Student Spring Break Behaviors and COVID-19 Transmission

Brenna Mehl, Dawson Brown, Leo Pang, Aidan Holland

Introduction

The COVID-19 pandemic is an ongoing global pandemic caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and presents major worldwide health risks. As of April 28th, 2022, there have been over 512 million global cases and more than 6.2 million deaths according to the Johns Hopkins Coronavirus Resource Center (Johns Hopkins University & Medicine, 2022).

After the World Health Organization (WHO) characterized COVID-19 as a pandemic in March of 2020, communities around the world took drastic measures to curtail local epidemics (Ghebreyesus, 2020). Colleges and universities developed plans to reduce transmission risks of SARS-CoV-2, including travel restrictions (University Communications, 2020) and changes to instruction methods including online and hybrid instruction (Fausset, 2020). However, thousands of college students neglected these travel restrictions and flocked to spring break destinations in March of 2020. This not only contributed to increased SARS-CoV-2 transmission both on campus and in nearby communities which led to higher mortality rates, the riskier spring break destinations such as Miami Beach were correlated with worse outcomes (Mangrum & Niekamp, 2022, p. 14-19). As a result, universities introduced additional measures to decrease the transmission of SARS-CoV-2 for the 2021-2022 academic year. According to the College Crisis Initiative at Davidson College, about 60% of colleges canceled spring break during the 2021-2022 academic year. Instead, campuses offered smaller shorter breaks, or wellness days as an attempt to curb travel away from campus in order to reduce transmission of SARS-CoV-2. (The College Crisis Initiative, 2022). Additionally, some universities implemented monetary incentives for students to stay on campus for spring break (Pinho, 2021). Despite these measures, thousands of college students continued to flock to popular spring break destinations such as Miami Beach, introducing 5 new variants of SARS-CoV-2 and skyrocketing cases (Baker, 2021). At the University of North Carolina at Chapel Hill, the return of spring break during the 2021-2022 academic year coincided with the lifting of indoor mask mandates and terminating updates of campus testing data (The University of North Carolina at Chapel Hill, 2022).

The Pfizer-BioNTech COVID-19 vaccine was the first COVID-19 vaccine to be approved in the United States by the Food and Drug Administration in August of 2021 (US Food and Drug Administration, 2021). President Joe Biden unveiled COVID-19 vaccine and test mandates on September 9th, 2021, which requires healthcare and private business employees to receive full doses of a COVID-19 vaccine (Mason et al., 2021). However, this mandate did not affect universities. While most private universities required vaccines, some public universities were legally barred from requiring vaccines, instead opting for an option to get vaccinated or undergo frequent testing (Murphy & Leonard, 2021). A collaborative survey conducted by researchers at Harvard, Northeastern, Northwestern, and Rutgers determined that 74% of university students received at least one dose of a COVID-19 vaccine in November of 2021 (The COVID-19 Consortium for Understanding the Public's Policy Preferences Across States, 2021). That same month, University of North Carolina at Chapel Hill reported a 90% vaccination rate for students (Wall, 2021).

Due to the substantial variations in the circumstances surrounding the spring breaks over the COVID-19 pandemic, it is difficult to understand the direct effects that university spring breaks have on the transmission of SARS-CoV-2. University student behavior can vary from travel to popular spring break destinations and COVID-19 hotspots in states such as Florida, Michigan, and New York, to students staying on campus. University spring break policies have also varied, from travel restrictions and no spring break during the 2020-2021 and 2021-2022 academic years, to the loosening of travel restrictions and the return of spring break. Additionally, the vaccination status of students will alter transmission rates. Understanding these relationships is imperative so universities can be better prepared when planning future academic years during a global pandemic.

