

# Modeling for Cornell's Fall 2021 Semester

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## Summary

This document describes modeling performed at the start of the fall semester to incorporate new information that had just become available and to support new interventions brought to bear against cases in the student population at that time: more frequent surveillance testing for students affiliated with greek-life organizations; stronger measures improving compliance with student surveillance testing; increased staffing allocated toward contacting positive individuals and performing contact tracing; and a more robust adaptive testing program. Case trajectories since these interventions were put into place have tracked between the nominal and optimistic scenarios developed at the time. While significant uncertainty remains about cases going forward and work continues to understand and combat the spread of virus, modeling suggests that these interventions played a significant role in reducing student case counts. We also briefly discuss the health outcomes associated with cases among vaccinated individuals, observing that the protection against severe disease offered by vaccination causes 1000 cases in vaccinated students to be roughly comparable in terms of significant illness to 60 cases in unvaccinated students.

## 1. Introduction

This document describes modeling of undergraduate student infections performed at the end of August and in early September, as the semester was beginning. This work updated earlier analysis conducted June through early August to incorporate new information as it became available: new estimates of vaccine effectiveness that had just appeared in the literature and prevalence estimates based on arrival positivity at the start of the semester. It also included a new analysis of the elevation in undergraduate student contact relative to the 2020-21 academic year.

This analysis was undertaken as part of a broader effort to combat infections detected as surveillance began at the start of the semester: Cornell daily cases rose during the week preceding the semester from 5 on 8/23 to 57 on 8/28, and remained above 30 cases through Sep 2, later falling to current levels after this analysis was completed. These case counts were due, in part, to students infected before arrival, but also due to spread among the undergraduate student community before and during the week of 8/23. In that broader context, this analysis was delivered in pieces as it was completed to those in operational roles fighting the pandemic, to help them direct their efforts and to know what to expect moving forward.

The analysis made projections for undergraduate student cases under the interventions in place at the time, and the potential for new interventions to reduce cases. It specifically examined the benefits of:

- more frequent surveillance testing and whether, in view of limits on testing capacity, this testing should be enhanced for certain sub-segments of the student population;
- reducing the time from collecting a sample in surveillance to acting on it through isolation and quarantine; and
- improving the effectiveness of contact tracing.

Supported by this analysis, several interventions were put into place over the weekend of 8/28-8/29:

- An elevation in the surveillance testing frequency for students involved in greek-life organizations
- Interventions to improve compliance with surveillance testing (gating of access to Canvas, university buildings, and university internet for students out of compliance).
- Increased staffing provided by Cornell's Masters in Public Health Program to shorten the response time from receiving a positive test result in surveillance to contacting and isolating positive students and (where appropriate as per health department guidance) quarantining close contacts, and to allow more time to be spent contact tracing positive cases;
- A more robust adaptive testing effort focusing on small cohorts with temporarily elevated positivity, typically based on housing, membership in a sports team, or greek-life chapter membership. We have also experimented with adaptive testing based on classroom attendance when positivity in a classroom is high, but have not yet found this to be effective at identifying new positives.

The analysis focused on students because (1) this was the population in which the vast majority of cases were appearing at the time of the analysis, and (2) past analysis and data suggest that transmission from infected students to other individuals is quite rare, making its order of magnitude difficult to estimate. We do not, however, believe that the rate of transmission from infected students to other individuals is 0. With each student case, there is the potential, which we believe to be small, for an infection among other individuals. We believe this scales approximately linearly in the number of students infected. For example, if the number of secondary cases collectively in staff, faculty and the community is 1/100 for each student positive (this includes both the person infected by a student, the people they infect and so on), then we would expect 20 student-sourced cases in staff, faculty and the community if there are 2000 student cases during the semester. If the number of secondary cases is actually 1/1000, then we would expect 2 student-sourced cases in staff, faculty and the community resulting from 2000 student cases. While separate theoretical and empirical analyses both suggest that the chance of infecting a faculty member in a classroom is small, and most other interactions with staff and faculty during the work day appear to also be low-risk, there are some interactions that are higher risk, e.g., coaches accompanying a sports team on a camping trip. There is much that we do not know about the risks created by students' other interactions with non-students,

though our experience from the 2020-21 academic year is that very few infections result from this pathway.

Under the new interventions put into place starting on 8/28, substantial uncertainty remained in the projections. While the nominal scenario called for approximately 2,000 infections in the student population over the course of the fall semester, the optimistic scenario (with pessimism level 10%, explained below) called for just under 500 infections. Comparing these predictions to our experience so far, since the onset of regular surveillance testing and additional interventions that were put in place near the end of August, the daily (real) case numbers have fallen to the point where our real case numbers fall substantially below our nominal prediction, closer to our optimistic prediction. We believe that this is because the parameters governing reality, in particular vaccine effectiveness and the rates of student contact, are better than assumed in our nominal scenario. The initial surge in real cases was close to, but higher than, in our nominal scenario, likely because the additional interventions assumed in the nominal scenario had not yet been put into place, counteracting the conservatism in the parameters chosen for the nominal scenario. Observed trajectories may also be below the nominal scenario, in part, because our modeling does not include the effect of adaptive testing.

The effectiveness of these new interventions is encouraging, though work continues. Surveillance testing and case counts give us the ability to monitor the situation and support the design of additional interventions. Work has specifically continued to improve the effectiveness of adaptive testing and contact tracing, to further shorten the delay between sampling and isolation, and to continue to improve our understanding of how virus spreads within the Cornell community and beyond.

In contemplating case number predictions for the fall semester, it is important to keep in mind that the vast majority of our population is vaccinated and the vast majority of our students are young and very healthy. Indeed, the vast majority of vaccinated COVID-positive Cornell students have been asymptomatic or have had only mild symptoms. Vaccination substantially reduces the possibility that an individual COVID-positive patient will become seriously ill. Indeed, considering a vaccine whose estimated efficacy is 95% in preventing serious illness (see, e.g., [Rosenberg et al. 2021](#)), one needs  $1/(1-.95) = 20$  cases in vaccinated individuals to create the same expected number of cases with serious illness as 1 case in an unvaccinated individual. Using this conversion, 1000 student cases in a 99%-vaccinated student population (Greek-life affiliated undergrads are currently vaccinated at a rate of 99.2%, compared to 99.8% of the rest of the undergraduate population) would be expected to result in a comparable amount of serious illness as 60 cases in an unvaccinated population. We summarize literature below suggesting that each infected student has a chance of requiring hospitalization of between 0.036% and 0.072%, suggesting that 1000 student cases would be expected to result in fewer than 1 student hospitalization. At the same time, while student cases so far have exhibited extremely mild symptoms, variability across individuals in their ability to fight infection creates the potential for a significant negative health outcome.

