COVID-19 Epidemiological Projections for Penn State University under its current testing plan[*]

Version: August 25, 2020

Changes with respect to previous version (of August 15, 2020): We correct typographical, cosmetic, grammatical, and other small errors and inconsequential oversights. We also clarify and emphasize some of the points made in the previous version, especially our modeling of the effect of *contact tracing*. The calculations and conclusions are the same as in the previous version.

Summary

- We present projected scenarios of the likely effect of the current policies announced by the Pennsylvania State University (PSU) administration to contain the spread of COVID-19 on the University Park (UP) undergraduate population. The basic epidemiological model we use, a compartmental model due to Paltiel et al. [10] is a discrete-time SEIR (susceptible-exposed-infected-recovered) model that considers the possibility of repeated testing a fraction of students with a test of given sensitivity and selectivity. We conducted Monte Carlo simulations on the key SEIR parameters from estimates in the medical literature, and investigated the effect of the Fall semester university plans on the Faculty, Staff and surrounding adult population in State College.

- Our main finding, under optimistic assumptions for the model parameters and including contact tracing in an approximate manner, is that the current PSU plan, which calls for testing 30% of all persons on campus before arrival and daily surveillance testing of 1% per day (about 700 tests/day at UP) will be insufficient to contain the spread of the disease in the UP campus. The quarantine capacity set by the university (which we assume to be about 350 rooms) will overflow at some point halfway through the Fall semester. It is then quite possible that thousands of asymptomatic infected students could further spread the disease outside State College upon their return to their homes in Thanksgiving. The possibility of observing some student deaths under the PSU plan cannot be discarded.

- We compare the PSU testing plan with an alternative where 100% screening of all students is conducted upon arrival to the UP campus, which has a large effect on reducing the total number of infected students through the Fall. Furthermore, we consider a policy that includes testing 10% of the undergraduate population per day instead, and show how it drastically reduces the number of infected students. We include a comparison with the safest plan we considered, which calls for both 100% initial screening of all students and tests at a rate of 10%/day, showing how this would keep the median quarantine utilization under capacity, would drastically reduce asymptomatic cases, and would make the possibility of student death very unlikely.

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[*]These projections were prepared by an interdisciplinary group of faculty from the PSU College of Engineering and Eberly College of Science. We welcome feedback and comments at cjupsuscience@gmail.com.

- A brief analysis of the effect of of the PSU plan on the Faculty, Staff, and adult population in the State College area indicates the likelihood of observing some deaths among these groups, as well as hundreds of infections.

On July 30, 2020, the Pennsylvania State University administration revealed their testing plans to manage the COVID-19 epidemic on its campuses for the Fall 2020 semester. In addition to the normal measures of social distancing and use of masks and disinfectant in all its campuses, the PSU mitigation and testing plan contains three additional components[1]:

1. Testing up to 30,000 faculty, staff, and students across the PSU system prior to their Fall arrival;

2. Surveillance testing of 1 % per day of faculty, staff and students, at random irrespective of symptoms;

3. Testing of symptomatic individuals, and isolation and contact tracing of the close contacts of those who result COVID-19 positive.

Isolation space for students living on-campus will be provided by the university. Students living off-campus will be accommodated in on-campus isolation to the extent the university is able (no more information is available at the present time). Pre-arrival tests and surveillance tests in commonwealth campuses will take place via a COVID-19 testing company (Vault-Health). Surveillance tests at UP will take place at the Testing and Surveillance Center (TASC) in UP and will be based on pooled samples.

The object of this technical report is to evaluate the proposed PSU plan using basic epidemiological modeling and to provide projections, under both the PSU plan and some alternatives, focusing particularly on University Park (UP). We choose to focus on UP in this exercise because it includes a large fraction of the PSU population concentrated in a single campus and living in high-occupancy buildings. The population density will be high even with the special arrangements made for Fall 2020. Moreover, the students at UP make up a large fraction of the population of the town of State College and they interact extensively with the town population.

In what follows, we present projections for the PSU plan, as announced on July 30, 2020, using for this purpose a SEIR model due to Paltiel et al. [10]. This model permits us to directly explore the first two components in the PSU plan above. By choosing the parameters of this model appropriately, we also approximate the effects of contact tracing. We present two different modeling efforts:

1. Projections for PSU using a deterministic SEIR model, and

2. A Monte Carlo simulation of the main SIER model parameters to assess the uncertainty in current parameter estimates and other model uncertainties and their effect in the corresponding projections.

In both types of projections, point and interval parameter estimates of the key drivers of the SEIR model were taken from recent COVID-19 literature, and were used to inform the model. We document these parameter choices below.

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[1]See:
https://news.psu.edu/story/627214/2020/07/30/administration/back-state-testing-contact-tracing-and-monitoring-pl

1 Model assumptions

The Paltiel et al. model we adopt [10] is a discrete-time SEIR model (see [6]) with parameters tuned for a population of given age in a single campus, which are supposed to be homogeneous and well-mixed. Not more than one group of persons is considered at a time (although we are able to model the interaction of students and older adults in State College with our model, see section 5). There is an initial number of asymptomatically infected persons $A(0)$ who arrive on campus at time $t = 0$ (corresponding to August 21) that represents those undetected by the 30% testing the university will conduct. Depending on the amount of testing and contact tracing done afterwards, some of these asymptomatic individuals may be detected and isolated, a (relatively small) fraction of them may become symptomatic and be quarantined, and a fraction of them may become seriously ill and die. Furthermore, another fraction of asymptomatic students may remain undetected and will contribute over time to the generation of more infected individuals on campus and beyond. There is an incubation period for the virus during which exposed persons are neither detectable nor infectious.

The model accounts for testing with a specified Sensitivity[2] S_e and a given Specificity[3] S_p. The model does not explicitly consider contact tracing, which is a difficult feature to incorporate into compartment models (see [1, 2]), but our simulations deal with the effects of contact tracing approximately. Efficient contact tracing reduces the effective reproduction number R_t, a key parameter in SEIR and other types of compartmental models which equals the average number of new infections caused by an infected person at a given point of time[4]. The model we use considers R_t a constant, and this is an evident approximation. We approximate the effect of contact tracing, masks, social distancing while on campus, etc. by using reduced values of R_t compared to the current best estimate for COVID-19. Our choice of R_t is justified by the recent work of Grassly et al. [5] who estimate the reduction in the COVID-19 R_t value due to a test-trace strategy that covers 80% of the contacts and quickly isolates them 24 hours after the primary infection occurs to be about 26% on average. **In our simulations, we account for contact tracing, use of masks, and social distancing on campus, by *optimistically reducing* R_t *further than this amount*, by 40% in two of our basic scenarios ($R_t = 1.5$) and by 34% in our Monte Carlo simulations ($R_t = 1.66$).**

We estimate the isolation dormitory capacity at PSU-UP at about 350 students (3 of the 8 buildings in Eastview Terrace, which has a total capacity of 800) although in our simulations the isolation capacity is assumed to be infinite in size (i.e., the simulation is allowed to continue until the end of the simulation time). The pool of isolated/quarantined individuals is made up of persons who test positive for COVID-19, who are either symptomatic or asymptomatic with a positive test result, or are uninfected with a false positive test result.