The Model

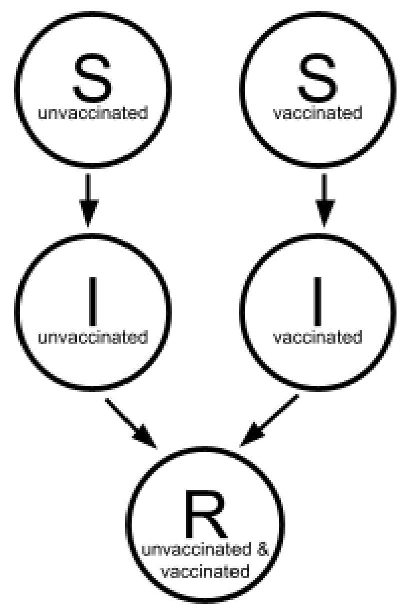

Figure 1: Classes of students in our modified SIR model. This figure depicts how students can progress from one class to another. Notice how recovered individuals can no longer become susceptible.

We take a student population with both vaccinated and unvaccinated individuals. We differentiate between vaccinated and unvaccinated students because evidence has suggested that the former group fares better than the latter in terms of COVID-19 recovery and transmission. This fundamental difference between the two groups of students on campus is concrete to the model we developed as susceptible (S) and infected (I) individuals are split until they are eventually joined in the recovered (R) stage. Thus, our model could be interpreted as $S_{u/v}I_{u/v}R$. Additionally, individuals are not able to loop back into the cycle by re-entering their respective susceptible class. This could realistically be accredited to a resistance developed after having been infected. We assume that individuals, once infected and recovered, cannot be reinfected, which is realistic considering the short time frame of our model. Regardless, because vaccination status becomes irrelevant once an individual has entered the recovered stage, there is not a split R_u and R_v class; there is only one collective R class.

If we were to group the students regardless of treatment status, the results from the differing transmission rates that would be expected from the two different spring break environments would be confounded by the lack of clarification on vaccination. Our research indicates a wide range of vaccine efficacy depending on the time since vaccination, booster shot administration, COVID strain, and type of vaccine (Kissler, Stephen M., et al., 2021). While we can reasonably group students based on their vaccination status, the proposed efficacy range introduces far too many variables to account for. A primary issue lies in the data available to us about the thousands of students on UNC Chapel Hill's campus. Adding just one facet such as type of vaccine splits our vaccinated category into at least three, applying to Moderna/NIAID, Pfizer/BioNTech, and Johnson & Johnson. While this may be the easiest element to harvest data for, a factor such as time since vaccination playing into our model would be far too complex for the scale we intend to achieve. Data on booster shot administration status lies in a similar vein in terms of lack of availability. Thus, we choose to generalize to only two groups. We consider this generalization inconsequential because the bottom line is that vaccinated individuals fare better than those that are unvaccinated.

Since we are using UNC Chapel Hill as the campus of interest, we can feel confident in the student base size and vaccination rate data available online from their resource Campus Together. However, another point of clarification is necessary because the information available pertains to both undergraduate and graduate students. Graduate students at UNC Chapel Hill do not technically have a spring break as undergraduate students do because they are not on the same curriculum or schedule. Therefore, using our model to send graduate students to different spring break environments is not pertinent, and we do not account for the graduate student base in our model. This reduces the number of individuals in the model to 19,742, the current undergraduate population. A further issue is that Campus Together's vaccination rate statistics apply to both undergraduate and graduate students. The rate is 93%, which we have chosen to simply extrapolate from both groups to only undergraduates. There is no other feasible method of determining undergraduate vaccination rate alone. However, if one wanted to model using a different vaccination rate, that parameter and its application to the student population is all that needs to change. It must be mentioned that Campus Together's vaccination rate data applies to vaccination attestation. We assume that attestation and reality are the same. Additionally, we assume that no unvaccinated students choose to vaccinate within the time frame of the model. The expectation is that, at this point in time, any individual who has a desire to become vaccinated has already taken that initiative. Vaccines have been public since early 2021 and UNC Chapel Hill's Coming Together program has made that option more than available to its student base. Having to move students from S_u to S_v during the course of the model would add an unnecessary layer of complexity. The vaccination rate at UNC Chapel Hill seems to be approaching an asymptote in that the remaining 7% unvaccinated students will likely not make the choice to vaccinate any time soon.