## 2. Methods

In describing the modeling performed, we first describe the overall modeling setup, and then describe in detail how ranges for uncertain parameters were chosen.

### 2.1 Modeling Framework

We use the same modeling setup and student groups used in our [analysis of fall 2020 data reported in February 2021](#). Additional details are also available in this [document](#). In particular, we considered 3 student groups: undergraduate students affiliated with greek-life organizations and varsity athletics, other undergraduates, and graduate + professional students.

The modeling of student infections is performed without a detailed model for other individuals (staff, faculty, the local community, and travel outside of Tompkins County). Instead, we model infection from these populations into the student population by modeling a constant rate of infection into the student population from outside (the “outside infection rate”). We have already commented above on infections from the student population into these other populations.

Most parameters are taken directly from the analysis of fall 2020 data linked above. The following adjustments have been made:

1. Delta adjustment: We increase the transmissibility of the virus by a factor of 2.5 because of the delta variant. This factor is estimated based on the estimated R0 of 5-7 for the delta variant [[Nunes-Vaz and Macintyre, 2021](#)] and the estimated R0 of 2.5 for the original strain [[CDC, 2021](#)]. Taking the middle value of the R0 range for the delta variant and dividing it by the R0 for the original strain gives 2.4. We use a slightly more pessimistic value of 2.5 as our estimate.
2. Initial Prevalence: we estimate the initial prevalence in each student group as described below.
3. We assume that 95% of students are vaccinated. This is lower than the student vaccination rate in steady state during the bulk of the semester, once student vaccinations upon arrival are complete. Vaccination decreases the probability that a person becomes infected when exposed and also decreases the rate at which they infect others when infected. The precise effect of the vaccine is uncertain and is controlled through two parameters described below.
4. The outside infection rate and number of contacts per day are increased relative to fall 2020 because of a relaxation in pandemic restrictions and changing attitudes to risk.
5. Contact tracing effectiveness (the number of positives isolated per contact trace) is altered because of a change to quarantine & isolation protocols (asymptomatic vaccinated close contacts are not quarantined) and because of the challenges presented to contact tracers by relaxation of social distancing and the increase in contacts it creates.

We assume a one day delay between collecting a sample and isolating the individual. Before the interventions initiated 8/28, this was two days but has since been reduced to 1 day. We discuss these delays below.

Based on arrival testing data at the start of the fall 2021 semester, we estimated the following values for the prevalence in each of the three student groups at the start of the semester.

Group	Initial Prevalence
UG Greek / Athlete	0.3%
UG Other	0.3%
Grad / Professional Student	0.1656%

Unless otherwise noted we set parameters to their values estimated in the analysis of fall 2020 data. The additional parameters mentioned above are modeled with the following ranges for uncertainty. These ranges are discussed further in Section 2.2 below.

Parameter	Definition	Uncertainty Range (Lower Bound, Upper Bound)
Vaccine Susceptibility Multiplier	In an interaction with an infectious person, if the exposed person is vaccinated, what is the reduction in risk of becoming infected?	(9.8%, 94%)
Vaccine Transmission Multiplier	In an interaction with a susceptible person, if the source is vaccinated and infectious, what is the reduction in risk of their becoming infected?	(25%, 100%)
Close Contact Multiplier	Relative to Fall 2020, how much more physical contact are students having with others? This is realized both through interacting with more people and through reduced masking (which exposes others to more respiratory particles). 1x corresponds to the same amount of transmission per day as Fall 2020. The effect of the delta variant is modeled	(0.9x, 2.7x)

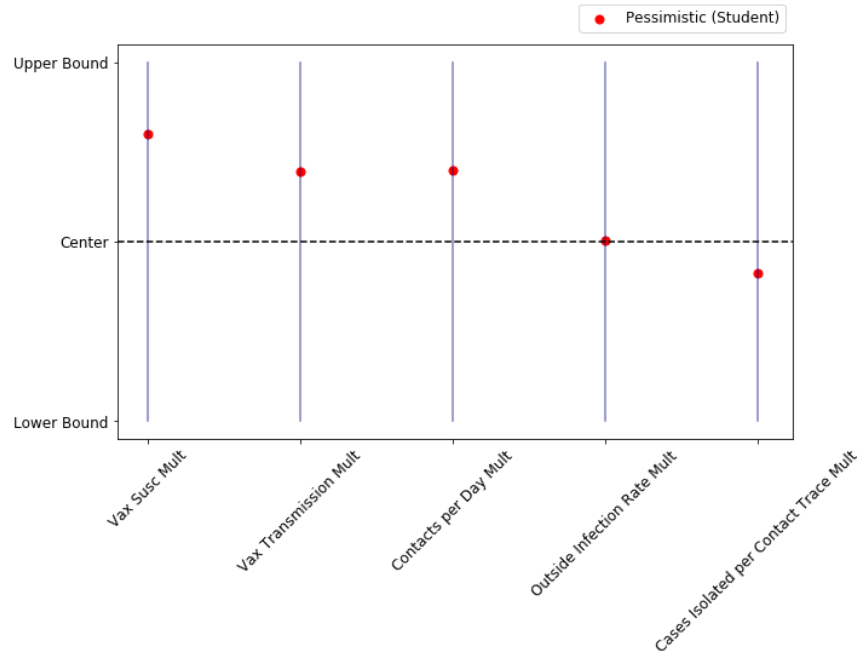
	separately.	
Outside Infection Rate Multiplier	Relative to Fall 2020, how often do we expect cases to be imported from the outside community (Ithaca and beyond)?	(1x, 5x)
Contact Tracing & Adaptive Tracing Multiplier	Relative to Fall 2020, how many positive individuals are we finding and preventing from infecting others per student found via surveillance or symptomatic self-reporting? This implicitly includes the effect of both contact tracing and adaptive testing.	(0.5x, 1.5x)

We set our nominal scenario so that parameter values are equal to the middle of this range.

We set our pessimistic scenario from these uncertainty ranges via a methodology described below that first appeared in a paper we submitted for publication and are currently revising for resubmission. In brief, we use the above ranges to identify a probability distribution that describes the relative likelihoods of the input parameters. The center of that probability distribution corresponds to our nominal scenario. We then identify the pessimistic and optimistic scenarios from that probability distribution through a trade off of how unlikely the scenarios are with the number of cases that result.