The individuals who recover are assumed to be immune. This is probably a safe assumption in particular given the short simulation time of 90 days. We also make the assumption that test results from the surveillance testing will return within 8 hours. It is also assumed that individuals always comply with testing, isolation, and quarantine orders. The sensitivity and sensibility of the test in use (assumed to be PCR) is assumed to be a constant, when in fact the sensitivity of a test is known to differ depending on the time since infection.

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[2]Or "True positive rate", the percentage of infected individuals correctly detected

[3]Or "True negative rate", the percentage of non-infected individuals correctly identified as such

[4]The paper by Browne et al. [2] incorporates contact tracing into a compartmental model by making the effective reproduction number R_t a function of various *additional* parameters that are also difficult to estimate in the present situation.A direct reduction in R_t is a simpler approach to account for contact tracing.

2   Model parameters and estimates

The time unit in the model is a cycle of 8 hours, thus all rates reflect this time unit. The physical system is described by a set of difference equations shown in the Appendix, which we include here as the original equations published in [10] contained important typos, here corrected. The model parameter values that were used are justified below. This is a deterministic model, with no stochastic components. We therefore will show first three basic scenarios, followed by a Monte Carlo simulation that tries to incorporate the variability in the key model parameters.

The parameter estimates used in our first three basic scenarios are shown in Table 1. The fatality risk and probability of having symptoms given infection are tuned for a young population of 40,000 undergraduate students arriving to the PSU-UP campus. The value of $R_t = 2.5$ is the best estimate the CDC indicates for planning purposes [3]. **We also show two projections with a considerably lower value ($R_t = 1.5$) to account for contact tracing (known to reduce the reproductive number), use of masks, and social distancing**. The sensitivity and specificity of the test used were set at 0.8 and 0.98 respectively, which roughly correspond to the estimates for RT-PCR testing [11] and were used as base values by [10].

The model parameters σ (the rate of symptom onset for infected individuals), β (the rate at which infected individuals infect other, susceptible individuals), and δ (the rate at which symptomatic individuals die) were computed from values in table 1 using the following formulae (see [10] for details)

$$\sigma = \frac{\rho\, P_{s|i}}{1 - P_{s|i}}, \qquad \beta = R_t\,(\sigma + \rho), \qquad \text{and} \qquad \delta = \frac{\rho\, F}{P_{s|i}(1 - F)}\;. \qquad (1)$$

The expected initial number of asymptomatic students can be estimated with the expression:

$$A(0) \approx N(0) \cdot (1 - T) \cdot P + N(0) \cdot T \cdot P \cdot (1 - S_e)$$

where $100P$ is the prevalence (%) of COVID-19 among the initial population from which the $N(0)$ individuals originate, and T is the fraction of the initial population that is tested (with a test of sensitivity S_e). The first term is the number of infected individuals not tested, and the second is the number of infected individuals not detected among those tested[5]. We use $S_e = 0.8$ throughout this report. Depending on the way the prevalence of COVID-19 is estimated, we get different estimates of $A(0)$, see table 2.

T	P	S_e	$A(0)$	Using prevalence (P) from:
0.3	0.0099	0.8	301.6	PA–all time
0.3	0.0160	0.8	487.6	USA–all time
0.3	0.0086	0.8	261.4	Purdue prevalence
0.3	0.0050	0.8	152.0	WVU prevalence
1.0	0.0099	0.8	79.4	PA–all time
1.0	0.0160	0.8	128.3	USA–all time
1.0	0.0086	0.8	68.8	Purdue prevalence
1.0	0.0050	0.8	40.0	WVU prevalence

Table 2: Estimated values of $A(0)$ from different prevalence estimates using $N(0)$=40,000 and different fractions of initial testing T (WVU=West Virginia University). Prevalence data source: The New York Times.

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[5]An earlier version incorrectly included the S_e (sensitivity) on the first term, an error that does not change any of the results that follow.

Parameter	Description	Estimate(s)	Sources
R_t	Effective reproduction number	1.5 or 2.5	[3]
τ	Rate at which individuals are tested	$\frac{1}{100\times3}$	PSU plan
$N(0)$	Total population of arriving individuals	40000	PSU
$A(0)$	Number of asymptomatic infected individuals arriving to campus	200 or 50	See text
ρ	Rate at which infected individuals recover and are removed	$\frac{1}{14\times3}$	see [10] for sources
$1/\theta$	Incubation period	3×3	[7, 10]
μ	Rate at which false positives are returned to the uninfected compartment	$\frac{1}{3}$	see [10] for sources
F	Fatality rate among symptomatic individuals	0.0005	[3, 4]
S_e	Sensitivity of the test used, S_e	0.8	[10, 11]
S_p	Specificity of the test used, S_p	0.98	[10, 11]
$P_{s|i}$	Probability of symptoms given infection	0.3	[9, 10]

Table 1: Parameters used for the undergraduate student simulations. All rates and times units are on a per cycle (8 hours) base.

While we can use national or state prevalence measures, we can also look at the prevalence at universities that have started testing their arriving students: as of this writing, Purdue reports a 0.86% positive rate[6] among more than 15,000 students tested, while West Virginia University reports 0.5% in more than 11,000 tested[7]. Based on table 2, we decided to fix $A(0) = 200$ to represent the result of 30% testing in the PSU plans, as it is a number that falls between the estimates that would result had the prevalences at Purdue or WVU been used, which are for an age group similar to PSU's and is therefore approximately representative of what PSU will experience[8]. Likewise, for similar reasons we use $A(0) = 50$ to represent the case of an alternative testing plan where 100% testing is done before arrival.

3   Projections for three basic scenarios for PSU-University Park

To implement the model described above, three different members of our team independently wrote different computer codes in different languages and compared results. Once we verified that the results of the three codes agreed, and that the results in [10] could be reproduced as well, we first carried out the analysis described in this section. We then expanded one of the codes to carry out the Monte Carlo simulations described in the next section.