Throughout our model, each student exists in one of five classes: susceptible and vaccinated (S_v), susceptible and unvaccinated (S_u), infected and vaccinated (I_v), infected and unvaccinated (I_u), and recovered (R). Some models similar to ours account for births and deaths that occur within the time frame of the model. Births could be modeled akin to students that are transferring into UNC Chapel Hill or maybe are returning from a situation such as study abroad.

These individuals could be added from some outside pool into their respective susceptible class during the model. However, we choose to disclude these individuals because they represent a very minute percentage of the population and add unnecessary complication to the model. Additionally, we have considered the rate at which death occurs within the model time period to be negligible. In the 109 day period, we can not account for deaths outside of COVID-19, but also we believe death occurring to be so highly unlikely that it is entirely disregarded by the model. Death is also not a relevant factor to the model's objective.

We use discrete-time modified SIR equations to model students as they move from one class to the next. Each time step represents one day of student interaction. Additional parameters were needed to track the progression of the pandemic through the student population. Our transmission rates, b_u and b_v, track the likelihood that individuals get infected in a given day. These values encompass both the rate of encounter and the probability of an encounter leading to infection. Since the campus population is so high, students tend to interact with only a small proportion of the individuals on campus. So, our transmission rates had to be very low. After experimentation with our model, we found that transmission rates between 0.000001 and 0.00002 showed realistic disease progression without shooting other parameters out of bounds. We used campus transmission rates of 0.00002 for unvaccinated students (b_u) and 0.000012 for vaccinated students (b_v) through the model. As aforementioned, vaccine efficacy varies greatly depending on a variety of factors. Our transmission rates differ by 60%, indicating that unvaccinated individuals get infected 60% more than vaccinated individuals. This vaccine efficacy falls within the range of vaccine efficacies found in "Viral Dynamics of SARS-COV-2 Variants in Vaccinated and Unvaccinated Persons" (Kissler, Stephen M., et al., 2021). We chose a value on the higher end of vaccine efficacies in this study so the effects of vaccination would be more visible in our simulation.

The recovery rates (a_u and a_v) indicate the likelihood of an infected individual recovering in a given timestep. These values were calculated by taking the inverse of the length of infections from "Prevention and Attenuation of Covid-19 with the BNT162B2 and MRNA-1273 Vaccines" (Thompson, et. al., 2021). This journal article concludes that the average length of infection for vaccinated individuals was 5.5 days, and the average length of infection for unvaccinated individuals was 7.5 days. Taking the inverse of each value yielded a vaccinated recovery rate (a_v) of 1/5.5 and an unvaccinated recovery rate (a_u) of 1/7.5.

Equations A - E are discrete equations that we used to find S_u, S_v, I_u, I_v, and R in the next generation. Here, the prime (') is used to denote the value of the variable at time t+1.

$$S'_u = S_u - b_u S_u \left(I_v + I_u\right) \quad \text{[A]}$$

$$S'_v = S_v - b_v S_v \left(I_v + I_u\right) \quad \text{[B]}$$

$$I'_u = I_u + b_u S_u \left(I_v + I_u\right) - a_u I_u \quad \text{[C]}$$

$$I'_v = I_v + b_v S_v \left(I_v + I_u\right) - a_v I_v \quad \text{[D]}$$

$$R' = R + a_u I_u + a_v I_v \quad \text{[E]}$$

To find the two susceptible individuals in the next time step (equations A and B), we took the current susceptible individuals (S_u for the unvaccinated group and S_v for the vaccinated group). We then subtract a term that models new infections. These terms, $b_uS_u(I_v+I_u)$ and $b_vS_v(I_v+I_u)$, are directly related to the transmission rate, number of individuals in that category, and the total number of infected individuals. Notice how the transmission rates and number of individuals in the susceptible class differ between vaccinated and unvaccinated susceptible students.

