Addendum: COVID-19 Mathematical Modeling for Cornell's Fall Semester

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Overview:

This document contains additional analyses performed after the release of the June 15 main modeling report (Cornell COVID-19 Modeling Team, 2020). It is a companion to our posted responses to questions on the Frazier Modeling portion of the University Faculty website (Cornell University Faculty, 2020) for public comments on the C-TRO report. It explores the following questions:

- **Alternative methods for estimating contacts per day based on the literature**, expanding on the discussion in the response found on the University Faculty C-TRO website. This alternative methodology finds support for the value (8.3 contacts / day) used in the June 15 report, but also includes a more pessimistic methodology that results in 10.8 contacts / day, and an extremely pessimistic methodology resulting in 17.3 contacts / day. We see 10.8 contacts / day as entirely plausible while viewing 17.3 as an unlikely value that is nevertheless useful for assessing robustness.

- **Responding to higher-than-anticipated contacts per day and transmission rate through increased test frequency.** Achieving the same health outcomes as the June 15 modeling report (which assumed 8.3 contacts / day and testing once every 5 days on average) under an increased contact rate of 10.8 contacts per day would require testing once every 3 days, and an increase to 17.3 would require testing once every 2 days.

  Work continues (outside the modeling team) to build unprecedented test capacity at Cornell. In concert with this effort, more modeling work is in progress to identify a test capacity and protocol that will provide robustness to extremely high contact rates but be easier to implement than screening everyone on campus once every 2 days. This work leverages opportunities to improve test efficiency. Major opportunities include screening different sub-populations at different frequencies, using adaptive screening in which a sub-population's average test frequency is elevated when cases are found, and moving toward a better-performing and easier-to-implement deterministic test schedule and away from the easier-to-model random test schedule assumed here and in the June 15 modeling report. We also see other small opportunities to improve efficiency such as reserving Fridays to screen groups with higher weekend contact rates.

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- **The effect of non-compliance on the residential instruction setting.** We study non-compliance with a given fraction of test requests, say 20%, distributed evenly across the population. The resulting modeled outcomes are the same as those with full compliance with a decreased test frequency. For example, 80% compliance with a test protocol that tests 25% of the population every day is equivalent to full compliance testing .25*.8=20% of the population daily. This assumes, as does the June 15 modeling report, that testing is random.

- **The effect of offering optional testing in the virtual instruction setting, and a sensitivity analysis to the size of the unmonitored student population and contact rates** in this setting. Increased testing and reduced contact rate reduce the fraction of unmonitored students with negative health outcomes and have the largest benefit, while reducing population size changes the absolute number affected but has little effect on the fraction over reasonable population size ranges.

- **The impact of varying these parameters and assumptions on whether the residential fall semester is safer than one with virtual instruction.**

  While we find settings where virtual instruction has fewer infections and hospitalizations[1] than residential instruction, these settings arise from parameter choices that seem less likely given the capability to do frequent asymptomatic screening.

  The most likely settings where virtual instruction has better health outcomes than residential instruction are ones where virtual instruction outcomes are much better than expected, either because of lower-than-expected contact rates (equivalently, lower-than-expected transmission probability) or higher-than-expected compliance with optional asymptomatic screening or optional behavioral modifications by unmonitored students. Such surprisingly good contact rates, transmission and compliance are likely to also provide better-than-expected outcomes in the residential semester. On the other hand, we continue to see as most likely those settings where (1) virtual instruction results in a large fraction of unmonitored students being infected and (2) asymptomatic screening prevents this from occurring under residential instruction. Thus, we continue to view residential instruction as less risky than virtual instruction.

  We emphasize that the health benefits of residential instruction are predicated on building the capability to do extremely frequent asymptomatic screening if needed. Under pessimistic contact rates, the frequency required could be as fast as once every 2 days.

In reading these additional analyses, we ask that readers recall the warnings from the executive summary of the June 15 report, which remain valid despite the additional work that has gone into this addendum: *In all of our modeling results, modifying modeling parameters by only a modest amount from nominal values can result in substantially different numbers of infections and hospitalizations. ... In addition to uncertainty about parameters, our model cannot fully capture the intricacies of the real world.* Thus, while the results from our analysis do represent our best estimate of what may happen, uncertainty remains about what the future will bring.

The analyses we report in this addendum focus on questions that were a strong focus of public comments. We also describe other questions that we believe could significantly influence results but that were not raised in public comments. We are continuing to analyze these questions while

[1] As we explain in our posted response to public comments on the University Faculty C-TRO website (Cornell University Faculty, 2020), while we do not model fatalities explicitly, this should not be understood as implying fatalities will not occur. A discussion of fatalities resulting from hospitalizations can be found in that posted response.

balancing time with other modeling work that must happen to execute operational plans effectively as students return.

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1 Estimating Contacts Per Day From the Literature

The June 15 report assumed that infectious individuals have an average of 8.3 close contacts per day within the Cornell community, averaging across faculty, staff and students. One of the major themes in comments on the June 15 report was that the true number of close contacts per day could be substantially higher, with many comments focusing on undergraduates.

Some of this concern seems to derive from a misunderstanding of what constitutes a close contact. As reflected by the CDC's definition of close contacts (CDC, 2020), interactions that are brief or at a distance, such as between two people exchanging a brief hello as they walk past each other in a corridor or between two students seated 30 feet far apart in a lecture hall, are substantially less dangerous than interactions that are prolonged and at a proximity allowing for droplet-based transmission (6 feet or less). The danger of these interactions decreases further when participants wear masks and buildings are well-ventilated.

It is also worth clarifying two other points. First, the number 8.3 does not include close contacts with the outside community. Table 8 in the main report shows that the additional number of contacts per day with those outside of the Cornell community is assumed to be 0.5 for students (aggregating across off-campus/on-campus and undergraduate / graduate) and 5.8 for faculty and staff. Second, the value 8.3 represents an *average* across the entire Cornell community, of which roughly 44% are undergraduates, 26% are graduate / professional students, and 29% are faculty/staff. To illustrate, the following would be consistent with the numbers assumed in the main report: 12 within-Cornell + 0.3 outside-Cornell close contacts per day for undergraduates, 9 within-Cornell + 0.9 outside-Cornell for graduate students, and 2 within-Cornell + 5.8 outside-Cornell for faculty / staff.