Here we first show three scenarios: two were the effective reproduction number R_t is 1.5 ($A(0) = 200$ and $A(0) = 50$) and one where we use what the CDC considers its best estimate for COVID-19[9], $R_t = 2.5$ (and $A(0) = 200$). We simulated each of these three scenarios under the PSU plan. We use the parameters in table 1 unless otherwise indicated. We incorporated imported infections (a.k.a. shocks, possibly a result of "superspreader" events) by introducing five additional cases every seven days. We ran simulations over 270 cycles t (90 days), corresponding to the number of days from on-campus undergraduate arrival (August 21) to undergraduate dismissal before Thanksgiving (November 21) at PSU in Fall 2020.

Figure 1 shows the trajectories for the number of asymptomatic and quarantined individuals as well as the number of deaths for the 90-day Fall semester on a log-log plot to better visualize the different scales of the series (displayed in this report as continuous functions of time). Under the $R_t = 2.5, A(0) = 200$ scenario (all other parameters as in table 1), 15 student deaths are possible towards the end of the Fall semester. The capacity of the quarantine dormitory will be reached by the first 30 days into the Fall. Without stopping earlier, this is a scenario in which almost the totality of the undergraduate population (40,000) would become infected at some time by the end of the semester.

The projections under the more probable value of $R_t = 1.5$ (with $A(0) = 200$) indicate that the predicted number of deaths goes down but it still close to 2, with a number of asymptomatic cases towards the end of the Fall that exceeds 1700, and a quarantine utilization which will reach 100% after about 70 days.

Finally, for $R_t = 1.5, A(0) = 50$, a scenario aimed at illustrating the benefits of a reduction in the initial number of infectious individuals on campus, the number of deaths is practically zero (0.6). Under this latter scenario, all trajectories are "pushed" down significantly, with the

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[6]See https://protect.purdue.edu/updates/purdue-reports-over-99-of-students-are-covid-free-thus-far/.

[7]See https://www.msn.com/en-us/news/us/west-virginia-university-67-cases-of-coronavirus-out-of-11604-tests/ar-BB17OdNg.

[8]As of August 21 there have been reports at PSU of 148 positive cases in approximately 12,000 pre-arrival tests giving a prevalence is 0.0123. Using this prevalence, the resulting $A(0)$ would equal 374.9. Our relative lower estimate of $A(0) = 200$ seems reasonable for the fact that PSU is testing more students who live in areas of the USA with highest prevalence.

[9]For references in the CDC best current estimates, see [3].

quarantined reaching a manageable peak level of ≈ 200 students towards the end of the semester, the number of asymptomatic students is ≈ 700, and not more than 2000 students in total are infected over the entire semester. This projection underlines the critical importance of decreasing the initial number of infected individuals at the beginning of the Fall semester.
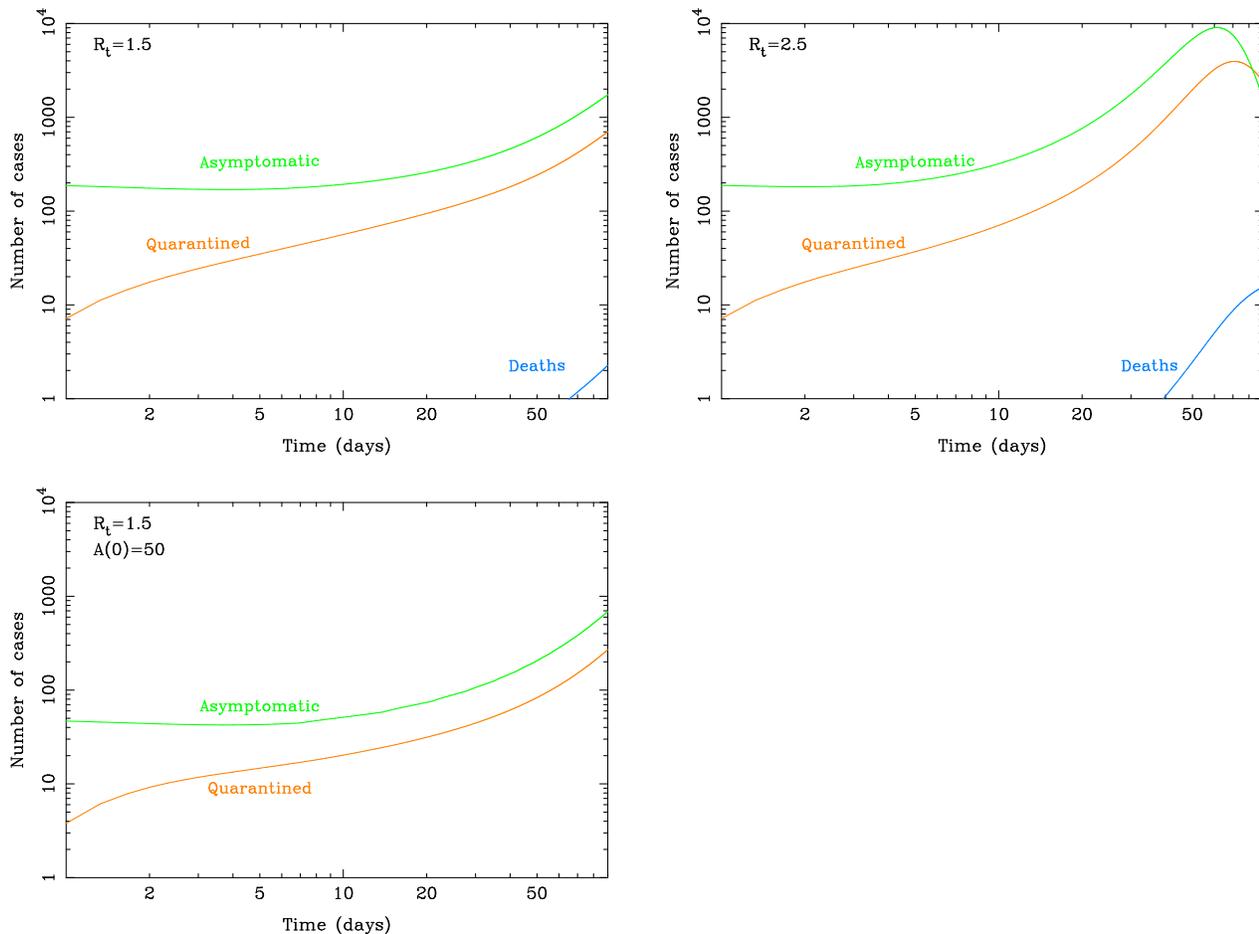

Figure 1: Projections of three basic scenarios for the first 90 days of the Fall semester at PSU UP (log-log scale). 40,000 students, 1%/day surveillance testing and isolation. Top left: $R_t = 1.5$, $A(0) = 200$ (for 30% initial testing), top right: $R_t = 2.5$, $A(0) = 200$ and bottom: $R_t = 1.5$, $A(0) = 50$ (for 100% initial testing). All simulations incorporate shocks that inject five cases every seven days. Reducing the number of infections initially present on campus, thanks to more testing prior to students arrival (from $A(0) = 200$ to 50) leads to an important reduction in subsequent infections. **We adopt a scenario with an effective reproduction number of $R_t = 1.5$ as our base case, to account for the reduction in R_t due to contact tracing, masks, and social distancing.** This value is down from $R_t = 2.5$, the recommended CDC best estimate for planning purposes for COVID-19 [3]. The reduction from the CDC best estimate of $R_t = 2.5$ is *greater* than the effect estimated by Grassly et al. [5], who determined how a well-carried out test-and-trace strategy reduces the effective reproduction number by an average of 26%. Note that there are no deaths expected in the last scenario.