The next two equations (C and D) model the infected individuals in the next day. We again take the current infected students, and add the new infections using the same term (but negated) from equations A and B. We then subtract the infected students who recover in a given day, which is modeled by subtracting the new recoveries. We find new recoveries by taking the current infected individuals (vaccinated or unvaccinated depending on the equation) and multiplying by the recovery rates a_u or a_v. Again, we use different recovery rates depending on the vaccination status of the student.

We model the recovered individuals the next day in equation E. We take the total recoveries and add the new recoveries, from the two terms in equations C and D.

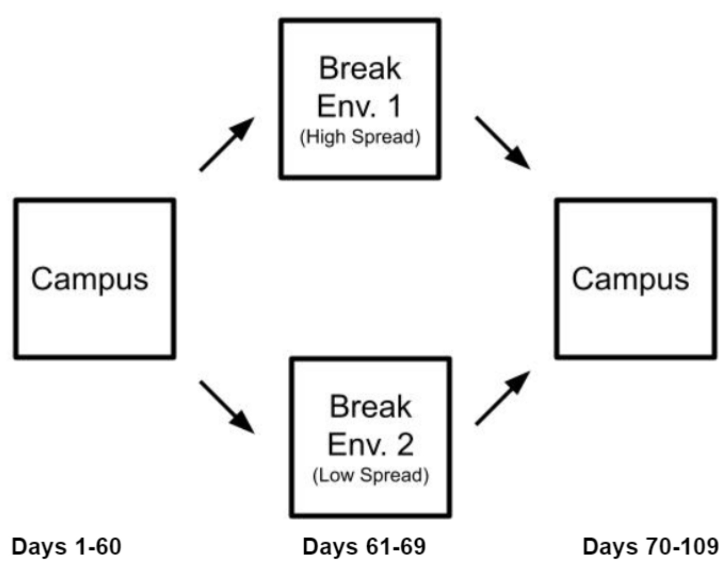

Figure 2: This graphic shows where students are across the 109-day semester. Students start in the campus environment. At day 61, students split and go to either break environment 1 or 2. On day 70, students from both break environments return to the campus environment for the remainder of the semester.

We track the progression of the COVID pandemic over a single semester. We consider the spring 2022 semester at the University of North Carolina at Chapel Hill, which had a 109-day semester with a 9-day spring break in 2022 (The University of North Carolina at Chapel Hill, 2022). For simplicity, we model two different spring break scenarios. Students either visit spring break environment 1, where COVID transmission occurs at a higher rate than on campus, or spring break environment 2, where transmission is lower than on campus. Break environment 1 is meant to model students who visit population-dense spring break locations like Miami Beach, where students interact with many other students in party environments. Break environment 2 is meant to model students who either travel with a smaller group of friends and stay with a smaller peer group, or students who go home for break. It would raise a serious challenge for the model if we were to attempt to account for a variety of different environments in which students would spend their spring break. While it could potentially increase specificity, we believe that the objective of the model is effectively accomplished by comparing a low spread environment to a high spread environment. The conclusions we could draw and resulting actions reaped from this simplified idea are sufficient. Another step we had to take for the simplicity of the model is assuming that student social interaction is limited entirely to other students for the duration of the spring break. We choose to be very nonspecific in what either of the environments are like aside from their rates of spread, but it is also very unrealistic to try to include social interactions with individuals outside of the student base. Including interactions with individuals not connected at all to UNC Chapel Hill would introduce many new variables that we are unable to account for. Thus, student peer groups will exclusively interact with one another. While this is an unrealistic scenario, we believe the purpose of the model is achieved regardless. Students go to break environment 1 with proportion p, and students go to break environment 2 with proportion (1 - p).

