Considerations Factoring in the Speed of CoVID-19 Spread

Team 46, CoVID Vixens

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Executive Summary

The novel CoronaVirus Disease (CoVID-19) has infected 29.7 million people in the United States as of March 19, 2021. Of those, 529,000 people died.[2] CoVID-19 is caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) which is extremely contagious and has resulted in a worldwide pandemic. Our model, Masking_Up_Against_CoVID, built in NetLogo[9] from the foundation of the Virus - Alternative Visualization model[8] in the library, can demonstrate a range of scenarios of different amounts of people wearing masks at varying levels of effectiveness and show how people get sick, recover or die, and become immune.

We included information from real world data and adjusted the parameters in our model to best represent realistic CoVID-19 conditions in our experiments. We ran experiments in Behavior Space to demonstrate scenarios where more or less people wore masks and scenarios where the masks were at various levels of effectiveness for spreaders and receivers of the virus. Our analysis of the results from these experiments brought us to the conclusion that most people should wear masks and those masks need to have a high effectiveness, for example an N-95, KN-95 or other tested highly effective mask instead of a cotton mask. Ultimately, our results show we would always want everyone wearing masks and for those masks to have an effectiveness of at least 70 percent combined mask effectiveness if everyone wore their masks 100% of the time. Our model actually shows it would be worse to wear masks with a moderate prevention effectiveness of 40-60% than it would be to not wear masks at all as loss of immunity could lead to repeated infections and the virus becoming endemic rather than dying out.

Introduction

Problem Statement

The question we asked is: would how many people wearing masks, and/or how effective those masks are, change how fast or slow the CoVID-19 virus spread? The problem we see is that people are not following lockdown procedures when ordered. However, this may be because they can't afford to or can't access the appropriate tools. Our project looks at how people wearing effective masks affects how people are getting sick, and how many people are getting sick all at one time. We expected that more masks, and more effective masks, would result in less people dying of CoVID-19.

Background Research

Masks are effective in preventing the spread of CoVID-19 . It has been found that, "...face masks were 79% effective in preventing transmission,".[4.] Another study shows "wearing a mask cuts your own risk of getting infected with the CoVID virus by 65%."[5] Additionally, the type of mask determines its effectiveness, for example there is a difference in effectiveness between wearing a standard cloth mask or an N95 mask.[7] Masks help reduce the droplet spread from your nose and mouth, which lowers the transmission rate of the CoVID-19 virus. So, with more people wearing their masks there will be a lower rate of transmission which will lower the amount of people getting infected, especially if those masks have a high level of effectiveness.

The basic reproductive number, R_0, represents the rate of spread for a disease and depends on the growth rate of an outbreak, the latent period (the time from infection to infectiousness), and the infectious period.[1] The current rate for R_0 is considered to be 2.5.[2]

Figure CDC Current Best Estimate R_0

Table 1. Parameter Values that vary among the five COVID-19 Pandemic Planning Scenarios. The scenarios are intended to advance public health preparedness and planning. They are **not** predictions or estimates of the expected impact of COVID-19.