In more detail, we think of each uncertainty range as the 95% credible interval for a Bayesian prior distribution on that parameter and then form a joint Bayesian prior over all parameters in which each parameter is independent. We then construct a 1-dimensional family of parameter configurations of increasing pessimism, where the nominal scenario corresponds to pessimism level  $q=0.5$ . Using a linear approximation to the function that maps input parameters to median simulated student infections, the scenario with pessimism level  $q$  (between 0 and 1) is the most likely configuration under the prior for which median infections is equal to the  $q$ -quantile of infections under the prior, assuming that infections for a given parameter configuration are given by the previously fitted linear model. The two pessimistic scenarios are those with pessimism levels 95% and 90%. The two optimistic scenarios are those with pessimism levels 5% and 10%. The simulation used to calculate this family of scenarios tests  $vax$  students 1x/week and  $unvax$  2x/week.

The pessimistic scenario with pessimism level 95% is illustrated below in Figure 1.



**Figure 1:** The pessimistic scenario, representing a 95% level of pessimism, i.e., a scenario where the median student infections are higher than those of 95% of the scenarios under the prior. From left to right are the Vaccine Susceptibility Multiplier, Vaccine Transmission Multiplier, Close Contact Multiplier, Outside Infection Rate Multiplier, and the Contact Tracing & Adaptive Tracing Multiplier. The y-axis gives the value of the parameter scaled to the uncertainty ranges given above, with a red dot at the upper bound corresponding to a value at the upper end of the confidence range, and similarly for values at the center (dashed line) and lower bound.

We do not explicitly include adaptive testing in our analysis, but past experience points to its effectiveness and indeed the university has an aggressive adaptive testing policy in place.

Our modeling assumes that isolation, contact tracing, and notification and quarantine of close contacts (when applicable) is as effective as in Fall 2020. This is likely optimistic: changing policies prevent quarantining asymptomatic vaccinated contacts and the initial large caseload associated with student return has sometimes slowed isolation and notification of contacts. At the same time, fast isolation of positive cases remains a powerful tool and indeed the university has reduced the time from testing to isolation of positive cases from 2 days to 1 day.

## 2.2 Parameter Range Discussion

### 2.2.1 Vaccine Susceptibility & Transmission Multipliers

We assume vaccination provides protection against infection with efficacy **50%** for susceptible individuals

- We collect estimates from the literature, including 42% [[Puranik et al. 2021](#)], 79% [[Sheikh et al. 2021](#)], 88% [[Bernal et al. 2021](#)], 40% [[Pouwels et al. 2021](#)] for Pfizer and 76% [[Puranik et al. 2021](#)], 66% [[Fawkes et al. 2021](#)] for Moderna.
- We aggregate these estimates using a mixture model, accounting for the number of observations and uncertainty reported for each of them.
- The aggregated vaccine efficacy for protection is 52%. We use 50% as the nominal value in our simulation.
- This estimate is optimistic in the sense that some of these results are measured shortly after vaccination, while [Pouwels et al. 2021](#) observed that the protection provided by vaccination decays over time.
- This estimate is conservative in that the studies above were performed on general populations. Cornell has a larger fraction of young people, and vaccine efficacy was observed to be higher for younger people and lower for older [[Pouwels et al. 2021](#)]. However, there is not sufficient evidence in the literature to support further investigation of age-stratified vaccine efficacy.

We assume vaccination results in a **0%-50%** reduction in the viral load of a source case.

- The literature reports varying results, ranging from a 2.8-4.5 fold reduction in viral load [[Levine-Tiefenbrun et al. 2021](#)], 40%-50% reduction of transmission risk [[Harris et al. 2021](#)] to no reduction in viral load [[Brown et al. 2021](#)] or peak viral load [[Pouwels et al. 2021](#)].
- Given the significant uncertainty around this parameter, we use 0% reduction as a pessimistic estimate and 50% reduction as an optimistic estimate.

## 2.2.2 Close Contact Multiplier

We use the SafeGraph foot traffic data [<http://www.safegraph.com>] to estimate the mean close contact multiplier modeling the elevation in contacts due to loosening social distancing interventions. We find that the foot traffic in Ithaca Collegetown in Fall 2019 is 80% higher than that in Fall 2020. Assuming that people's physical contact in Fall 2021 returns to the same level seen in Fall 2019 and foot traffic is a reasonable proxy for physical contact, we estimate that the mean close contact multiplier is 1.8.

We estimate an upper bound for the close contact multiplier by comparing the transmission of COVID-19 in the US in fall 2020 to its basic reproduction number  $R_0$ .

The  $R_0$  for the original strain of COVID-19 is best estimated to be 2.5 [[CDC 2021](#)]. The effective reproduction number ( $R_t$ ) in fall 2020 is lower bounded by 0.9 [[covidestim.org](#)].

Assuming that reduction in transmission above results from social distancing interventions, we can estimate that loosening social distancing interventions leads to an increase in contacts by a factor of  $2.5 / 0.9 = 2.7$ . This estimate is considered to be the upper bound for the close contact multiplier because it ignores the effects of other interventions such as contact tracing in reducing transmission and therefore overestimates the elevation in contacts due to loosening social distancing interventions.



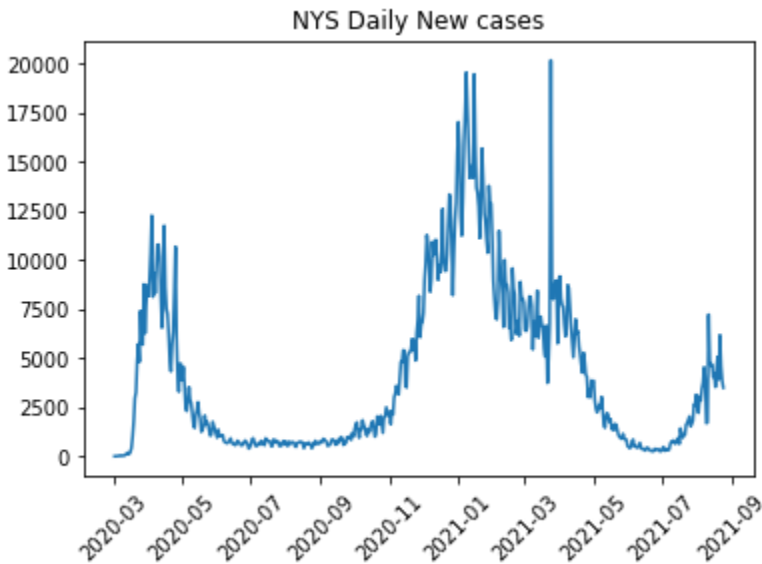
We then set the lower bound by assuming a symmetric credible interval centered at 1.8. This provides a lower bound of  $1.8 - (2.7-1.8) = 0.9$ . Thus we use **(0.9, 2.7)** as the (lower bound, upper bound) range for the close contact multiplier.

### 2.2.3 Outside Infection Rate Multiplier

Our modeling of outside infection rate relative to Fall 2020 (the “outside infection rate multiplier”) depends on two factors: the change in prevalence and the change in mobility.