A general lesson borne out by the simulations shown in figure 1 and additional simulations that we have ran is that the value of R_t stretches or compresses the time scale and the value of $A(0)$ affects the overall number of cases. Referring to figure 1, a larger value of R_t allows the trajectories to reach their peak sooner and a higher value of $A(0)$ shifts the trajectories up. It is also noteworthy that a peak (or turnover) in the trajectories indicates that a large fraction of

the population has experienced an infection and the number of new cases stops growing because there are not many susceptible individuals left.

4   Accounting for the uncertainty in parameter estimates: a Monte Carlo Simulation

The projections shown in the previous section are based on a deterministic, discrete-time SEIR model that requires using parameter estimates that have different degrees of uncertainty. In this section, we place distributions on the most important parameters "driving" the spread of the infections according to table 3 and figure 2. The rest of the parameters were set as in table 1 and formulae (1).

Parameter	Distribution	Mode	Source
Reproduction no., R_t	$\text{Beta}(2, 6, 1.4, 3.0)$	1.66	(1.4,3.9) is a 95% C.I. in [8]
Incubation period, $1/\theta$	$\text{LogN}(1.621, 0.418)$	4.24	[7] fit this distribution
Weekly shocks, X	$\text{Poisson}(5)$	5	Base case in [10]
$P(\text{symptoms} \mid \text{infection})$	$\text{Beta}(5, 5, 0.15, 0.45)$	0.30	from [4]

Table 3: Distributions used in the Monte Carlo simulations of the SEIR model. $\text{Beta}(\alpha, \beta, \min, \max)$ is the 4 parameter Beta distribution with mode $\frac{\alpha-1}{\alpha+\beta-2}(\max - \min) + \min$. $\text{LogN}(m, s)$ is a Lognormal distribution where m and s are the mean and standard deviation *in the log scale*. Here, $\exp(m + s^2/2)$ is the mean and $\exp(m - s^2)$ is the mode. The parameter X models exogenous sudden infections, due to superspreader effects (e.g. large gatherings or parties) or from visitors outside town, assumed to occur weekly.

Ten thousand Monte Carlo draws were taken from the joint distribution of the parameters in table 3 (assumed independent) and the SEIR model was run for each of them. In figures 3 and 4 the "shadow" of the ensemble of trajectories is displayed, with a grey region indicating the set of trajectories that excludes the 20% most extreme, the red lines indicating the boundary of the 1% most extreme trajectories observed (99% of the trajectories are inside these lines), and the dark lines represent the median trajectories.

From figure 3, the effect of increasing the testing rate 10 times over its level in the PSU plan (i.e. up to 10%) shows a considerable decrease in the median quarantined number (which remains below the estimated isolation dormitory capacity of 350). Here testing prior to arrival was fixed at 30% as per the PSU plan. The same "push down" effect can be observed in the quarantined and death trajectories, with a 10%/day testing rate and isolation strategy eliminating almost all risk of any death among students.

In figure 4 we increased the initial testing to include 100% of the students (resulting in an estimated $A(0) = 50$ asympotmatic students undetected initially, see table 2 and its discussion in section 2). The column on the right is close to what the U. of Illinois has recently declared to be its testing strategy[10], namely, testing 10% of the campus population per day (screening every student on average once every 10 days) and testing 100% of the arriving students. The projected 80% most likely scenarios in this case indicate a manageable quarantine utilization, 200 asymptomatic individuals towards the end of the semester, and an even lower probability of any student death. This is the safest testing plan we studied in the present report.