Nevertheless there remains a significant possibility that the average number of within-Cornell close contacts per day may be substantially larger than 8.3. While this uncertainty about contacts per day reflects uncertainty about *all* parameters used in the modeling analysis, as reflected in the executive summary of that document, we pay special attention to this particular parameter because it attracted more attention than other parameters, and we agree that it plays an important role. In this section we explore alternate estimation methodologies based on the scientific literature, focusing

on Wallinga et al. (2006); Mossong et al. (2008); Edmunds et al. (1997, 2006); Leung et al. (2017) as most meaningful for informing our estimates, but also leveraging the 17 papers providing empirical estimates of contact rates as surveyed by Leung et al. (2017) and discussing Weeden and Cornwell (2020). Then in the next section we discuss our ability to respond to higher-than-anticipated contact rates with additional testing.

Overview of Estimation Methodology We see two opportunities to better leverage the scientific literature to estimate contacts per day.

First, we can directly use the numbers provided in that literature. In the literature we survey in detail below (Wallinga et al., 2006; Mossong et al., 2008; Edmunds et al., 1997, 2006; Leung et al., 2017) we find respectively 8.4, 13.4, 16.8, 22.8, and 8.1 contacts per day. A review of 17 sources in Leung et al. (2017) finds a median number of contacts per day of 13.9. Unfortunately, however, the literature measures contacts in ways that are easier for participants to report on surveys but that do not necessarily correspond to the significant probability of transmission that we assume in our model. For example, one common way that the literature defines a "contact" is as a conversation between two individuals. If a conversation is less than 15 minutes in length, then it would not meet the CDC definition of a close contact. Moreover, if the two individuals are wearing masks that reduce droplets and aerosols emitted while speaking, the risks decline further. Pointing in the other direction, being in close contact with one's spouse for many hours would be considered to be a single contact in the methodologies used by several papers in the literature, despite the fact that the risk of transmission is significantly greater than other kinds of CDC-defined close contact. Thus, it seems clear that the contacts reported in the literature should be adjusted to account for the level of risk associated with the particular definition of contact that is used. As the literature is based on data from before COVID-19, contacts should also be adjusted for social distancing measures. While we could attempt to make these adjustments manually, this seems difficult to do well. We view this first approach as inferior to the second estimation methodology we discuss now.

A second and potentially more accurate opportunity presents itself. Several papers in the literature (described in detail below) study how contacts per day changes with the age of the individual. Indeed, there is substantial variation, with adolescents and young adults having more contacts per day than older individuals. Quantification of this variation can be used to adjust the methodology used in the June 15 report to estimate contacts per day.

To estimate contacts per day, the June 15 report first made an assumption about R_0 among the Cornell population. It assumed that the university population would have an R_0 of 2.5 based on the following logic: the CDC recommends the use of $R_0 = 2.5$ for modeling pre-social-distancing pre-mask disease transmission; because Cornell has a large fraction of young people, its R_0 in the absence of social distancing and masks should be larger than the general population; Cornell's plan to institute social distancing and masks will reduce its R_0; in the absence of other information, the June 15 report then assumed these two effects would cancel each other out, and the R_0 in the fall would be 2.5 in the absence of asymptomatic screening. This value of R_0, the assumed probability of transmission per contact, and the number of infectious days per infectious case then results in 8.3 contacts per day.

The concern expressed by commentators with this methodology is that students (1) may have dramatically more contacts than the general population and (2) may fail to comply with social distancing and masks. As a result, the increase in R_0 due to our young population may outweigh the reduction in R_0 due to social distancing and masks.

By using estimates from the literature quantifying the elevation in contact rates between young

people and the general population, we can significantly reduce uncertainty about this first point. We can additionally base our assumptions about the impact of social distancing and masks on R_0 in the general population based on observations for what has happened in Tompkins County after these were instituted, and make conservative assumptions about compliance with behavioral modifications among the student population.

In the detailed literature review below, Wallinga et al. (2006); Mossong et al. (2008); Edmunds et al. (1997); Leung et al. (2017) all provide estimates for the difference in contacts per day among university-student-aged individuals and the general population. Across different choices for the age range and survey method used, the estimates enumerated below give values of 27%, 15%, 31%, 1.5%, 13%, 31%, -10%, 10%, and 4% more contacts among these young individuals.

We use these ideas to create three different revised estimates of contacts per day: two with varying levels of pessimism, and one that is more balanced and aligned with the approach of the nominal estimate in the main report.

Pessimistic Estimate of Contacts Per Day Let us pessimistically take an estimate for the elevation in contact rate among young individuals at the upper end of those values reported in the literature: 30%. Let us also pessimistically assume that *all* of the on-campus population is in the high contact-rate younger age group, and that *no one* complies with social distancing orders. Let us also assume that non-Cornell contacts are *in addition* to the ones used to compute R_0, rather than (more realistically) being included in this R_0. This would lead us to increase R_0 from 2.5 to a value that is 30% larger, and commensurately increase contacts per day by 30% to **10.8**.

Extra-Pessimistic Estimate of Contacts Per Day There is one way in which the above estimate is not pessimistic: its choice of R_0. While the CDC does call 2.5 its "current best estimate" of R_0 (Centers for Disease Control and Prevention, 2020), significant uncertainty surrounds this number. They also provide other scenarios in which R_0 ranges from 2 to 4. Thus, to be more conservative, we would take $R_0 = 4$ as our estimate for the general population. Adopting the methodology above then provides a conservative estimate of $8.3 * (4/2.5) * 1.3 = \mathbf{17.3}$ contacts per day.

Nominal Estimate of Contacts Per Day As an alternative and more balanced estimate, let us replace pessimistic estimates biased toward inflating contacts per day with ones that are intended to be unbiased.

First, let us assume that the staff and faculty continue to behave in a manner that would keep the epidemic under control in the absence of asymptomatic screening and in the absence of students, even once social distancing restrictions are eased in the fall. One can argue that this is reasonable because cases have remained under control in Tompkins County even as social distancing restrictions ease. This would put the R_0 in this population low enough that contact tracing would be able to control the epidemic on its own. Let us assume it is equal to 1.5. Although the asymptomatic rate varies slightly with the age of those considered, and this affects the mapping between R_0 and contacts per day, this corresponds approximately to a number of contacts per day of $8.3 * 1.5/2.5 = 5.0$ across both Cornell and non-Cornell contacts. Let us then suppose that 30% of faculty / staff contacts are with non-Cornell individuals. This brings the number of within-Cornell close contacts to 3.5.