#### Prevalence Multiplier

We will use the count of daily cases in New York State (Figure 2) to approximate the increase in outside prevalence between Fall 2021 and Fall 2020.



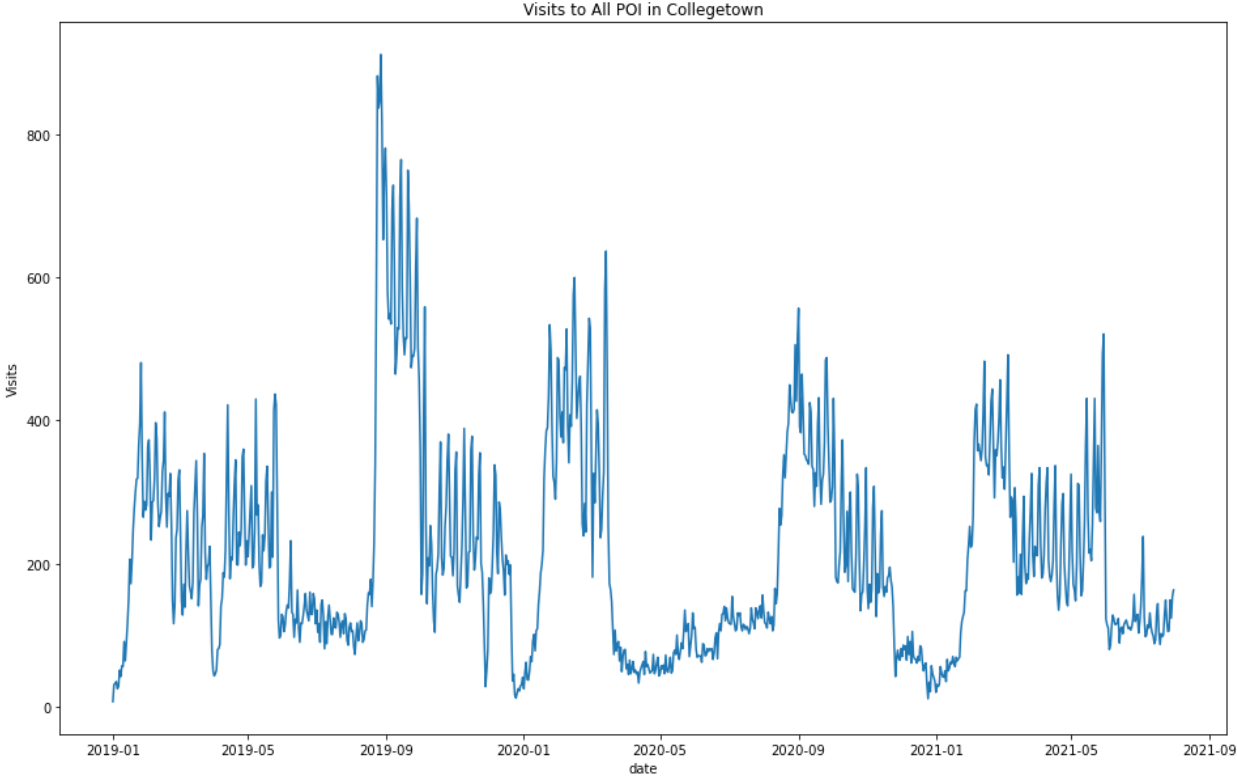
**Figure 2:** A time series plot of daily cases in New York State based on data published by the New York Times [<https://github.com/nytimes/covid-19-data>].

We compare the average number of weekly cases from 7/24/2021 - 8/24/2021 to the average number of weekly cases in the Fall 2020 semester to obtain the prevalence multiplier for this fall **(0.79)**.

#### Mobility Multiplier

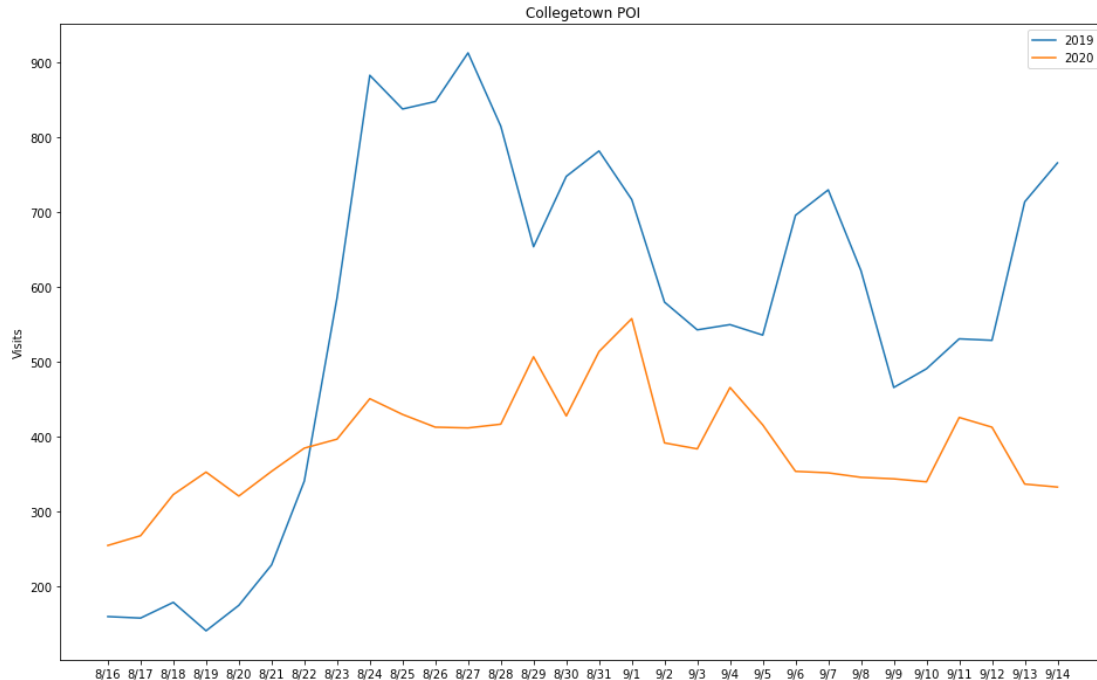
As social distancing requirements relax, we anticipated an increase in outside infections from activities around campus compared to Fall 2020. We approximate this increase using anonymized cellular location data provided by SafeGraph [<http://www.safegraph.com>]. Using

SafeGraph data, we can count the number of visits to restaurants, bars, stores and other points of interest (POI) around Cornell's campus (Figure 3).



