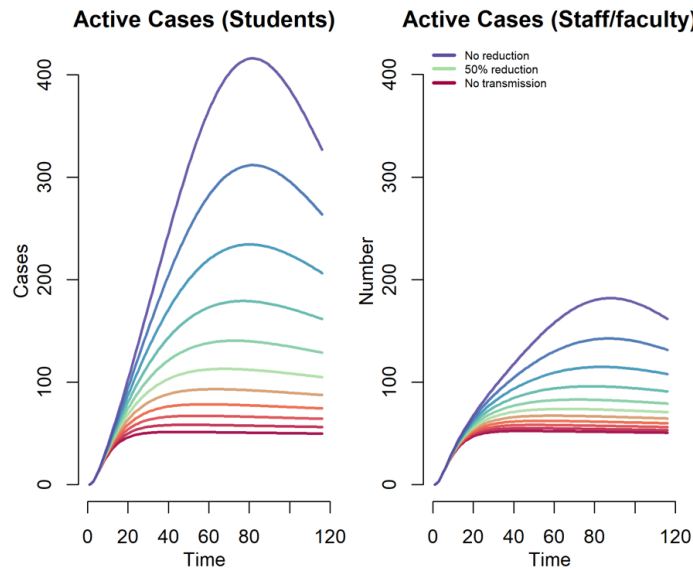
Discussion

We find that unmitigated transmission of Covid-19 in a population of 30,000 staff, faculty and students would lead to hundreds of illnesses, many hospitalizations and likely some deaths in this population, which would be an unacceptable outcome by administrators and the university community. A testing strategy whereby symptomatic students, staff and faculty are identified, administered viral testing, and isolated is 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. 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 do not make any assumptions about the efficacy of any prevention and control measures aside from testing that are implemented on campus for Fall 2020. Smaller class sizes, staggered class times, use of face coverings, use of other protective equipment and general behavior change are not explicitly accommodated in this model.[16] In that sense, our results are conservative in that we may overestimate risk. We suggest that this is an appropriate baseline scenario for risk-averse planning. 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]

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Appendix I. Model equations

$$\frac{dS_i}{dt} = \frac{-\lambda_i S_i}{N} - community * S_i - testing * sensitivity_t * \left(1 - p_{asy.i}\right) * (contacts - Ro_i) * p.contacts * I_i + \frac{1}{isolation} * Q_i * (contacts - Ro_i/contacts$$

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

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

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

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

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

where

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

$$\lambda_{on} = \beta_{stu,stu} \left(I_{on} + I_{off}\right) + \beta_{on,on} (I_{on}) + \beta_{stu,saf} (I_{saf})$$

$$\lambda_{off} = \beta_{stu,stu} \left(I_{on} + I_{off}\right) + \beta_{stu,saf} (I_{saf})$$
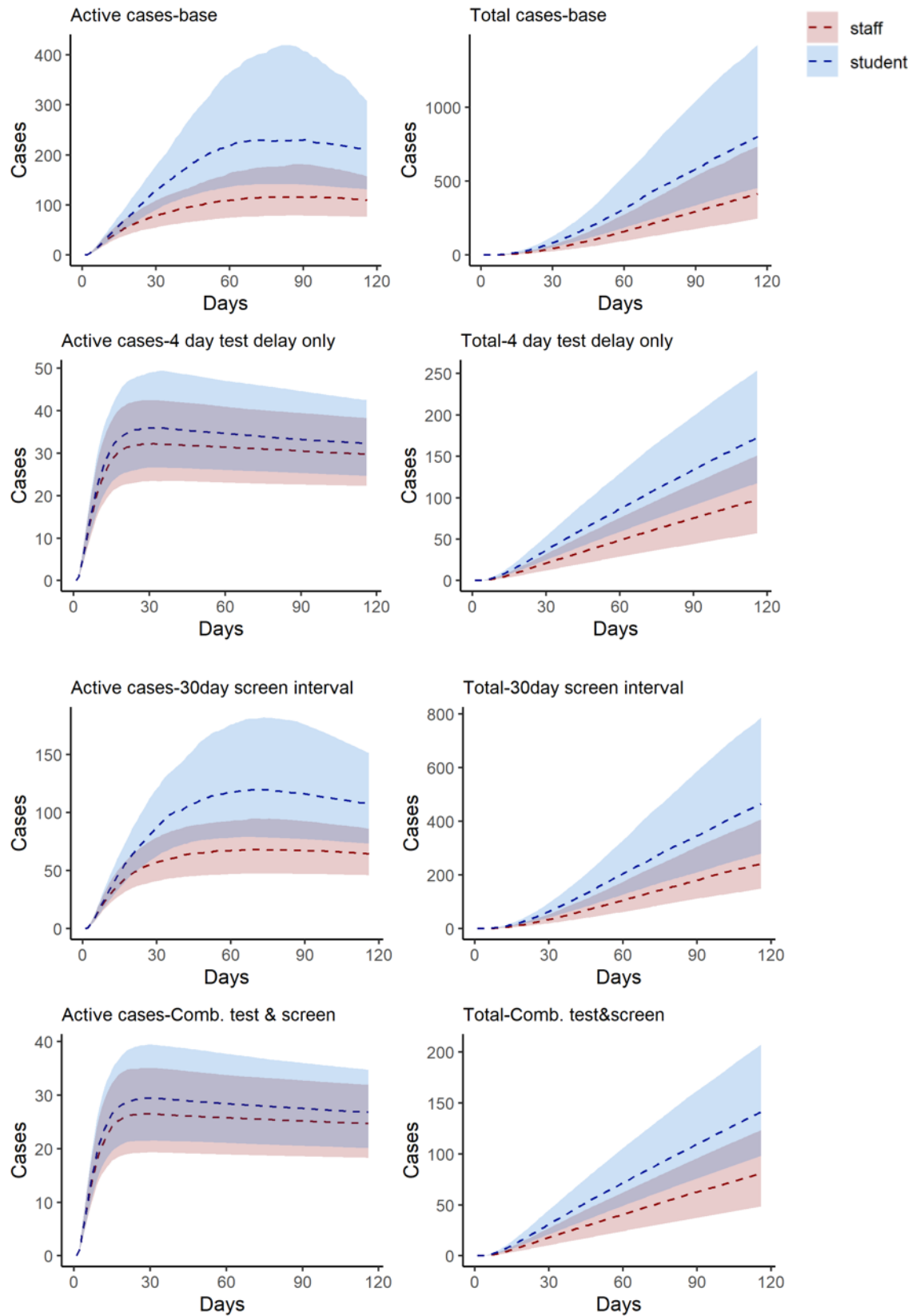
$$\lambda_{saf} = \beta_{saf,stu} \left(I_{on} + I_{off} + I_{saf}\right)$$

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

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

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

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.

Patial Rank Correlation Coefficient of variables