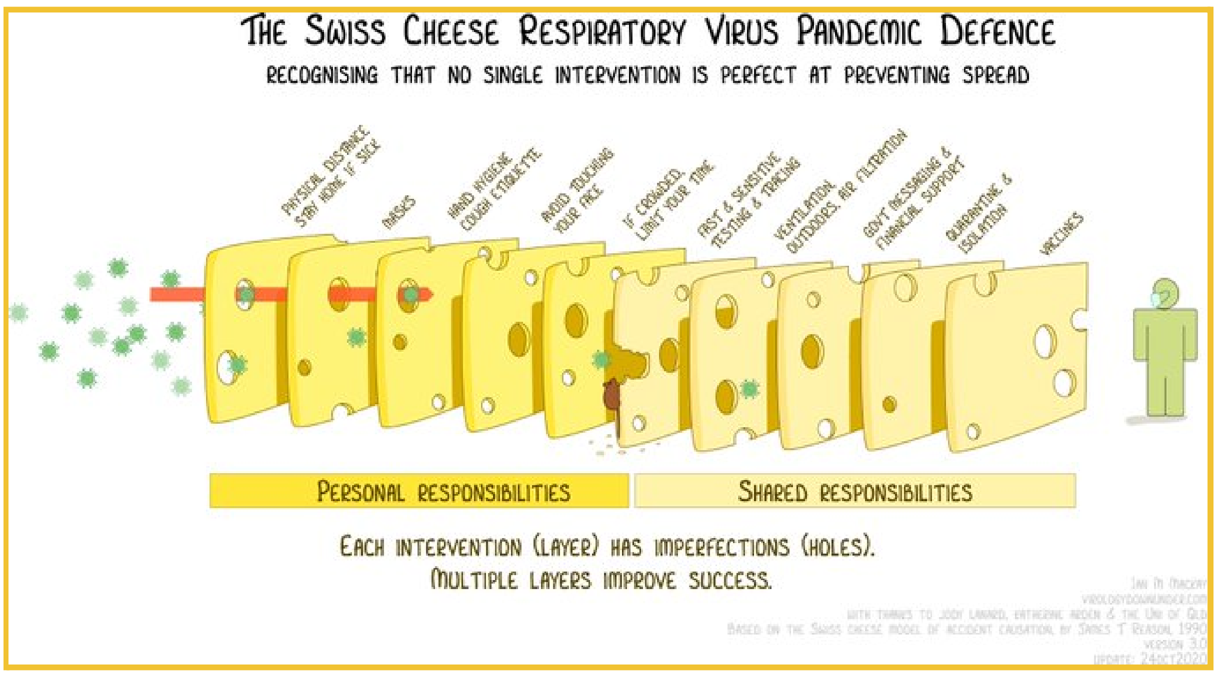
Parameter	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5: Current Best Estimate
R_0*	2.0		4.0		2.5
Infection fatality ratio (Estimated number of deaths per 1,000,000 infections)†	0–17 years old: 6 18–49 years old: 150 50–64 years old: 1,800 65+ years old: 26,000		0–17 years old: 80 18–49 years old: 1,700 50–64 years old: 20,000 65+ years old: 270,000		0–17 years old: 20 18–49 years old: 500 50–64 years old: 6,000 65+ years old: 90,000

As research continues with the better understanding of the virus each day, various articles say different things at different times ranging from about 2 to about 6, so we set ours at about 4, about in the middle.

Herd immunity is the natural method by which a virus dies out. Although herd immunity kills the virus fast, it also kills lots of people - to get there everyone has to get sick, if everyone gets sick lots of people die. Also, everyone will get sick all at once, overloading the healthcare system so even more die. Setting masks at zero in our model demonstrates natural herd immunity where everyone gets sick fairly quickly, many people die, and the virus dies out quickly as well because it cannot spread.

Masks are an effective way to reduce the spread of CoVID-19.[4] However, the best method is to use multiple preventative measures in conjunction with each other, as demonstrated by the Swiss Cheese model of virus spread which can be applied to CoVID-19. The Swiss Cheese model is like saying when you have a virus that spreads so easily, doing one thing to stay safe is not going to be enough to keep you safe. The more things you do the safer you will be and each layer of protection that you can add, will reduce the virus from spreading more and more. In the diagram of the model below, the holes represent imperfections and more layers cover those holes and imperfections. Using multiple layers also helps protect people in case some layers malfunction, do not work as well as expected, or have some other problem. As each layer of protection, such as social distancing, masks, washing hands, testing, vaccines, etc., is added, the amount of protection from the virus increases.[3]