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[10]For the U. Illinois testing plan, see `https://massmail.illinois.edu/massmail/87835966.html`.
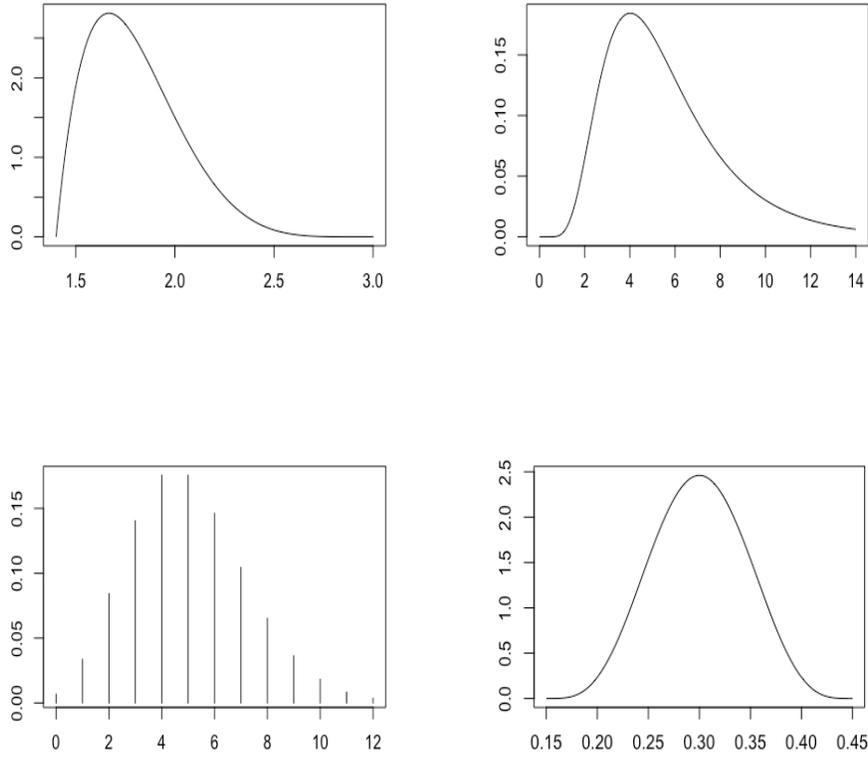
Figure 2: Distributions used in the Monte Carlo simulation, from left to right, top to bottom: effective reproduction number, $R_t \sim \text{Beta}(2, 6, 1.4, 3.0)$; incubation time $1/\theta \sim \text{LogN}(1.621, 0.418)$ (compare to [10] who used $1/\theta = 3$ days), additional infectious shocks $X \sim \text{Poisson}(5)$ assumed to occur every weekend, and $P(\text{symptoms} \mid \text{infection}) \sim \text{Beta}(5, 5, 0.4246, 0.8731)$. *Note that we use a low value of $R_t = 1.5$ to account for social distancing and use of masks in campus, and for the effects of contact tracing* (cf, the CDC's best estimate, used in [10], $R_t = 2.5$,)
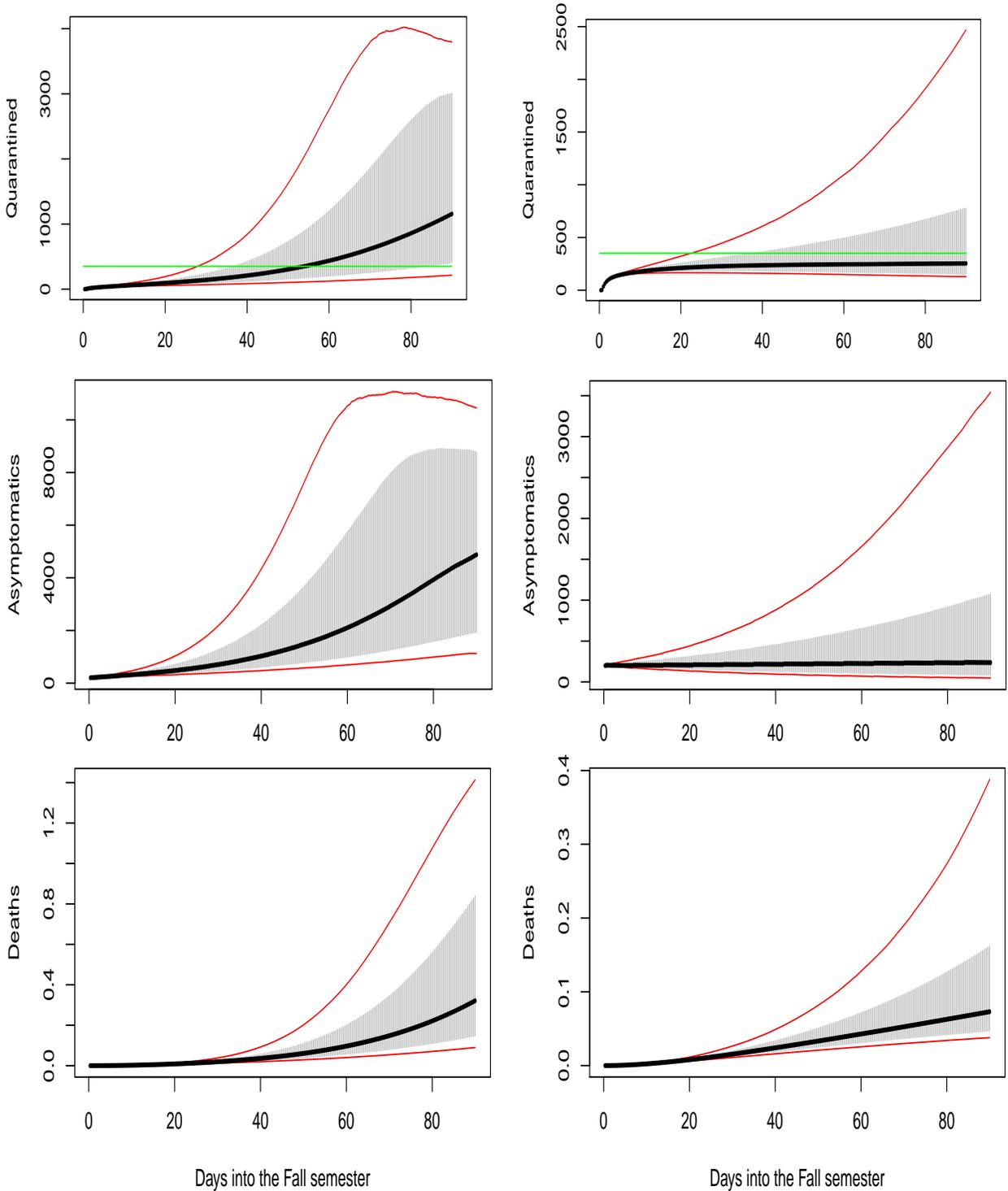
Figure 3: Effect of increasing surveillance testing per day, with a fixed testing rate of 30% before arrival. All units on the vertical axes are in number of persons. From top to bottom: quarantined students (green line is PSU quarantine dormitory capacity, approx. 350), number of asymptomatic students, and deaths among undergraduate students. Left column: under PSU plan (1%/day surveillance). Right column: increasing daily surveillance to 10%/day (every student tested once every 10 days on average). Ten thousand trajectories were simulated, the middle 80% quantiles are highlighted (grey, these are the most likely scenarios), the red lines indicate the boundary of the 1% most extreme trajectories observed (99% of the trajectories are inside these lines), and the solid black line is the median trajectory. Testing 10% per day keeps the median number of those that need to be quarantined below 350 over the duration of the 90-day period in the Fall 2020 semester. In contrast, the PSU plan will result in an overflow of the quarantine/isolation dormitory sometime between 40 to 50 days into the semester. The fatality risk of the undergraduate age group is very low. Still, the possibility of one death by Thanksgiving under the PSU plan on the left cannot be totally discarded.
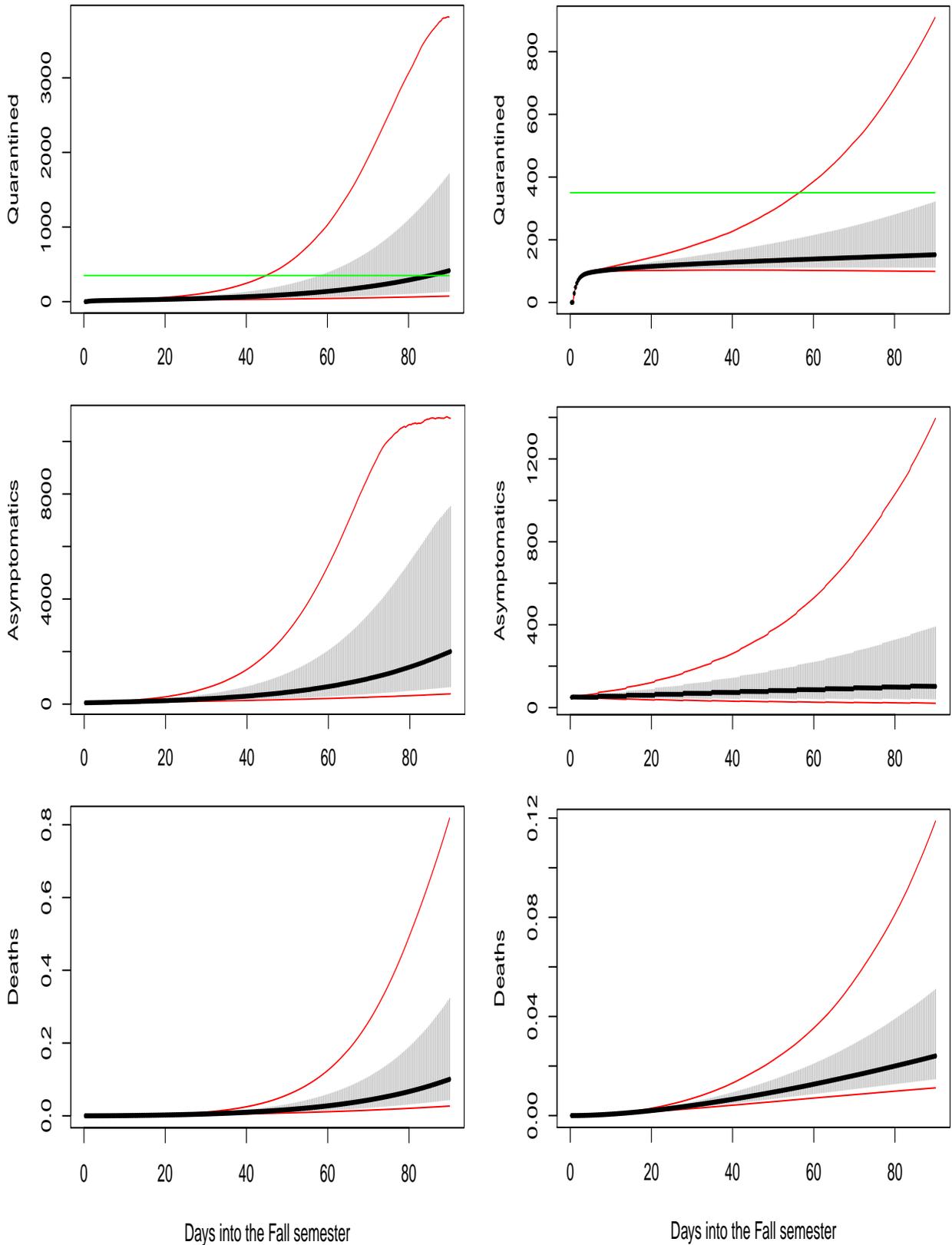
Figure 4: Effects of increasing initial screening testing of students upon arrival to campus (to 100% testing) and increasing surveillance testing per day to 10%/day. All units on the vertical axes are in number of persons. Left column: with 100% testing (screening) of all students upon arrival and 1%/day surveillance. Right column: under a "U-Illinois"-like plan, testing all 100% students upon arrival and increasing daily surveillance to 10%/day. Ten thousand trajectories were simulated, the middle 80% quantiles are highlighted (grey, these are the most likely scenarios), the red lines indicate the boundary of the 1% most extreme trajectories observed (99% of the trajectories are inside these lines), and the solid black line is the median trajectory. The 80% most likely scenarios under the U.Illinois-like plan on the right indicate low utilization of the quarantine dormitory, a manageable median number of asymptomatic infections, and very low probability of any student death.