We start with our campus population of 19,742 individuals. We assume that no individual has already recovered from this example strain of COVID-19 and thus, no individual has already developed a resistance to it. Because our model is trying to come to a conclusion on how spring breaks affect the spread of COVID-19 on campuses, our hypothetical strain having individuals be pre-resistant adds a complicating factor that is not necessary to account for. Every student being susceptible allows us to get a closer look at the proliferation that a virus would cause on a campus like UNC Chapel Hill's and advise better on what steps can be taken to mitigate its effects. We use the average of infections over the first week to determine how many individuals would start in the infected class. Average was used due to a lack of data on specific days and would provide a mostly accurate idea of COVID-19 spread's beginning on campus.

We used the UNC vaccination rate of 93% to split both the susceptible and infected initial populations, with proportion 0.93 going into the vaccinated groups and proportion 0.07 going into the vaccinated group at the start of the simulation. To run our model, we first model the campus spread before spring break, from days 1-60, using equations A-E. We used a table to keep track of the number of students in each group each day. At day 60, we take the total number of individuals in each category (S_u, S_v, I_u, I_v, and R) and split them into their spring break groups by multiplying by p for break environment 1 and by 1-p for break environment 2. Therefore, we need two more sets of equations A-E, one for each break environment. We use the same recovery rates for the break environments as the campus environment, since this is dependent on viral stain, which would not change over break. However, we vary transmission rates to model the change in student behavior over break. In break environment 1, where we assume transmission rate to be higher, we increase transmission rate by adding a transmission difference (tD) to each of the transmission rates (b_u and b_v). In break environment 2, where transmission rate is lower, we subtract the transmission difference from b_u and b_v. We run the simulation for nine days to model the length of the break. Throughout these nine days, we sum the total S_u, S_v, I_u, I_v, and R between the two environments in the same table as before.

On day 69, we use the total S_u, S_v, I_u, I_v, and R at the end of spring break as initial values for our last set of equations A-E. We revert to the same transmission rates we used for days 1-60, since this part of our simulation models the return to campus. This part of the simulation runs for the last 39 days of the semester.

At the end of this simulation, we have tables containing the total susceptible, infected, and recovered individuals. We can use these tables to graph SIR curves and gauge the total recoveries at the end of the semester.

We also used a control model in which there was no spring break. This model used equations A-E with the on-campus transmission rates and ran for a consecutive 109 days.

Results

Running the SIR model in total demonstrated a slight difference between the spring break model and non spring break model.

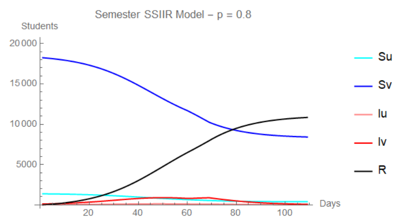

Figure 3: Susceptible (vaccinated and unvaccinated), infected (vaccinated and unvaccinated), and recovered students for each day of the 109-day semester. This model includes a 9-day spring break, with p = 0.8. Other parameters: tD = 0.00001, a_u = 1/7.5, a_v=1/5.5, b_u=0.00002, b_v=0.000012. Modeled off of UNC's spring semester, with a population of 19762 students, vaccinated proportion of .93, and 119.7 initial infections (average over the first week). There are 10845 recovered individuals at the end of the 109-day period.

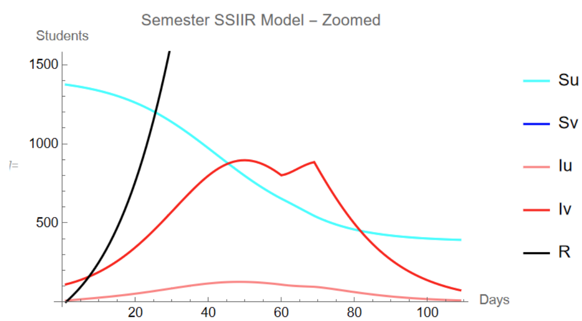

Figure 4: Same as figure 3, but zoomed to show the infected (I_u and I_v) and susceptible unvaccinated (S_u) curve Notice the sharp increase in infections at day 61, the start of break, and the sharp decrease in infections when students return back to campus on day 70.