**Figure 3:** A plot of the number of visits to POIs in collegetown per day for the past 2 years.

We use the time period from 8/16/2019 to 9/14/2019 as a proxy for the back-to-normal activity that we will expect this fall. We compare this to 8/16/2020 to 9/14/2020, the activity that occurred when strict social distancing measures were implemented. A plot with these two time periods overlaid is shown below in Figure 4.



**Figure 4:** The number of visits to POI in Collegetown from 8/16/2019 to 9/14/2019 and from 8/16/2020 to 9/14/2020.

Taking the ratio of total visits in 2019 over the total visits in 2020 in this time period gives us the estimate for the mobility multiplier for this fall (**1.45**).

To obtain our outside infection rate multiplier, we multiply our prevalence multiplier with our mobility multiplier to obtain  $0.79 \times 1.45 = \mathbf{1.145}$ .

## 2.2.4 Contact Tracing & Adaptive Tracing Multiplier

Each time a new positive is found through surveillance or symptomatic self-reporting that is not part of an existing contact trace, we model this as initiating contact tracing and potentially also adaptive testing. This has several effects in reality:

- Unvaccinated and symptomatic vaccinated close contacts are quarantined.
- Close contacts are alerted that they have been exposed and asked to reduce social contact.
- Testing of close contacts and others identified in adaptive testing occurs.

This prevents some positive individuals from infecting others.

The “Contact Tracing & Adaptive Tracing Multiplier” determines the number of such positive individuals contained per contact trace relative to Fall of 2020. In constructing a prior on this parameter, there are two countervailing effects:

- The amount of contact is larger, which leads to more close contacts.

- Health department policies on quarantine have changed and close contacts are not quarantined if they are vaccinated and asymptomatic.

Given that we have significant uncertainty about this multiplier, we set the range to (0.5 to 1.5), reflecting a prior belief that the number of positives contained per contact trace is within the range of 50% to 150% of the fall 2020 number with 95% probability.

## 2.2.5 Hospitalization

To provide context for the case count predictions, we estimate the probability of hospitalization for a vaccinated individual who is infected as follows.

$P(\text{hospitalized} \mid \text{vaccinated}, \text{infected})$

$$= \frac{P(\text{hospitalized} \mid \text{vaccinated})}{P(\text{hospitalized} \mid \text{unvaccinated})} * \frac{P(\text{infected} \mid \text{unvaccinated})}{P(\text{infected} \mid \text{vaccinated})} * P(\text{hospitalized} \mid \text{infected}, \text{unvaccinated})$$

In deriving this expression, we use that hospitalization (for COVID-19) implies infection. Thus,

$$P(\text{infected} \mid \text{unvaccinated}) * P(\text{hospitalized} \mid \text{infected}, \text{unvaccinated}) = P(\text{hospitalized} \mid \text{unvaccinated})$$

and the denominator in the first term cancels the numerator in the second term and the third term. On the right-hand side we are left with

$$P(\text{hospitalized} \mid \text{vaccinated}) / P(\text{infected} \mid \text{vaccinated})$$

which is equal to the left-hand side,  $P(\text{hospitalized} \mid \text{vaccinated}, \text{infected})$ .

To calculate this expression:

- The first term is estimated to be 18% based on [Sheikh et al. 2021](#), [Puranik et al. 2021](#), [Israel Ministry of Health 2021](#), and [Rosenberg et al. 2021](#).
- The second term is the inverse of the vaccine susceptibility multiplier, whose nominal value is 50%. Thus, the second term is 2.
- We calculate the third term as follows:
  - The existing studies of which we are aware focus on the hospitalization rate among recorded cases, rather than all infections. We believe that this is because it is difficult to identify asymptomatic cases in most populations because large-scale surveillance testing is seldom implemented.
  - Thus, we calculate the third term by taking the product of two subterms:  $P(\text{hospitalized} \mid \text{infected}, \text{symptomatic}, \text{unvaccinated})$  and  $P(\text{symptomatic} \mid \text{infected}, \text{unvaccinated})$ .
  - Both subterm probabilities vary across age groups. For the first subterm, Figure 4

of [Papst et al. 2021](#) presents age-stratified hospitalization risks among recorded infections before vaccinations were available. Using their [source data](#), we assume the following values for  $P(\text{hospitalized} \mid \text{infected}, \text{symptomatic}, \text{unvaccinated})$ :

- 0.5% - 1% for students
- 2% - 3% for those aged 30-60
- 10% - 20% for those aged 65-75
- For the second subterm, [Poletti et al. 2021](#) reported age-stratified symptomatic rate among close contacts of confirmed infections before vaccinations were available. Based on their analysis, we assume the following values for  $P(\text{symptomatic} \mid \text{infected}, \text{unvaccinated})$ :
  - 20% for students
  - 30% for those aged 30-60
  - 50% for those aged 65-75
- Combining these estimates, we obtain the following values for the hospitalization probability of a vaccinated infected individual:
  - 0.036% - 0.072% for students
  - 0.22% - 0.32% for those aged 30-60
  - 1.8% - 3.6% for those aged 65-75

Two observational studies reported  $\text{Prob}(\text{hosp} \mid \text{infection}, \text{vaccination})$  directly and either do not stratify by age, or only provide coarse stratifications.

- [Griffin et al. 2021](#) (Los Angeles County, May 1 - July 25)
  - Percentage of fully vaccinated persons infected with SARS-CoV-2 that were hospitalized was 3.2%.
  - The dataset is 43,127 reported SARS-CoV-2 infections in Los Angeles County.
  - This number is towards the upper end of our estimates above, which could be explained if older individuals had a higher vaccination rate in the dataset.
- [Rosenberg et al. 2021](#) (NYS, May 3 - July 25)
  - This paper reports vaccine effectiveness against hospitalization well in excess of 90% over several age groups.
  - The dataset is the entire population of New York state (9675 cases among vaccinated adults, 38505 among unvaccinated).
  - This number is not stratified by age; figures in the report show that the hospitalization rate among infected in the older population is significantly higher than the younger, but the report does not contain hospitalization numbers broken down by age.
  - The reported values in this paper for vaccine effectiveness against hospitalization are in line with those we have assumed above.

The estimated hospitalization rates for students we estimated above are consistent with our experience to date at Cornell. As of Sep 1 (Sep 12), we have had 325 (486) student infections and to the best of our knowledge none of these infections has resulted in a hospitalization.

These estimates of hospitalization rates are subject to much uncertainty. Indeed, it is very difficult to estimate small probabilities accurately, simply due to the rarity of the events in question. This leads to uncertainty in the estimates, which is compounded by limited understanding of the disease and vaccine effectiveness over time on the one hand, and variation of methodologies and subjects in the existing literature on the other hand.