Second, let us take the median of the estimates from the literature for the elevation in contacts per day among younger individuals. This is 13%. Thus, in the absence of social distancing and

masks, students would have a number of contacts per day of $8.3 \times 1.13 = 9.4$. Let us continue to assume that students do not comply with social distancing or mask requirements, giving them a number of contacts per day of 9.4 across both Cornell and non-Cornell individuals. As in the main report, let us continue to assume that students have 0.5 close contacts per day with non-Cornell individuals, bringing their within-Cornell close contacts to 8.9.

Since 70% (24K) of the Cornell population are students and 30% (10K) are faculty, staff and academic professionals, the average number of contacts per day is .7 * 8.9 + .3 * 3.5 = **7.3**, which is smaller than the value of 8.3 assumed in the June 15 report.

Detailed Discussion of the Most Relevant Literature To support the above discussion, we briefly enumerate literature that quantifies contact rates (understanding that not all contacts are close contacts commensurate with a high level of transmission) and how they vary with age.

- Wallinga et al. (2006) studies the general population in the Netherlands and considers one or more conversations between two individuals to constitute a contact. Not including those living in the same household, and averaging across the population age distribution using Table 1 and Appendix Table 1 in Frazier (2020), each person has on average 45 unique conversational partners per week. Dividing by 7 to normalize to a single day (understanding that two conversations with the same individual on different days in the week will contribute only 0.5 to a single day), this is 6.4 contacts / day, not including household members. If we assume a household size of 3, (so each individual has two other members of theirs household), this would bring us to 8.4. Those aged 13-19 have 57.2 conversational partners per week, 27% more than the population average, and those aged 20-39 have 51.8, 15% more than the population average.

- Mossong et al. (2008) studies contacts in the general population in several European countries, studying both physical contacts (for example, a kiss or a handshake) and nonphysical contacts (a two-way conversation). The average number of contacts per day across the population is 13.4 (based on Table 1 in that paper as processed in a spreadsheet Frazier (2020)). Those aged 15-19 had 17.6 contacts per day, a 31% increase, and those aged 20-29 had 13.6 contacts per day, a 1.5% increase.

- Edmunds et al. (1997) finds an average of 16.8 contacts per day in a convenience sample of students, staff, faculty, family and friends from two British universities. A contact is defined to be a two-way conversation. Having several conversations on the same day with the same individual is considered to be a single contact. Those aged 20-29 are found to have 13% more contacts than those aged 30 and as computed from Table 1 in that paper in a spreadsheet Frazier (2020).

- Edmunds et al. (2006) studies students from University of Warwick. Contacts consisted of conversations and physical contact. Multiple interactions on the same day are viewed as a single contact. Using data from Table 1 post-processed in a spreadsheet (Frazier, 2020), the average number of contacts per day is 22.5. Because only students are studied, the paper does not quantify the relationship between student and non-student contacts.

- Leung et al. (2017) studies contacts in Hong Kong using both online and paper surveys, finding 8.1 contacts per day on average overall. Table 1 and calculations in Frazier (2020) find those aged 21-40 have 10% and 4% more than the surveyed population in the two survey types.

Supplementary Table S1 in that paper summarizes the mean number of reported contacts in 17 papers, with a median as computed in Frazier (2020) of 13.86.

- Weeden and Cornwell (2020) studies the interaction network with students based on co-registration in lectures. Because students will be spaced 6 feet apart in lectures, co-attendance of a lecture does not constitute close contact. In addition, large lectures will move online, students will be required to wear masks, surface cleaning measures will be instituted, and ventilation will be examined and improved. Additionally, even in normal times, the number of students who attend class is smaller than the number registered. Thus, while some close contact through class attendance may occur, the number of close contacts will be significantly smaller than the number of students who were simultaneously registered for the class in the period studied by Weeden and Cornwell (2020).

- Paltiel et al. (2020) studies asymptomatic screening for COVID-19 focused specifically on college campuses, for a cohort consisting entirely of students. It sets the number of secondary cases resulting from a positive individual over an 8 hour period to 0.085. This corresponds to setting (contacts / day) * (probability of transmission) to 3 times this value, or 0.255. Although Paltiel et al. (2020) does not model contacts separately from transmission rate, under our assumed transmission rate of 2.6% this corresponds to 0.255 / .026 = 9.8 contacts per day.

Summary After a detailed review of the literature, we provide 3 alternate estimators of the number of (close) contacts per day within the Cornell population.

- First, we provide a pessimistic estimate of **10.8** obtained by adjusting the CDC-recommended R_0 for the general population for the fact that our population has a large number of young people. To arrive at this value of 10.8, we made 4 conservative assumptions: (1) the increase in contacts per day among young people relative to the general population is on the high end of the values reported in 4 papers (30%); (2) the entire campus population consists of young students, rather than the 70% that actually holds in reality; (3) within-Cornell contact rates are not reduced due to interaction outside of Cornell; (4) no one complies with social distancing or mask regulations, and instead behaves as if COVID-19 did not exist.

- Second, we provide an extra-pessimistic estimate of **17.3** obtained by also replacing the CDC's best estimate of $R_0 = 2.5$ in the general population by its most pessimistic estimate of $R_0 = 4$.

- Third, we provide a nominal estimate of **7.3** that uses the CDC best estimate of $R_0 = 2.5$, uses the median elevation in contacts among young people from the literature (13%), assumes that 30% of faculty/staff contacts are outside of Cornell, assumes that 70% of the population consists of students, assumes that faculty / staff compliance with social distancing and masks is consistent with a pre-student R_0 of 1, and assumes that graduate and undergraduate students do not comply with social distancing and mask requirements.