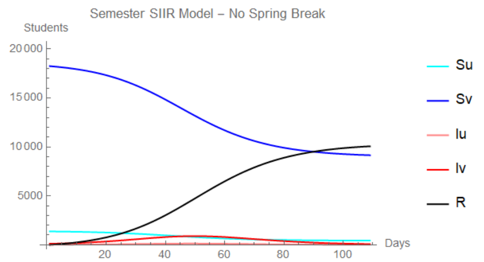

Figure 5: Susceptible (vaccinated and unvaccinated), infected (vaccinated and unvaccinated), and recovered students for each day of the 109-day semester, with no spring break. Other parameters: a_u = 1/7.5, a_v=1/5.5, b_u=0.00002, b_v=0.000012, starting population of 19762 students, vaccinated proportion of .93, and 119.7 initial infections. There are 10666 recovered individuals at the end of the 109-day period.

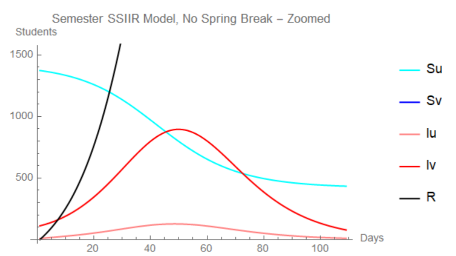

Figure 6: Same as figure 5, but zoomed to show the infected (I_u and I_v) and susceptible unvaccinated (S_u) curves. Notice the smooth curves, with infections peaking near day 50.

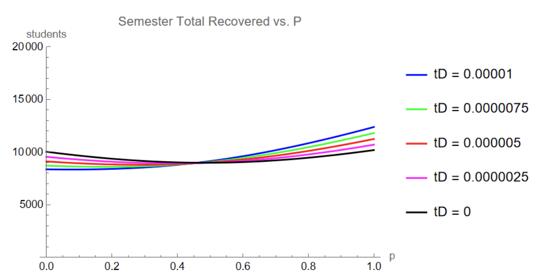

Figure 7: Semester total recovered individuals versus the proportion of individuals going to break environment 1 (p). Each colored line represents a different run, varying the transmission difference between the campus environment and the spring break environments between 0 and 0.0001. Other parameters: a_u = 1/7.5, a_v=1/5.5, b_u=0.00002, b_v=0.000012, starting population of 19762 students, vaccinated proportion of .93, and 119.7 initial infections.

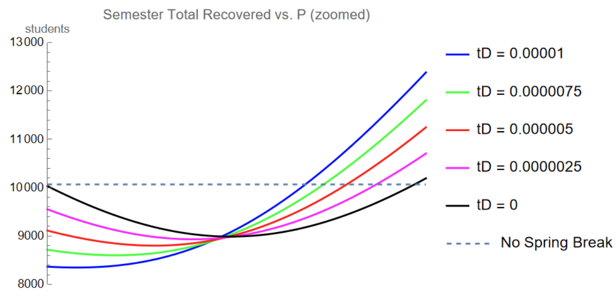

Figure 8: Same as Figure 7, but zoomed to show area of interest. The dashed line indicates a control where there is no spring break. Notice how all models with breaks (colored lines) have lower total recoveries than the No Spring Break model unless p is high.

Figure 3 and 4 demonstrate the inverse logistic curve between susceptible unvaccinated and recovered. As people recover, then fewer people can become infected and the graph will begin to max out. The zoomed in model demonstrates a more interesting picture. The infected individuals show a parabolic trend, however the infected unvaccinated demonstrates the potential spread of covid due to breaks. Instead of the cases reaching a maximum value and declining back down the breaks add another jump in the cases at 60 days. The trajectory of cases then returns to a normal downward trend. At the end of the break, 10845 people recovered.