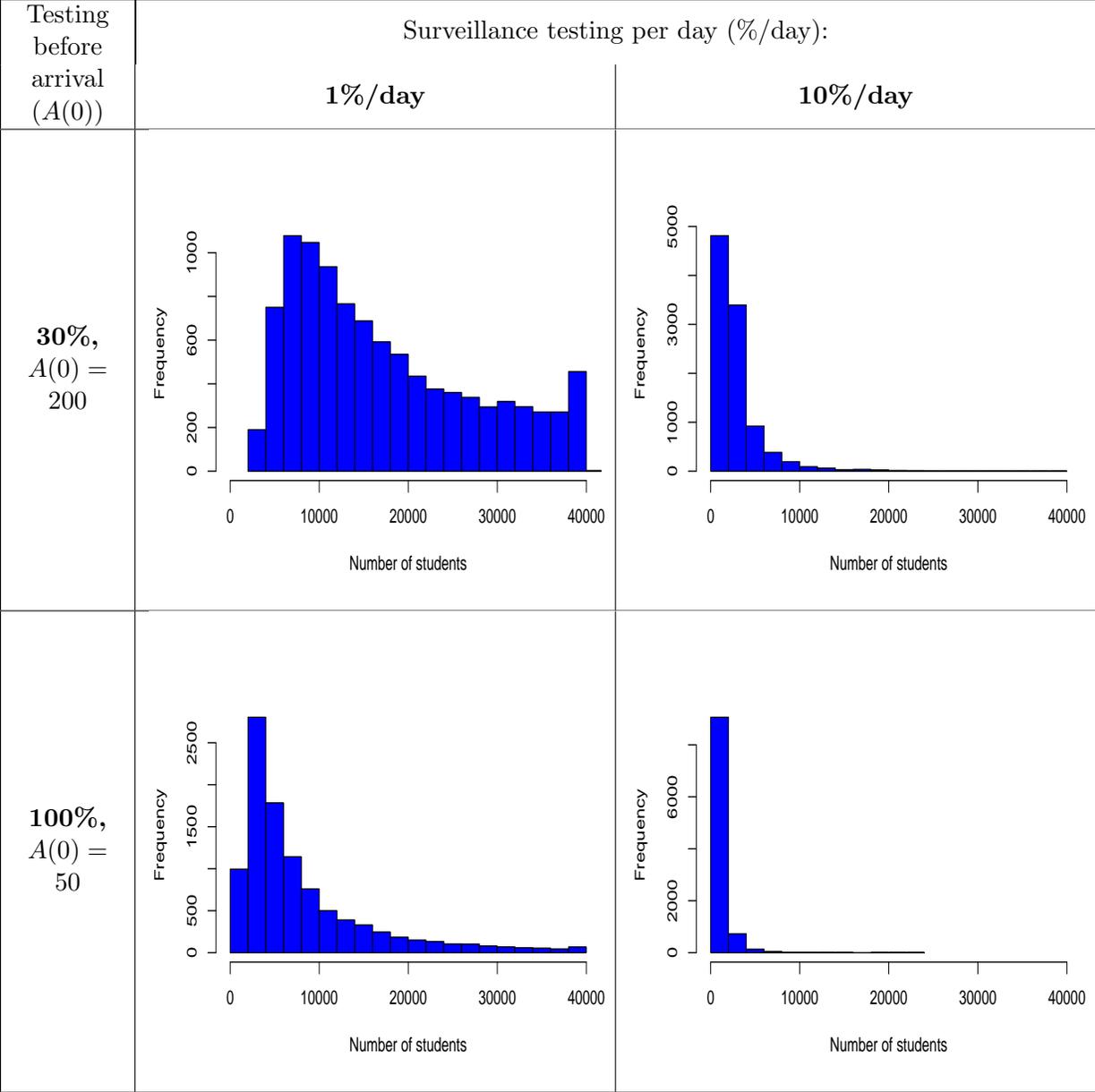| Testing before arrival ($A(0)$)	Surveillance testing per day (%/day):	
	1%/day	**10%/day**
30%, $A(0) = 200$		
100%, $A(0) = 50$		