2 Addressing High Contacts Rates with Additional Testing

Although the section above tries to provide additional knowledge, we cannot know contacts per day, transmission rate, or a variety of other important parameters before students arrive. As discussed

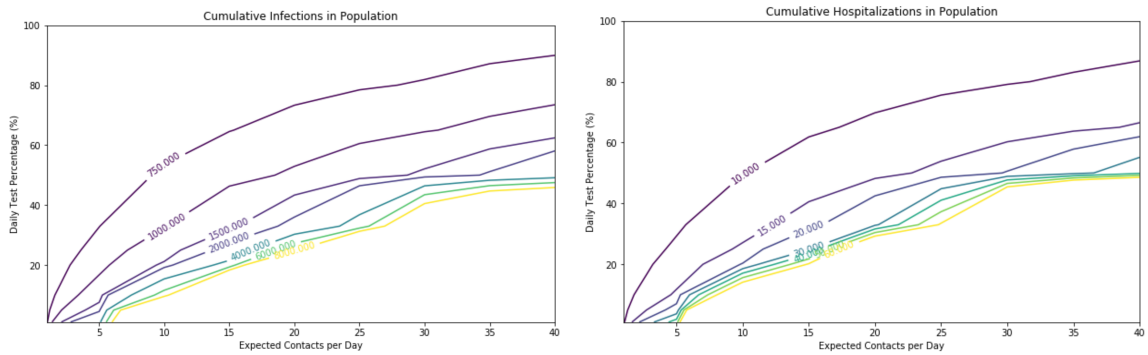

Figure 1: The fraction of the population that would be infected (left) and hospitalized (right) over the course of the fall semester under the June 15 report's residential scenario as a function of the number of close contacts and the fraction of the population tested per day. The June 15 report assumed 8.3 close contacts per day and a daily test percentage of 20%. This figure can be used to assess the ability to respond to higher-than-anticipated contact rates through increased testing.

above, while a more detailed review of the literature seems to support decreasing contacts per day from the 8.3 assumed in the main report, more pessimistic estimation methodologies support a larger value and it is certainly possible that contacts per day will be larger in the fall than estimated.

As discussed in comment #2 on the University Faculty C-TRO website, performing regular asymptomatic screening would allow us to observe that the transmission rate is higher than anticipated and would give us an opportunity to respond, either by reducing contacts, reducing transmission, or increasing test frequency.

To that end, we conducted an additional set of experiments, shown in Figure 1. These contour plots show the expected number of infections and hospitalizations under the nominal parameters of the residential scenario in the June 15 modeling report, as we vary the expected contacts per day (x-axis) and daily testing frequency (y-axis). As in the main report, we test the entire population in the same way and test assignments are chosen randomly each day[2]. The June 15 report assumed 8.3 close contacts per day with a daily test percentage of 20% of the population, corresponding to testing each person once every 5 days on average. This resulted in roughly 1250 infections and 16 hospitalizations.

We can use these plots to understand whether we can rely on additional testing to respond to a higher-than-expected number of contacts per day:

- If, instead of 8.3 close contacts per day, the value was our extra-pessimistic estimate of 17.3, then we would need to test a little less than 50% of the campus population per day (testing each person once every 2 days on average) to achieve the same epidemic control as the nominal June 15 scenario. If this could not be achieved logistically, testing 33% per day (or testing each person once every 3 days on average) would result in 2-4K infections and 20-30 hospitalizations.

- If the number of close contacts per day was our pessimistic estimate of 10.8, then achieving

[2]In practice we would test each person according to a deterministic schedule, which is likely to result in better health outcomes than random testing.

the same epidemic control as the nominal scenario would require testing everyone once every 3 days on average. If test frequency were not increased, this would result in roughly 2K infections and 20-30 hospitalizations.

- If the number of close contacts per day was our revised nominal estimate of 7.3, then improved epidemic control would be realized with the proposed 20% daily test frequency (once every 5 days on average).

As discussed in Section 6, we are considering a more targeted test protocol for the fall in which those groups believed to have more contacts per day would be tested more frequently. This is likely to achieve comparable epidemic control with a smaller amount of tests. We also envision adjusting test frequency based on results from tests. For example, if we find that the roughly 7K students in dorms have a very large amount of transmission, then we could plan to test this population every other day while testing others much less frequently. Such targeted testing would be easier to support logistically than increasing test frequency for the entire population.

3 Non-Compliance with Asymptomatic Screening

Another common question in public comments was about the sensitivity of estimates for the residential semester to non-compliance with asymptomatic screening. Concern was expressed that students would not comply with testing, potentially causing reality to be worse than estimated. In this section we study non-compliance with testing in the residential instruction scenario. We then build on the work we do here to consider testing in the virtual instruction scenario in Section 4 below.

Overview of Non-Compliance Analysis for Residential Instruction We consider two models for non-compliance.

First, we consider what happens if individuals choose to be non-compliant independently from test request to test request, i.e., if each time an individual is asked to be tested, they flip a weighted coin and do not comply if it comes up tails. This first form of non-compliance assumes that the person simply skips the test entirely if the coin comes up tails, and as such probably leads to worse outcomes than if the failure to test was simply an oversight and the person was instead tested on a later day. By adjusting the weight, i.e., the probability of a tails occurring, we can vary the extent of this type of non-compliance.

Second, we consider what happens if the same individuals fail to comply for multiple tests in a row. We call this latter behavior *persistent non-compliance*.

In the residential setting where the administration can pursue disciplinary action against individuals that miss tests, persistent non-compliance would seem to be less common, and reality may be closer to independent non-compliance. If testing is suggested but not required for some faculty and staff in the residential setting, then we are also likely to see some persistent non-compliance from these populations. In a virtual instruction setting (for which we consider testing below) with optional testing, persistent non-compliance would seem to be the better model.

Independent Non-Compliance Independent non-compliance (in which individuals flip a weighted coin each time they are asked to perform a test) can be modeled in a straightforward way. If we

aim to test a fraction p of the population every day and only a fraction q complies, then this is the same as testing a fraction pq every day with full compliance.

For example, if we aim to test 20% of the population per day (as we do in the June 15 modeling report) and we have independent compliance with 80% of test requests, then the fraction of the population that is actually tested every day is $.2 * .8 = 16\%$. Under the nominal setting of 8.3 contacts per day from the June 15 report, Figure 1 then shows that the number infected rises to closer to 1500 individuals.