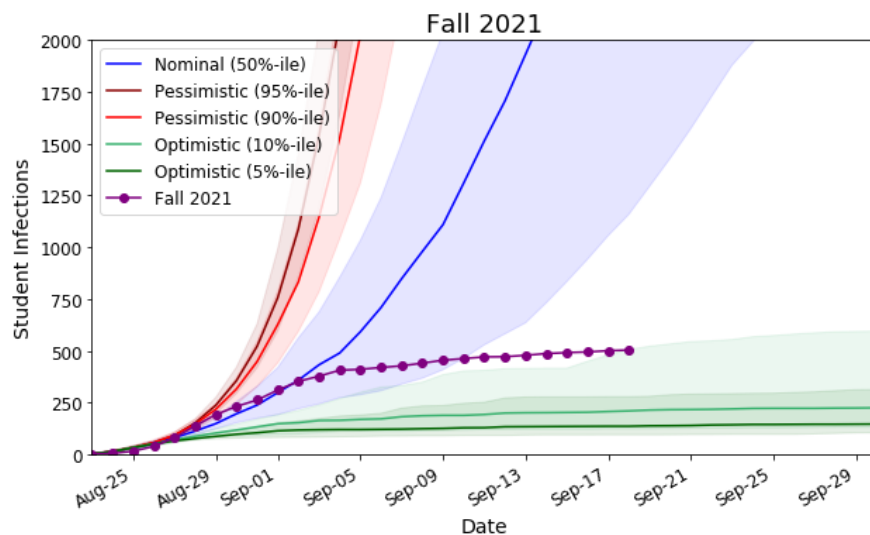
### 3. Results

Section 3.1 reports projected trajectories for the semester and observed cases to date. Section 3.2 explores the impact of interventions. Our simulation results only show student infections. To place these numbers in context it is useful to keep in mind that we have estimated the probability of hospitalization for each infection to be on the order of 0.036% to 0.072%, i.e., on the order of 1 in 2,000.

#### 3.1 Trajectories

The simulation starts on Aug 23rd and the corresponding cumulative cases are shown. We use initial prevalences corresponding to our estimates from before the semester began.

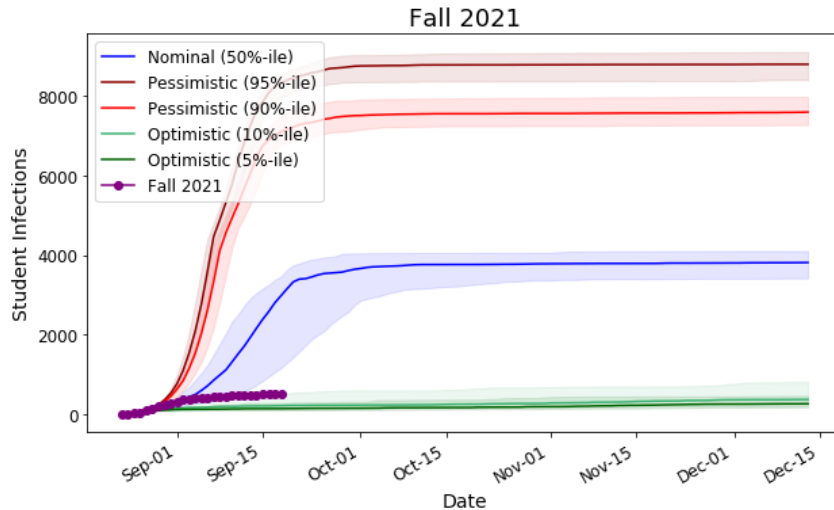
The testing frequency in Figure 5 below is: 2x/week for students in greek organizations, varsity athletes and unvaccinated students, 1x/week for vaccinated students. The nominal scenario fits the early portion of the observed data very well, and then the trajectory of real cases becomes closer to the optimistic scenarios. This may be because the parameters governing reality are more in line with the optimistic scenario, but the full set of interventions simulated in this figure did not move into place until the weekend of 8/28-8/29. These two effects may have canceled each other for the early part of the semester until the full interventions took effect.



**Figure 5:** Number of student infections projected under the optimistic, nominal and pessimistic scenarios over time. Each shaded region contains 80% of simulated trajectories under that

scenario. Overlaid is the observed number of student cases. Up to Sep 1, the trajectory tracks the nominal curve, although the observed trajectory was not used to calibrate the nominal scenario. After Sep 1 the trajectories diverge with a smaller number of observed cases.

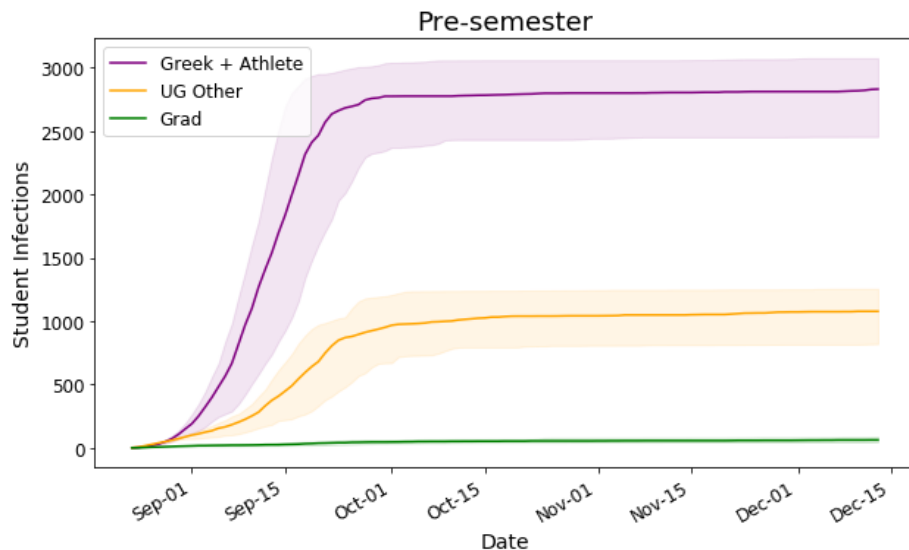
Below in Figure 6 is a longer view of this trajectory.



**Figure 6:** Number of student infections (the same data as Figure 5) over the full semester. Cases are projected to level off by the end of September as infections in high-transmission subgroups are slowed through a combination of interventions and immunity after infection.

Figure 7 below breaks out infections by student group under the nominal scenario. In the simulation, students in greek organizations and varsity athletes become infected at a much higher rate than others. The nature of the simulated outbreak is that it spreads primarily through the cohort modeled as having a higher transmission rate in the simulation (greek-life students and athletes) and less aggressively in the other undergraduates. In the simulation, we hypothesize that the growth rate of cases slows substantially in late September because infections in high-transmission subgroups are slowed through immunity after infection and simulated interventions. The combination of vaccination and interventions, even in the face of the delta variant, ensures that the effective  $R_0$  is lower than for circa-2020 SARS-CoV-2 without interventions. Thus the number of infections stops growing at a level of immunity that is lower than the 70% figure quoted at the start of the pandemic.