Table 4: Histograms of the cumulative total number of infected students (including those recovered) by the end of the Fall semester over 10,000 Monte Carlo simulations (bar heights represent the number of cases, out of 10,000, that the number of students infected was the value displayed under the bar, on the x-axis). The table helps to quantify the effect of reducing the initial number of infections (through more initial testing) and increasing the level of surveillance testing on the cumulative total number of infections. The effect of initially testing more students before arrival is shown top to bottom and the effect of the percentage of surveillance testing is shown left to right column. We assume increasing testing from 30% to 100% decreases initial asymptomatic cases from 200 to 50 (see text for justification). Estimated median cumulative numbers of students infected are: 14,737 ($A(0) = 200$ and 1%/day surveillance), 5222 ($A(0) = 50$ and 1% surveillance), 2,088 ($A(0) = 200$ and 10%/day surveillance testing), and 739 ($A(0) = 50$ and 10%/day surveillance).

The contributions to the reduction of the cumulative total number of infected students over the Fall semester are quantified in table 4. This illustration shows histograms of the distribu-

tion of total infected students (which in some scenarios can be the totality of the students, as shown earlier) over the 10,000 Monte Carlo simulations. These histograms represent the relative probability distributions that a given (total or cumulative) number of students will be infected by the end of the semester. For example, in the upper left histogram, the most likely cumulative number of infected students is 6,000–8,000 but there is a significant probability that this number can exceed 20,000. The effect of reducing the number of initial infected students is a 65% reduction in the median number of infected students. The effect of increasing the rate of surveillance testing from 1% to 10% per day is a reduction in the median number of infected students by 86%. Applying both effects, the reduction with respect to 1% testing, $A(0)$=200 plan is about 95% in the median number of total infected students, with a distribution with much lower dispersion, and is hence a robust plan.

5 Modeling the effect of the PSU plan on Faculty, Staff, and surrounding (older) adult population in State College

The previous modeling does not include the Faculty, Staff, and in general, the older adult population of State College, who will be at risk. Our final projections attempt to model the effect of the infectious process among students on this older population. Epidemiological models exist for heterogeneous populations where infection rates between the different population subgroups need to be estimated [1]. In the absence of relevant data and to provide a first approximation to this situation, we turn again to the SEIR model in [10]. In order to use this model in older adults, we must tune the model parameters for an older population. We do this by modifying P(symptoms|infection) to be 0.6923 ([9]) instead of 0.30 as before, and increasing the fatality risk using the CDC's general fatality risk of 0.65% [3] rather than the very low fatality risk among young adults we used before (0.05%). We recompute σ, β, and δ using (1).

We first consider 40,000 older adults in the State College area and assume these will follow more closely the masking and social distancing directives. This population includes all PSU UP faculty and staff (15,000 persons) as a subset. Therefore, we use the SEIR model in [10] considering this population with an effective reproduction number of $R_t = 1.0$, which would result in no growth of infections (i.e., this is borderline stable, [1]). We utilize the Paltiel et al. external or "imported" infections, X, as a daily mechanism that generates additional infections due to student-older adult interactions in the State College area. For the initial number of asymptomatic infections, we optimistically use Centre County's most recent prevalence data[11], and compute the estimate:

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[11]Source for all prevalence data: The New York Times, `https://www.nytimes.com/interactive/2020/us/new-york-coronavirus-cases.html`
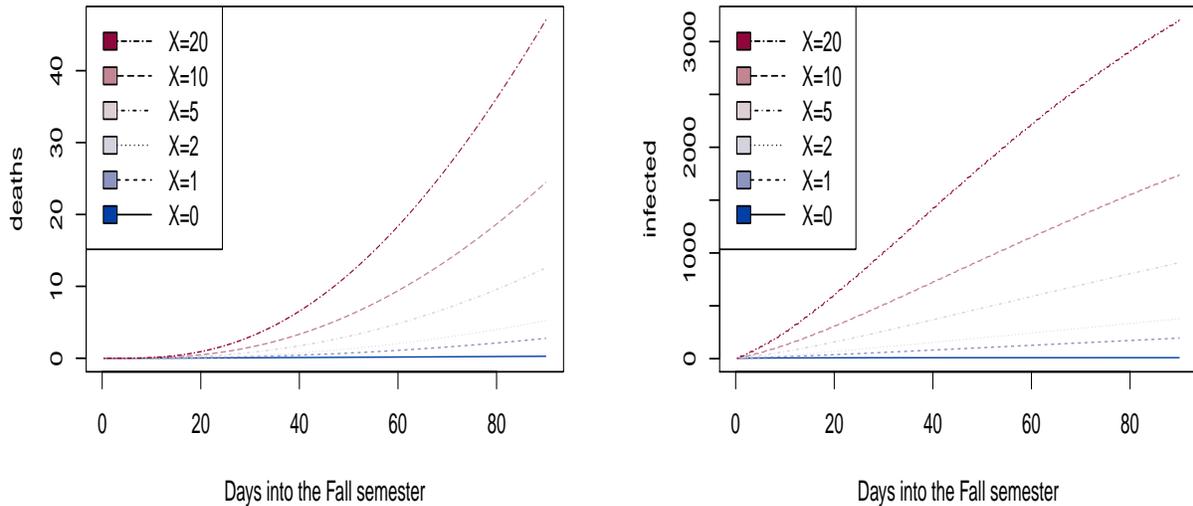
Figure 5: Projected number of deaths (left) and infected (right) among the 40,000 Faculty, Staff, and older adult population in the State College area, assuming $A(0) = 4$, no surveillance testing, isolation and quarantining only based on symptoms. The value of the external daily shocks modeling the interaction between undergraduate students and the adult population (X in the model) has been varied from 0 to 20.

$$A(0) = 40000 \cdot \frac{10}{100000} = 4$$

The effect of X is unknown and it is difficult to establish a priori. We therefore ran six different scenarios, for $X = 0, 1, 2, 5, 10$, and 20 infections (per day) due to daily student-adult interactions. Since this is a population most of which does not work for PSU, we use as a first approximation $\tau = 0$ (no surveillance testing), which implies isolation and quarantine is based on symptoms only. The results are shown in figure 5. As expected, the results greatly depend on the value of X used, with the number of deaths varying in the order of tens and the total number of infections varying from the low hundreds to 3000.