An alternate way to understand the effect of non-compliance is to choose the test frequency that should be requested to achieve the desired frequency of tests actually performed. With a compliance rate of $q = .8$, achieving a 20% test frequency requires requesting tests to $.2/.8 = 25\%$ of the population. In other words, to test 1/5 of the population every day, we should ask 1/4 of the population to be tested.

Continuing with the example of 80% compliance on average across faculty, students and staff, achieving a test frequency of 50% per day would require requesting 62.5% be tested each day. Achieving a frequency of 33.3% per day would require requesting 41.7% be tested per day.

While this would suggest that any amount of (independent) non-compliance can be easily combatted by increasing the requested test frequency, compliance may actually *depend* on the requested test frequency. Compliance may decline if the requested test frequency is too high. Thus, there is likely a maximum fraction of the population that can be tested each day that is lower than 100%.

It is worth noting that the amount of non-compliance likely depends on sub-populations. For example, as discussed above, off-campus students are likely to have lower compliance than on-campus students. In the additional work detailed in Section 6 we plan to build multi-group simulations that will allow modeling different rates of compliance in different populations.

Persistent Non-Compliance Persistent non-compliance is more difficult to model in our compartmental simulation. To study its effects we instead built an Excel spreadsheet that calculates the expected number of secondary infections resulting from each primary infection (the R_0), assuming asymptomatic screening but no contact tracing. (Unfortunately, contact tracing is difficult to model in this setting.) This is available at `https://drive.google.com/file/d/1bQHXq_dmgtG-ARQ5uelo4yp6fqKN0wyO/view?usp=sharing`.

To illustrate the difference between independent and persistent non-compliance, we consider the desired test frequency and amount of non-compliance considered above, comparing the assumption of independence above to what happens if it is persistent.

First, an assumed desired test fraction of 20% per day with 20% of the population non-compliant gives an equivalent test fraction of 20*.8 = 16%, as discussed above. This results in approximately 1.5K infected out of 34K. According to the spreadsheet, this corresponds to an R_0 of 1.15 before contact tracing. This suggests that contact tracing is then sufficient to prevent widespread epidemic growth, although obtaining more certainty would require building a full-fledged simulation with persistent contact tracing.

Second, in contrast, suppose that 20% of individuals are persistently non-compliant and 20% of the rest are tested every day. Then the R_0 for those that test is 1.01, those that do not is 2.42, and the weighted average, taking into account that those who comply are in the majority, is 1.29. This is larger than with independent non-compliance and is the same as the R_0 achieved by testing roughly 13% of the population per day with full compliance. Testing 13% per day with full compliance is low enough to prevent widespread epidemic growth, but results in a larger number of infections (approximately 2K) according to Figure 1.

Thus, persistent non-compliance is more problematic than independent non-compliance and results in a larger R_0 even if the amount of non-compliance is the same. This effect is more dramatic for larger amounts of non-compliance as we discuss below. In the residential setting, we will rely on strong mandates to significantly reduce the amount of persistent non-compliance.

4 Testing, Population Size, and Contact Rates in the Virtual Instruction Scenario

Here we provide plots to support exploring two questions in the virtual instruction scenario:

- What is the effect of offering optional testing to the unmonitored student population?
- What is the effect of varying the size of the unmonitored student population?
- What is the effect of varying the number of contacts per day in the unmonitored student population?

We then discuss the implications of these three sensitivity analysis for the comparison between residential and virtual instruction.

Optional Testing and Population Size To begin our discussion of testing in the virtual instruction scenario, we first recall Appendix D of the C-TRO report (C-TRO Committee, 2020) writes: "Cornell has the broadest authority and ease of enforcement over students living in residence halls. The University has broad authority but will face enforcement difficulties over students living off campus who want to attend classes in person or use University facilities. Cornell will have little authority over students living off campus and taking classes online only." Detailed questions about the reasons for this can be directed to University Counsel.

Based on this, we view the virtual instruction setting as one in which "Cornell will have little authority" to mandate testing. Thus, we focus on optional testing for the virtual instruction setting. Comparing optional testing under virtual instruction with mandatory testing under residential instruction, we feel it is likely that many fewer students will be tested if it is optional, and that those students who choose not to be tested will persistently make this choice through the semester.

Figure 2 examines what happens if we offer optional testing to the unmonitored student population, and also the sensitivity to the assumed size of this population. (The assumed size was 9K in the June 15 report.) It does not include infections and hospitalizations from the approximately 15K faculty, staff and graduate students who are assumed to work on campus and be protected by a mandatory asymptomatic screening program. This population is estimated to have an additional 590 infections and 12-13 hospitalizations.

The figure assumes that the choice to not take the (optional) test is made independently, in the same way that we model independent non-compliance in the residential instruction setting. The y-axis is then the *realized* fraction of the population that is tested every day. For example, if we ask 20% of the population to be tested every day, but only 50% comply, then this would constitute a daily test fraction of 10%. If only 30% comply, this is a daily test fraction of 6%.

As discussed above, independent non-compliance may be overly optimistic, especially in the virtual instruction scenario. Using the spreadsheet linked in the persistent non-compliance section, testing 20% of the compliant population per day with half of the population being persistently

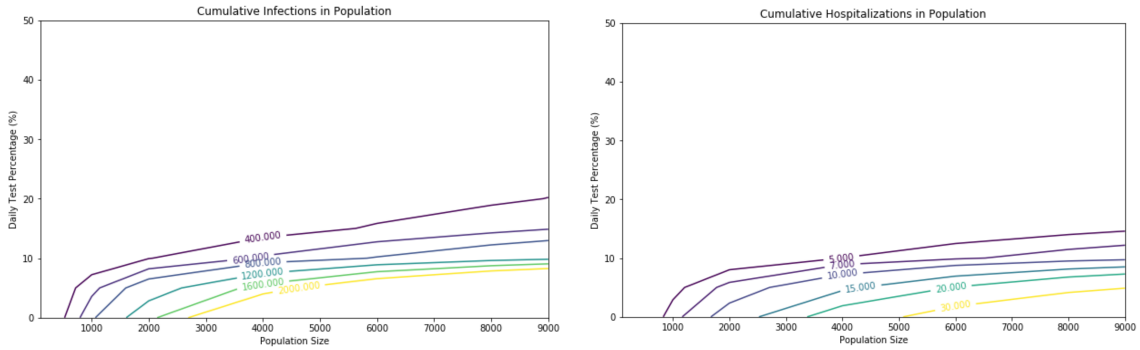

Figure 2: Number of infections and hospitalizations in the unmonitored student portion of the virtual instruction population, assuming that testing is performed randomly according to the specified rate after adjusting for non-compliance. For example, if we ask 20% of the population to be tested each day and half decide to comply at random, then the effective testing fraction would be 10%. This graph *does not* include infections and hospitalizations in the on-campus faculty / staff / graduate student population, which we expect to include about 590 infections and 12-13 hospitalizations. Persistent non-compliance from some individuals would generate worse outcomes than are pictured here and should be studied using the Excel spreadsheet linked in the text.