Reality differs from Figure 7 in several ways. First, while we have observed a significantly higher rate of transmission among students associated with greek life than among other students, this rate has been slow enough that 2x / week testing has prevented the rapid growth seen in the nominal scenario. Second, while we have observed some transmission among varsity athletes and have sometimes brought adaptive testing to bear, the rate of transmission in this population appears smaller than among students affiliated with greek life organizations. Nevertheless, Figure 7 is important for understanding that a higher transmission-rate cohort can contribute significantly to viral spread in a population.



**Figure 7:** Number of simulated infections by student sub-population over time under the nominal scenario. As above, each shaded region contains 80% of simulation trajectories for that sub-population. Infections grow rapidly in the greek + athlete population because they are modeled as having more social contact, and then tail off as discussed in the text. Infectious individuals in this population as well as secondary transmission also infect other undergraduates and a small number of graduate and professional students. Reality has proven to be closer to the optimistic scenario in terms of transmission rates and 2x / week testing has been sufficient to provide substantial infection control for students affiliated with greek life.

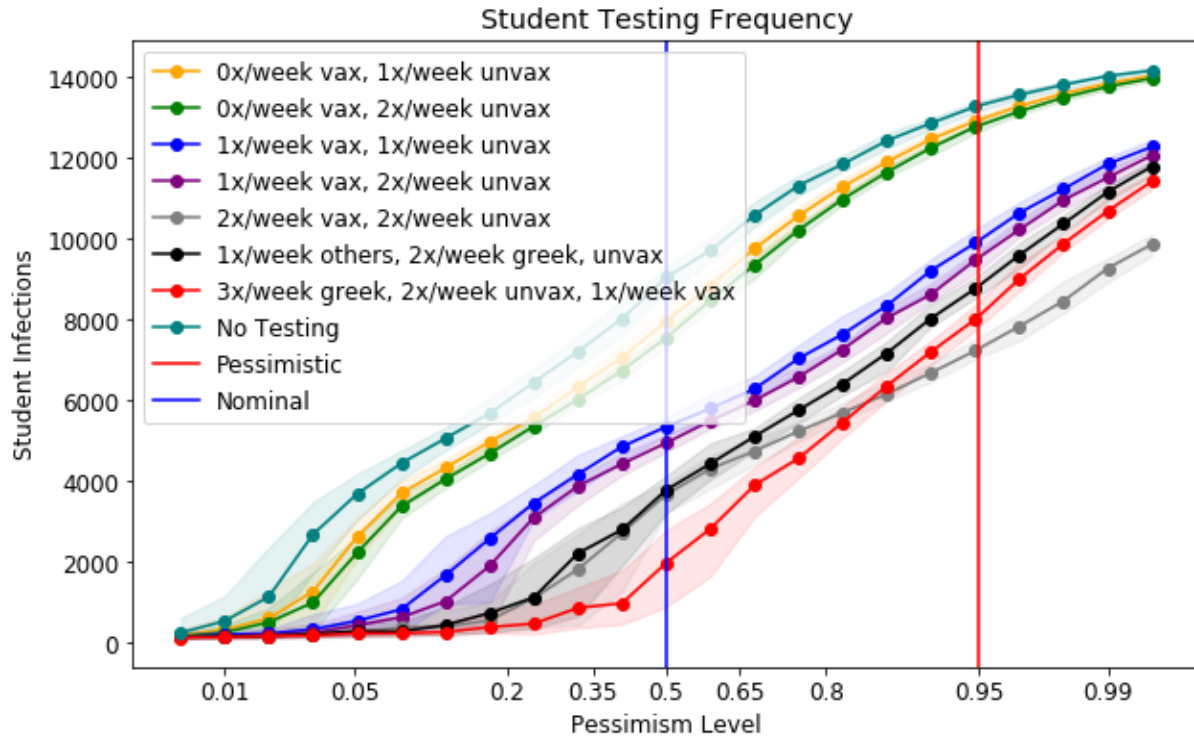
## 2.2 Interventions

In the following graphs the x-axis varies the “pessimism level”, which controls the level of pessimism in the simulation runs. The nominal scenario corresponds to a pessimism level of 50%, the two pessimistic scenarios correspond to pessimism levels of 90% and 95%, and the two optimistic scenarios correspond to pessimism levels of 5% and 10%.

### Testing Frequencies

In Figure 8, we see the effect of varying the testing frequency for different groups. We see that elevating the testing frequency for the greek / athlete population modeled as having higher transmission rates substantially reduces infection under the nominal scenario, and under a broad range of pessimism levels. There does not appear to be substantial benefits to testing other student groups more frequently for pessimism levels below 0.95. This is because it is only the high-transmission population that experiences exponential growth in infections under these pessimism levels, and it is among these students that an additional intervention that slows the spread of virus provides the most value.



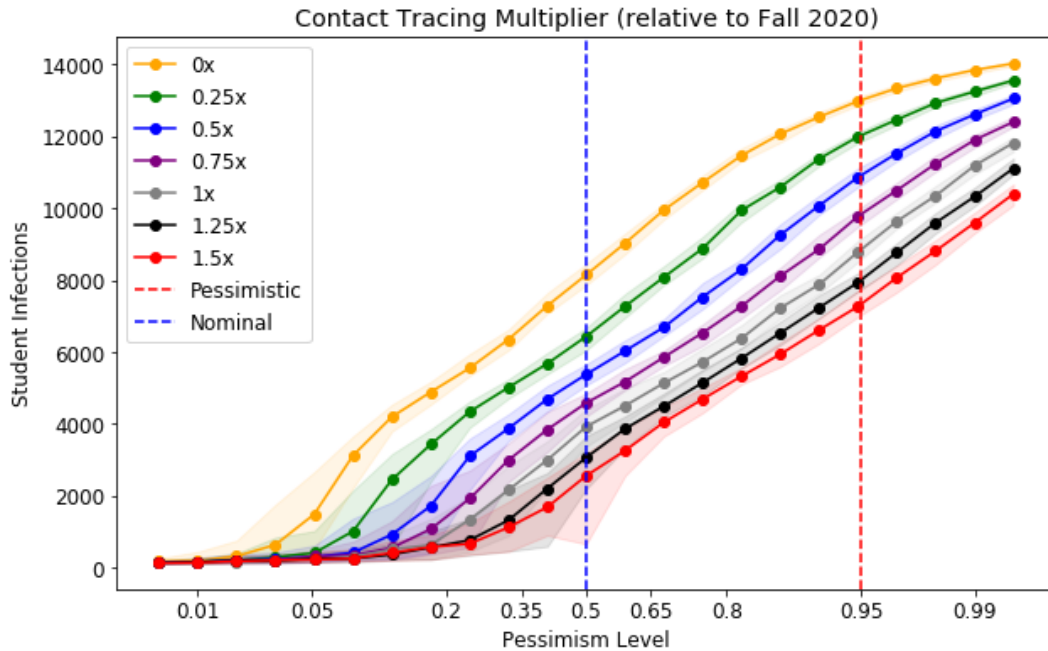


**Figure 8:** The effect of varying testing frequencies for different student groups. The nominal scenario appears on the x-axis at pessimism level 0.5. The y-axis gives total student infections over the course of the semester.