We repeated a second analysis for $N = 15000$ and $A(0) = 2$ (assuming again Centre county recent prevalence data) to model specofocally the Faculty and Staff at PSU-UP. We use $\tau = 1/(3 \times 100)$ to consider the 1%/day surveillance testing that will take place. Again, we model the impact of undergraduates on this population using the SEIR model and the X external shocks, varied at the same levels as before. Figure 6 shows the results. Despite the smaller population, the number of expected deaths is about the same as when using a population of 40,000. The number of infected faculty and staff is naturally lower than when considering $N = 40000$, ranging only up to ≈ 2000 individuals instead.
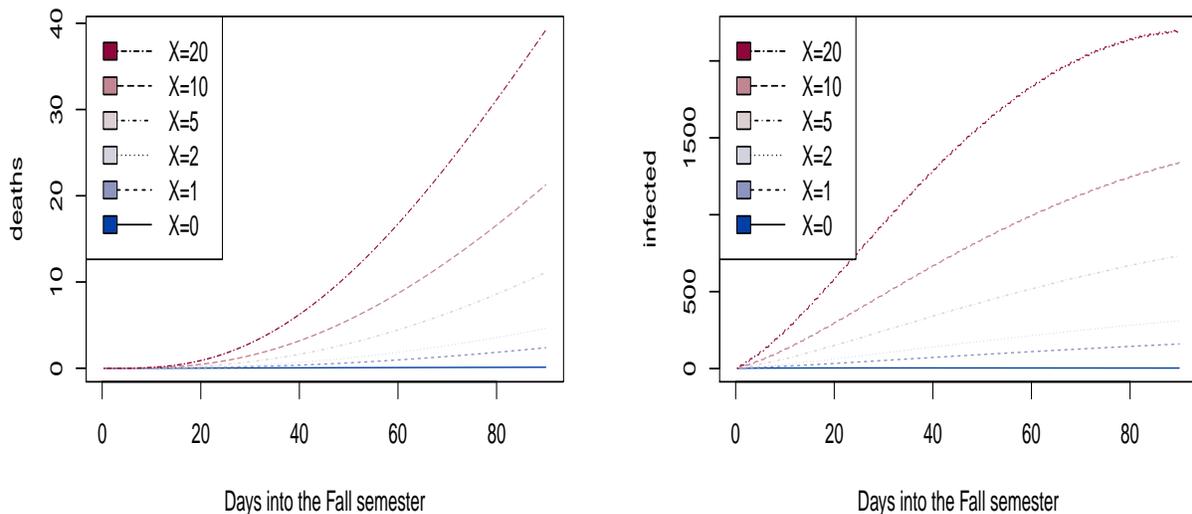
14

Figure 6: Projected number of deaths (left) and infected (right) among the 15000 Faculty and Staff at PSU-UP, assuming $A(0) = 2$, and 1%/day surveillance testing. The value of the external daily shocks modeling the interaction between undergraduate students and the adult population (X in the model) has been varied from 0 to 20.

6 Conclusions

We have simulated likely scenarios of the Fall 2020 semester for the PSU-UP campus. According to the simulations, the current PSU testing plan may result in hundreds of asymptomatic undergraduate students, overflow of the quarantine capacity at a point within the Fall semester that depends on the particular parameters used, and could even result in the possibility of some student deaths. We have shown, under relatively conservative parameter ranges, that reducing the initial number of infected students at the beginning of the Fall (via increased testing up to 100%[12]) can reduce the median number of total infections by about two thirds. Furthermore, increasing the number of tests from 1%/day to 10%/day (i.e., screening all students every 10 days on average) reduces the total number of infected students by about four fifths with respect to the performance under the PSU plan. Both strategies together (increasing initial testing to 100% and increasing surveillance/screening testing to 10%/day) can jointly reduce the number of infected undergraduates by almost 95% over the Fall semester and is a safe and robust strategy.

We reiterate that the model and parameters we have used apply specifically to University Park for the reasons mentioned in the summary section. In other campuses the conditions are

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[12]A strategy which could be complemented by the temporary closing of indoor bars and restaurants during a period of time when students arrive, an alternative to be implemented in Urbana and Champaign for the U. of Illinois arrival of students, see `https://www.news-gazette.com/coronavirus/c-u-preparing-additional-measures-to-handle-arriving-students/article_e887831f-68f1-5920-9dde-0c2cca24dea6.html`.

different the student populations are smaller compared to those of nearby towns and so are the relative degrees of interaction within the student population and between students and other residents of the nearby towns.

It is worth noticing that shutting down all in-person classes in the middle of the Fall semester due to overflow of the quarantine/isolation dormitory or due to an increase in asymptomatic infections (a very likely event according to our simulations) will not stop the epidemic process in State College, as it is likely most students living off-campus will remain in the State College area. Our projections show many of them could at that point be already infected.

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Appendix. SEIR model equations

The following equations are corrected[13] from the supplementary material in Paltiel et al. [10].

Uninfected

$$U(t+1) = U(t) \cdot \left[1 - \beta \frac{A(t)}{U(t) + E(t) + A(t)}\right] - U(t-1) \cdot \tau \cdot (1 - S_p) + \mu \cdot FP(t) - X \cdot I(t+1)$$

Exposed

$$E(t+1) = E(t) \cdot (1 - \theta) + \left[\beta \frac{A(t) \cdot U(t)}{U(t) + E(t) + A(t)}\right] + X \cdot I(t+1)$$

Asymptomatic

$$A(t+1) = A(t) \cdot [1 - \sigma - \rho] - A(t-1) \cdot \tau \cdot S_e + E(t) \cdot \theta$$

False Positives

$$FP(t+1) = FP(t) \cdot [1 - \mu] + U(t-1) \cdot \tau \cdot (1 - S_p)$$

True Positives

$$TP(t+1) = TP(t) \cdot [1 - \sigma - \rho] + A(t-1) \cdot \tau \cdot S_e$$

Symptomatic

$$S(t+1) = S(t) \cdot [1 - \rho - \delta] + \sigma \cdot [TP(t) + A(t)]$$

Recovered

$$R(t+1) = R(t) + \rho \cdot [TP(t) + A(t) + S(t)]$$

Deaths

$$D(t+1) = D(t) + \delta \cdot S(t)$$

Population size
$$N = U + E + A + S + TP + FP + R + D \quad \text{(constant)}$$

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[13]Private conversation with D. Paltiel.