non-compliant results in an R_0 among those that are tested of 0.95, those that are not of 2.4, for an average of 1.7. This is the same R_0 as testing 7% of the population per day with full compliance.

In general, our experience using the persistent non-compliance Excel spreadsheet as described in that section suggests that it is typically a reasonable approximation to take the daily test fraction corresponding to independent non-compliance and then adjust it downward by a few percentage points and read the result from the figure to obtain an estimate for persistent non-compliance.

To gauge the number of undergraduate students likely to return, a survey was run in which roughly 8K undergraduate students responded with 31% saying that they are very likely to return to Ithaca in a virtual instruction scenario. An additional 22% said that they were "somewhat likely." This survey is linked from the University Faculty C-TRO Frazier Modeling webpage (Cornell University Faculty, 2020). If we include most of those undergraduates who are very likely to come, some of those who are somewhat likely to come, and note that there are 15K undergraduates, then it seems reasonably likely that 5K or more unmonitored students would reside in Ithaca. While recent ICE announcements may reduce the number of international students who can return to campus, international students represent only 11% of the undergraduate student population (Cornell Institute for Research and Planning, 2019).

One may also wish to consider the possibility that some graduate / professional students would return unmonitored to Ithaca, since virtual instruction likely would leave out a significant number of them from in-person instruction. Prior to the ICE announcement, 53% of these students said they were very likely to return to Ithaca under virtual instruction. 51% of graduate students and 34% of professional students are international (Cornell Institute for Research and Planning, 2019).

Optional Testing and Contact Rates Figure 3 plots infections and hospitalization versus contacts per day and test fraction, focusing on two different sizes for the population of unmonitored

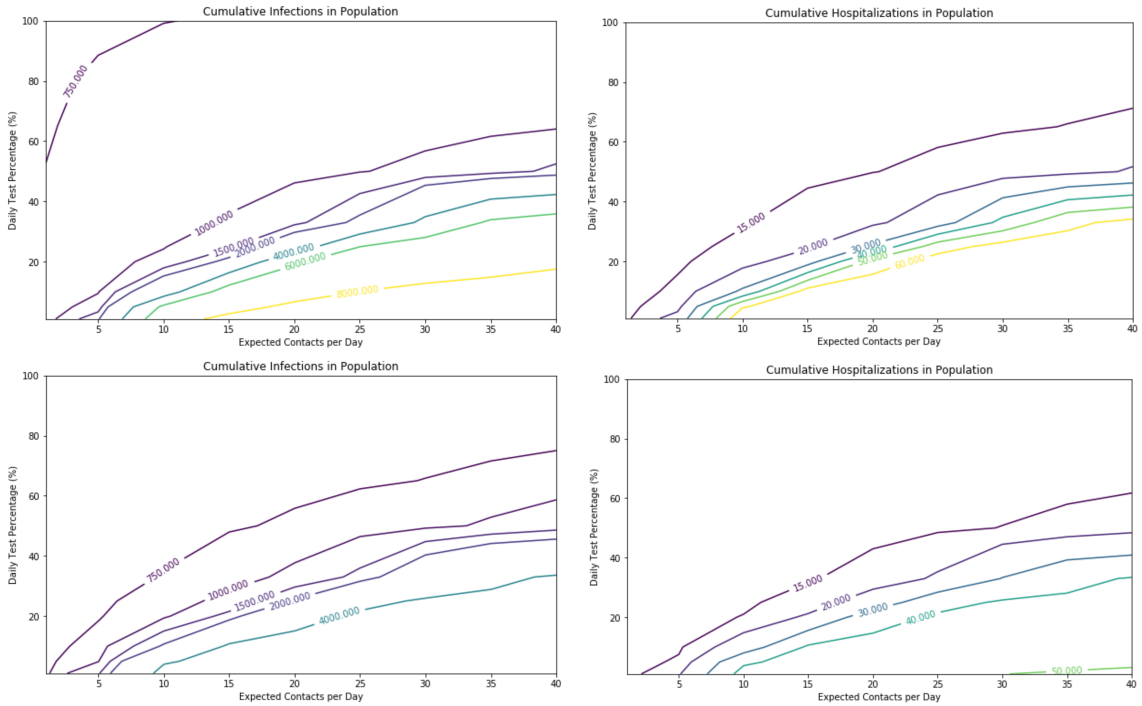

Figure 3: The fraction of the population that would be infected (left column) and hospitalized (right column) over the course of the fall semester under the June 15 report's virtual scenario as a function of the number of close contacts and the fraction of the population tested per day among unmonitored virtual instruction undergraduates. The top row assumes 9,000 unmonitored students returning while the bottom assumes 5,000 returning. We envision that most of the unmonitored students returning would be undergraduate or professional students. Both rows additionally include 590 infections and 12-13 hospitalizations from 15,000 faculty, staff and graduate students who work on campus with an average of 8.3 close contacts per day and a daily test percentage of 20%.

students: 9K and 5K. Unlike Figure 2, it includes the 590 infections and 12-13 hospitalizations from the on-campus population.

There are several effects that should be considered when estimating contacts per day in the unmonitored student population.

- Arguing for fewer contacts than in the residential scenario, this population will live in an environment where instruction is virtual and there is no need to leave one's apartment to attend class.
- Also arguing for fewer contacts, the number of students in Ithaca would be substantially smaller than in a residential semester, and reduced density typically results in fewer contacts (Hu et al., 2013; Tarwater and Martin, 2001).
- Arguing for more contacts than in the residential scenario, the unmonitored student population will be younger and thus likely to have more contacts Mossong et al. (2008); Wallinga

et al. (2006) than the on-average older population in the residential instruction setting that included faculty, staff and graduate students.