Figure 5 and 6 illustrate the slight impact of breaks. Fewer people became infected and therefore fewer people recovered from Covid-19. The lines are slightly closer together at the end of the run when compared to figure one. 10066 people recovered in the nobreak model which is 779 less than the spring break model. This seems like a small number but the model only runs with 19,742 students to become infected and recover. Avoiding spring breaks as a whole would stop about 4% of people from getting infected every semester. In the zoomed in version, the model follows an actual parabolic curve. Without the break environment at 60 days, nothing can create an artificial spike of infections and the cases will begin to decline.

Figure 7 and 8 demonstrate the importance of varying the transmission difference between the break environment and campus. These figures explain the power of p. As p increases the number of recovered individuals will also increase which is to be expected.However, a higher transmission difference and a low p-value can yield fewer recovered individuals. The extreme environment of p=0 and td=.00001 yields a super low recovered population. This point is not entirely realistic as it basically assumes people go home and do not have any interactions with anyone. As long as p-values maintain a generally low value then a break environment could yield an overall lower number of cases.

So, removing breaks from a school semester decreased the number of Covid-19 cases by about 775 infections if p=.8. This is important for people obtaining a 4 year degree. If a pandemic lasts for 2 years then that means students will go through 4 different breaks and stopping breaks could prevent a little more than 3000 infections, assuming Covid like transmission. Also the UNited states has more than 5000 colleges which means if every college followed these no break guidelines then they would prevent about 4 percent of their student population from getting infected. Forcing a specific behavior change could help alleviate Covid-19 cases and future pandemic cases.

However, transmission was still high in the overall Covid model. In order to truly mitigate the spread of Covid-19 other ideas would need to be used. But every piece of the puzzle that yields a net decrease in cases is a positive. This model only tackled the specific characteristics of UNC's campus. UNC had a particularly high vaccination rate among students which allowed for lower overall transmission. Other colleges would use different SIR models based on their vaccination rate.

Discussion

As expected, transmission in the no-break environment was lower than the break environment. Students couldn't go to higher transmission areas and become infected at a higher rate than on campus, but they also couldn't go to a lower transmission area. The people that went to higher spread areas outdid the mitigation of the lower transmission group. As the proportion of students who went to the higher-transmission environment increased, so did the overall transmission. It is crucial in a pandemic for fewer students to go to high transmission areas. The more students that go to high transmission environments the more at risk for infection.

One interesting part of the model showed that a larger transmission difference (see figure 7 and 8) resulted in more infections when $p>.5$. If the proportion of students entering a break environment is high then so is the spread of Covid 19. On the other hand, when $p<.5$ then the overall model yielded fewer Covid cases, which is unexpected. A heavily moderated break schedule could help mitigate the spread of Covid. If a significant portion of the population went to a low-spread transmission environment then breaks could be utilized to help slow the spread of covid. One way this idea could be achieved is by providing incentives to encourage students to stay home. Incentivizing a student population to stay in low-transmission environments is a very plausible task that school leadership could take up.

In the future, this model could be expanded to incorporate more parts of student life. For example, the number of breaks could be increased. During the spring semester 2022, campus leadership incorporated a wellness day before Good Friday which led to a four day weekend and for people lacking Monday, Wednesday, Friday classes, a six day weekend. This model could take into account smaller breaks and their effect on covid transmission. Another way this model could be expanded is the inclusion of vaccine effectiveness. This model assumed that vaccine effectiveness did not waver over time, but a more enhanced model could include a wavering vaccine effectiveness. It could also add the effect of a booster shot on the vaccine's effectiveness.

Another way this model could be modified is the addition of a mask mandate or a removal of one. Many states created different laws on mask mandates and they could be put to the test. Two models could be generated to demonstrate the difference between a college with a mask mandate and a college without. Furthermore, the model could expand the group that students interact with. For example, UNC, Duke, and NC State University are all within 30 minutes of each other. The model could assume the difference in transmission rates based on campus size or other parameters that colleges differ in. Duke was significantly more strict on their mask mandates than UNC and NC state so they could be modeled as a low-transmission environment.