This analysis suggests that increasing the testing frequency for vaccinated students affiliated with greek-life organizations was an important step toward reducing viral prevalence. Testing frequency remains 1x / week for vaccinated varsity athletes because viral spread has not been as pronounced in this population and because adaptive testing has remained an effective tool for containing the spread of virus in this group.

### Contact Tracing Effectiveness

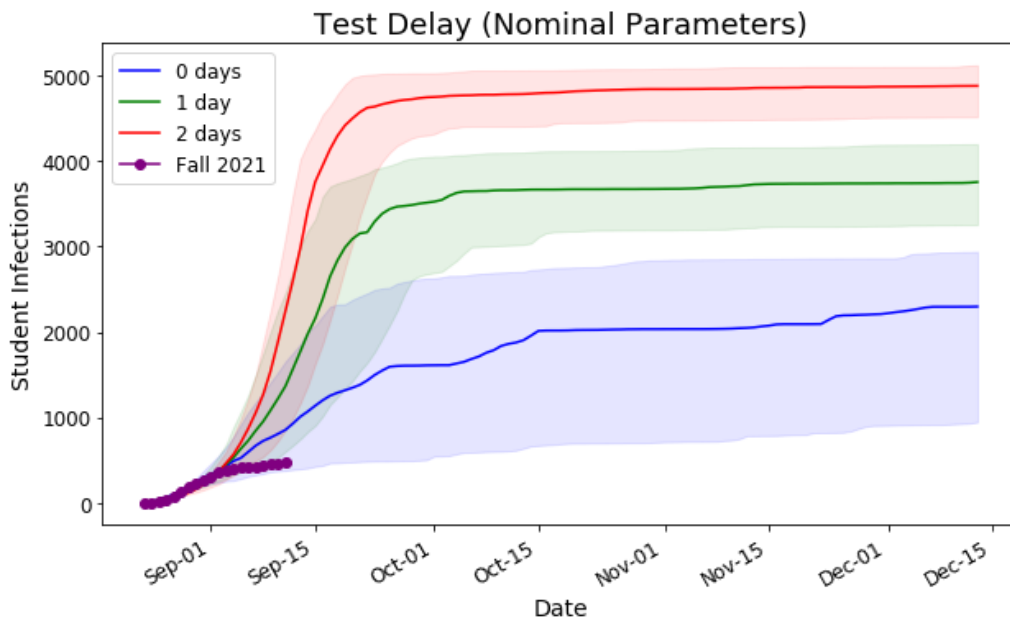
Figure 9 varies the effectiveness of contact tracing, i.e., how many additional positives are isolated or quarantined, thus preventing additional infections, by each contact trace, relative to the effectiveness estimated in the fall of 2020. The nominal scenario assumes that contact tracing effectiveness is equal to that in fall 2020. We see that if the contact tracing effectiveness is 0, i.e., no additional positives are prevented from infecting others, then infections grow to roughly 7000, even under the nominal scenario. This suggests that providing additional staffing from the Masters in Public Health program to support isolation, quarantine, and contact tracing efforts was a critically important intervention in late August.



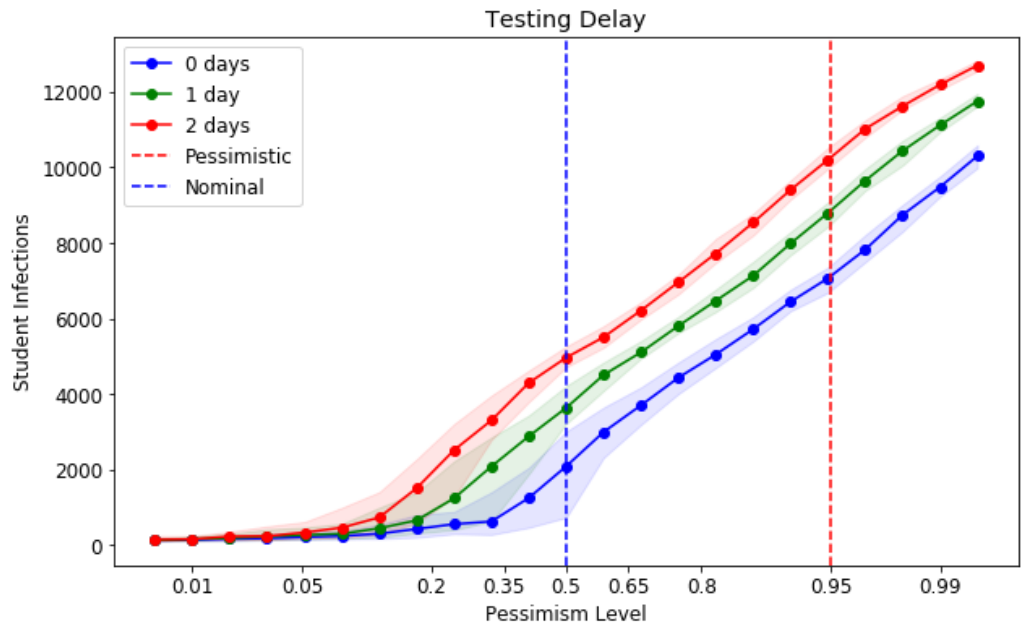
**Figure 9:** The effect of varying contact-tracing effectiveness. The nominal scenario appears on the x-axis at pessimism level 0.5. The y-axis gives total student infections over the course of the semester.

### Testing + Isolation Delay

Figures 10 and 11 below show the effect of increasing the delay between sampling and isolating positives. There is a significant benefit to reducing the delay between sampling and isolation. The addition of staffing for isolation, quarantine and contact tracing from the Masters in Public Health program at the end of August reduced this delay from 2 days to 1 day, providing significant infection control.



**Figure 10:** The effect of varying the delay from testing to isolation/quarantine.



**Figure 11:** The effect of varying the delay from testing to isolation/quarantine for different student groups. The nominal scenario appears on the x-axis at pessimism level 0.5. The y-axis gives total student infections over the course of the semester.