- Also arguing for more contacts, Appendix D of the C-TRO report states that Cornell will lack the authority to mandate behavioral changes in the virtual instruction setting.

5 Comparison between Residential and Virtual Instruction

To support comparison between the residential and virtual instruction scenarios, we focus on infections, since hospitalizations are nearly proportional to infections, and so the conclusions would be the same if we used that alternate measure. The same would likely be true for fatalities, if we were to model them.

In comparing these two scenarios, it is useful to first observe in Figures 1 and 3 that infections and hospitalizations change slowly over a large part of parameter space, with either a small fraction (say, less than $\sim 5\%$) infected if epidemic control is achieved, or a large fraction (say, more than 50%) if it is not. The region of parameter space that is in between these extremes is relatively small. Essentially, if asymptomatic screening is frequent enough (after adjusting for non-compliance) relative to contact rates, then the epidemic is controlled: clusters created by new infectious cases die out quickly. If, on the other hand, contact rates are too large for the rate of asymptomatic screening (or asymptomatic screening is non-existent), then clusters grow very quickly and a large fraction of the population is infected.

For the residential instruction setting pictured in Figure 1, given that the population is 34K individuals, "small" would correspond to 1700 infections and large to 17K. While these lines are not pictured, 1700 would fall between the closely spaced 1500 and 2000 lines whereas 17K is not too far away from the pictured 8K line.

In the virtual instruction setting, to interpret "large" and "small", keep in mind that 15K faculty, staff and graduate students are on campus and kept relatively safe using frequent asymptomatic screening: they are modeled as having a little under 750 infections regardless of what happens in the unmonitored student population[3], based on the full simulation methodology articulated in the June 15 modeling report, where the infections arise due to experiencing the same rate of outside infections from Tompkins County experienced in the residential semester. Epidemic control refers to the infections (and hospitalizations) in the unmonitored student population, which is either 5K or 9K in Figure 3. Thus, "small" with 5K unmonitored students would correspond to 750+.05*5000=1000 infections, and large would similarly correspond to 3250 infections. With 9K unmonitored students, small would correspond to 1200 infections and large to 5,250 infections.

We would like to describe in an easy-to-understand way how parameter choices influence whether the residential semester is safer than virtual instruction, as in the scenarios considered in the June 15 report, or whether the opposite is true. To do this, we first divide parameters based on whether they effectively control the epidemic in the residential instruction scenario.

Parameter Settings in Which Epidemic Control is Achieved under Residential Instruction Earlier we argued that epidemic control is likely achieved in the residential instruction

[3]In reality, if a large epidemic broke out among the unmonitored students, this would result in infections imported to greater Tompkins County and the staff/faculty/graduate student population on campus.

scenario (fewer than 1700 infections). This is because we have the flexibility to increase asymptomatic screening to deal with a range of contact rates that we believe to be wider than those we are likely to see in practice, even with a reasonable amount of non-compliance.

To outperform the residential instruction scenario, the virtual instruction scenario also needs to achieve epidemic control, or at least avoid a setting where the number of infections is large (more than 3250 with 5K in population). This statement remains true even if we reduce the size of the virtual instruction population from 5K to, say 2K, since a "large" number of infections in this case would be 1950, which is larger than 1700.

Moreover, the reasons that allow virtual instruction to achieve epidemic control should not simultaneously benefit residential instruction. For example, if virtual instruction achieves epidemic control because of lower-than-anticipated contact rates, this likely also benefits the residential instruction setting.

Perhaps the most likely way that virtual instruction could outperform the residential scenario would be that, simultaneously, (1) contact rates are lower-than-anticipated under virtual instruction because of reduced density, *and* (2) we are able to achieve a reasonable amount of testing under virtual instruction.

For example, with 5K unmonitored students, if (close) contacts per day were only 5 in the virtual instruction scenario but still 8.3 under residential instruction, *and* we were able to test 10% of the population per day with optional testing, then Figure 3 shows we would achieve between 750 and 1000 infections under virtual instruction.

If we set the bar at significantly outperforming the residential instruction scenario, this is much harder. Achieving fewer than 750 infections in Figure 3 with 5 or more contacts per day would require testing at least 20% of the population per day, which seems out of reach with optional testing.

Parameter Settings in Which Epidemic Control is *Not* Achieved under Residential Instruction Now we consider scenarios where epidemic control is not achieved under residential instruction. Above we argue that we can provide robust epidemic control in spite of uncertainty about contact rates by increasing the rate of asymptomatic testing. Indeed, 17.3 contacts per day is at the upper limits of what we are likely to see in practice, and this can be controlled by testing a little less than half of the campus per day. Thus, the most likely path by which a failure to control the epidemic would occur is one in which we had both substantially more contacts than anticipated and we were unable to scale up our testing to meet the challenge.

Although unlikely, we consider such a scenario here. In such a scenario where contact rates are extremely large, we would expect large contact rates to also occur in the virtual instruction setting. While they might be somewhat smaller (e.g., if reduced density helps, or if high contact rates are due to residence halls and not social behavior or off-campus living) they are likely to be too large to allow epidemic control with virtual testing.

While we would then have a large outbreak in both settings, virtual instruction would have fewer people at risk (20K instead of 34K, if we assume that 5K unmonitored students return) and so would have a smaller number of infections.

It is worth emphasizing that if this occurred, we would have greater visibility into the situation in a residential semester and would be able to respond earlier by instituting extremely strong social distancing measures. In contrast, under virtual instruction, because of the reduced availability of testing and the danger of statistical bias created by persistent non-compliance, it is entirely possible that we would not become aware of an epidemic until substantially later.