References

Baker, S. (2021, April 18). Florida Spring Break Party Triggers COVID-19 Cases Surge, As Feared. *Business Insider*. https://www.businessinsider.com/florida-variants-of-concern-covid-19-cases-surge-spring-break-2021-4

The College Crisis Initiative. (n.d.). *COVID-19 Data Dashboard*. The College Crisis Initiative. Retrieved April 28, 2022, from https://collegecrisis.org/covid-19-data-dashboard/

The COVID-19 Consortium for Understanding the Public's Policy Preferences Across States. (2021, November). *THE STATE OF THE NATION: A 50-STATE COVID-19 SURVEY*. The COVID States Project. Retrieved April 28, 2022, from https://news.northeastern.edu/uploads/COVID19%20CONSORTIUM%20REPORT%2069%20COLLEGE%202021.pdf

Fausset, R. (2020, August 17). UNC at Chapel Hill to Move Online as Coronavirus Spreads. *The New York Times*. https://www.nytimes.com/2020/08/17/us/unc-chapel-hill-covid.html

Ghebreyesus, T. A. (2020, March 11). *WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020*. WHO | World Health Organization. Retrieved April 28, 2022, from https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020

Johns Hopkins University & Medicine. (n.d.). *COVID-19 Map - Johns Hopkins Coronavirus Resource Center*. Johns Hopkins Coronavirus Resource Center. Retrieved April 28, 2022, from https://coronavirus.jhu.edu/map.html

Mangrum, D., & Niekamp, P. (2022, January). JUE Insight: College Student Travel Contributed to Local COVID-19 Spread. *The Journal of Urban Economics*, *127*(103311), 14-19. 10.1016/j.jue.2020.103311

Mason, J., Aboulenein, A., & Hunnicutt, T. (2021, September 10). *Attacking anti-vaccine movement, Biden mandates widespread COVID shots, tests*. Reuters. Retrieved April 28, 2022, from https://www.reuters.com/world/us/biden-deliver-six-step-plan-covid-19-pandemic-2021-09-09/

Moyer, D. (2020, October 8). UNC Announces Calendar for Spring 2021 Semester, Delays Start by 2 Weeks. *Chapelboro*. https://chapelboro.com/news/unc/unc-announces-plans-for-spring-2021-semester-delays-start-by-2-weeks

Murphy, K., & Leonard, J. (2021, September 16). UNC System won't mandate COVID vaccine for students, faculty. *Raleigh News & Observer*. https://www.newsobserver.com/news/local/education/article254278218.html

Nadworny, E. (2021, March 16). Majority Of Colleges Canceled Spring Break 2021. *NPR*. https://www.npr.org/2021/03/16/977568407/colleges-canceled-spring-break-but-students-are-traveling-anyway

Pinho, F. E. (2021, March 10). UC Davis offers to pay students $75 to stay put for spring break. *Los Angeles Times*. https://www.latimes.com/california/story/2021-03-10/uc-davis-offers-to-pay-students-to-stay-put-for-spring-break

University Communications. (2020, March 11). *Campus leaders provide operational updates for spring semester | UNC-Chapel Hill*. The University of North Carolina at Chapel Hill. Retrieved April 28, 2022, from https://www.unc.edu/posts/2020/03/11/spring-semester-updates/?utm_campaign=031120+Campus+leaders+provide+operational+updates+for+spring+semester)

The University of North Carolina at Chapel Hill. (2022, April 6). *Carolina Together COVID-19 dashboard changes - Carolina Together : Carolina Together*. Carolina Together. Retrieved April 28, 2022, from https://carolinatogether.unc.edu/2022/04/06/carolina-together-covid-19-dashboard-changes/

US Food and Drug Administration. (2021, December 16). *Comirnaty | FDA*. US Food and Drug Administration. Retrieved April 28, 2022, from https://www.fda.gov/vaccines-blood-biologics/comirnaty

Wall, J. (2021, September 3). What are COVID vaccine rates at NC colleges and universities? *Raleigh News & Observer*. https://www.newsobserver.com/news/state/north-carolina/article253915428.html