Summary of Comparison Between Residential and Virtual Instruction In summary, by scaling up asymptomatic testing rates, we can achieve epidemic control in a residential semester across the full range of contact rates we believe we will encounter in the fall. While there are scenarios in which virtual instruction outperforms a residential semester, these are relatively unlikely. Moreover, the most likely of these unlikely scenarios have lower-than-anticipated contact rates where both scenarios perform well and the health benefits of virtual instruction over residential are only moderate. On the other hand, in a number of reasonably likely scenarios, we achieve good epidemic control in the residential semester but fail to do so under virtual instruction, with a significant fraction of the unmonitored student population infected, which would likely threaten the broader community and the on-campus population. We conclude that the residential semester is the safer of the two options.

6 Additional Work

Each piece of analysis requires a significant amount of time to complete and communicate. As a result, we have not completed all analysis that we would like to do. We have prioritized those analyses that are likely to move our estimates in a pessimistic direction, as a way to make sure that we are prepared for pessimistic scenarios in the fall, and also prioritized those that were raised in public comments. Other issues receiving less attention or that would be likely to push our estimates in an optimistic direction have not been completed.

Here we briefly list some of these not-yet-complete analyses:

- Moving from a "well-mixed assumption" to one with more heterogeneity: on-campus students; off-campus students; faculty/staff with more frequent student interaction; faculty/staff that seldom interact with students. The fact that students interact more with students is likely to contain infections in less vulnerable populations.
- Using a more realistic and likely lower estimate of the rate of outside infections based on the contact literature.
- Modeling interactions with Tompkins County in a more detailed way. If R_0 in Tompkins County putting aside Cornell is below 1, as we believe it is based on case counts this summer, then the small number of infections that move from Cornell to greater Tompkins County will not result in large infection counts.
- Modeling the possibility that R_0 in the non-Cornell portion of Tompkins County will be significantly above 1 in the fall semester. This would create extremely poor health outcomes for Tompkins County even if Cornell could somehow ensure that all students, faculty and staff were entirely free of virus. While a recent rise in cases around the country and in Tompkins County has increased concern about this possibility, we believe the past success of Tompkins County Health Department and other stakeholders in controlling the local spread of disease will translate into control of this latest rise in cases.
- Moving to a deterministic test schedule, rather than the easier-to-model random one assumed in the June 15 report, because it will likely have better performance and is what we plan to implement in practice. Also, using a higher frequency of testing in subpopulations with more contacts, as this is likely to also provide value. These two interventions are likely to increase the effectiveness of asymptomatic screening.

- Modeling variability in transmission probability over the course of an individual's infection. While we model the transmission probability as constant once the pre-infectious period is complete, transmission probability (at least among symptomatic individuals) is believed to peak shortly before becoming symptomatic. This will tend to reduce the number of secondary infections prevented by a given frequency of asymptomatic screening, and reduce its effectiveness.

- Modeling variability in transmission probability, test sensitivity, and susceptibility with the age of the infected individual and whether that individual is asymptomatic. Some literature reports that young people are less susceptible to infection than older individuals (Davies et al., 2020), which is likely to create more optimistic outcomes.

- Modeling the effect of greater awareness of COVID-19 on symptomatic self-reporting rate. This is likely to have beneficial effects.

We hope to complete these analyses while prioritizing other analysis tasks that are important for supporting efficient operational execution as students return.

References

C-TRO Committee (June 15, 2020). Committee on teaching reactivation options final report. `https://covid.cornell.edu/_assets/files/ctro-final-report.pdf`.

CDC (2020). Public health guidance for community-related exposure.

Centers for Disease Control and Prevention (2020). Covid-19 pandemic planning scenarios.

Cornell COVID-19 Modeling Team (2020). Covid-19 mathematical modeling for cornell's fall semester.

Cornell Institute for Research and Planning (2019). Cornell university factbook. `http://irp.dpb.cornell.edu/university-factbook/employees`.

Cornell University Faculty (2020). Frazier modeling. `http://theuniversityfaculty.cornell.edu/covid-19-information-for-instructors/the-re-opening-committees/c-pot-and-c-tro-final-reports/frazier-modeling/`.

Davies, N. G., Klepac, P., Liu, Y., Prem, K., Jit, M., Eggo, R. M., working group, C. C.-., et al. (2020). Age-dependent effects in the transmission and control of covid-19 epidemics. *MedRxiv*.

Edmunds, W., Kafatos, G., Wallinga, J., and Mossong, J. (2006). Mixing patterns and the spread of close-contact infectious diseases. *Emerging themes in epidemiology*, 3(1):10.

Edmunds, W. J., O'callaghan, C., and Nokes, D. (1997). Who mixes with whom? a method to determine the contact patterns of adults that may lead to the spread of airborne infections. *Proceedings of the Royal Society of London. Series B: Biological Sciences*, 264(1384):949–957.

Frazier, P. (2020). Contact rate calculations based on the literature. `https://docs.google.com/spreadsheets/d/1kBuHNZKfOQbu1tmKiEvj1mXRAb-FNOtTpMTcbqYGYAA/edit?usp=sharing`.

Hu, H., Nigmatulina, K., and Eckhoff, P. (2013). The scaling of contact rates with population density for the infectious disease models. *Mathematical biosciences*, 244(2):125–134.

Leung, K., Jit, M., Lau, E. H., and Wu, J. T. (2017). Social contact patterns relevant to the spread of respiratory infectious diseases in Hong Kong. *Science Reports*, 7:7974.

Mossong, J., Hens, N., Jit, M., Beutels, P., Auranen, K., Mikolajczyk, R., Massari, M., Stefania, S., Tomba, G., Walligna, J., Heijne, J., Sadkowska-Todys, M., Rosinska, M., and Edmunds, W. J. (2008). Social contacts and mixing patterns relevant to the spread of infectious diseases. *Plos Medicine*, 5(3):e74.

Paltiel, A. D., Zheng, A., and Walensky, R. P. (2020). Covid-19 screening strategies that permit the safe re-opening of college campuses. *medRxiv*.

Tarwater, P. M. and Martin, C. F. (2001). Effects of population density on the spread of disease. *Complexity*, 6(6):29–36.

Wallinga, J., Teunis, P., and Kretzschmar, M. (2006). Using data on social contacts to estimate age-specific transmission parameters for respiratory-spread infectious agents. *American Journal of Epidemiology*, 164(10):936–944.

Weeden, K. A. and Cornwell, B. (2020). The small world network of college classes: Implications for epidemic spread on a university campus. *Manuscript under review. http://osf. io/t7n9f.*