Figure 2 Swiss Cheese Model



Computational Model

Selection

We chose as our base model, from netlogoweb.org, the model titled Virus-AlternativeVisualization[8]. Using this model for our foundation made it easier for us, as beginners in coding, to understand what the code does and how changing or adding things to the code affects the model itself. This particular model was easiest to use as a base for our own code and model about CoVID-19 because it already included the set up of people-shaped turtles which are color-coded to see who is sick, healthy, or immune. It also already included sliders that can set the max number of people, infectiousness of the disease, duration of the disease, and the chance to recover from the virus. This model also helps us keep track more easily of the weeks that have passed when we run the model, which we later changed and set to days. We can also keep track of the populations of people in total, people that are sick or infected, people that are healthy, and people that are immune. The base model also lets us know, on each day or year that passes in the simulation, the percentage numbers of people that, in that moment, are infected or immune.

Modifications

We modified our model by adding lots more things to it like more sliders and changing the shape of some turtles to tell the difference between which ones are wearing a mask (circle shapes) and which are not (people shapes). We also added an optional view setting "watch a person." The sliders that were already included with the base model were "number-people," "infectiousness" (of the disease), "chance-recover," and "duration" (of illness). The sliders we added were "number-of-masks," "mask-effectiveness," and finally, "immunity-duration." [6]

In the base model, all turtles were shaped as people. We looked in the code and changed it a bit so we could later be able to see the "number-of-masks" slider in action in the model and change the shape of turtles with masks on to circle shapes so we could tell each person apart. In our own modified model, we also added the optional setting named "watch-a-person." "Watch-a-person" stops automatically when the person/turtle you are watching has died from the virus. You can then renew "watch-a-person" to find a new turtle to follow or keep track of and see their own small journey.

Wearing masks changes the chance that someone gets infected with CoVID-19 in our model. The lines of code which cause that to happen in our model are lines 136 through 151.

Figure 3 Masking_Up_Against_CoVID Code Lines, To Infect

```
135
136 ;; If a turtle is sick, it infects other turtles on the same patch.
137 ;; Immune turtles don't get sick.
138 to infect ;; turtle procedure
139   let spreader-infectiousness infectiousness
140   if wearing-mask [ set spreader-infectiousness infectiousness * ( 1 - mask-effectiveness-spreader / 100 )]
141   ;; if not wearing-mask [ let spreader-infectiousness infectiousness ] changed it so default is not wearing mask
142   ;; let spreader-infectiousness infectiousness * ( 1 - mask-effectiveness-spreader * wearing-mask / 100 )
143   ask other turtles-here with [ not sick? and not immune? ]
144   [
145     let receiver-infectiousness spreader-infectiousness
146     if wearing-mask [ set receiver-infectiousness spreader-infectiousness * (1 - mask-effectiveness-receiver / 1
147     ;; if wearing-mask [set spreader-infectiousness infectiousness * (1- mask-effectiveness-receiver/100)]
148     ;; doesn't work as it doesn't change receiver infectiousness below
149     if random-float 100 < receiver-infectiousness
150       [ get-sick ] ]
151 end
152
```

These lines of code are the equations for how to infect.

For the spreader to infect, beginning at line 139, we let the infectiousness of the spreader be the infectiousness that the slider for infectiousness is set to, which is the infectiousness of the disease, or the chance per day that a person will make someone else sick if they are in the same square. Then, at line 140, if they are wearing a mask it reduces their chance of infecting others by setting spreader infectiousness to the infectiousness of the disease and multiplying that by 1 minus the mask effectiveness of the spreader divided by 100. For the receiver to be infected, beginning at line 145, we let the receiver infectiousness be the infectiousness of the spreader. Then, at line 146, if they are wearing a mask it reduces their chance of being infected by setting the receiver infectiousness to be the infectiousness of the spreader times 1 minus the mask effectiveness of the receiver divided by 100. This, again, allows us to get a percentage result. For both equations, spreader and receiver, we subtract from 1 in order to determine what amount of the infectiousness is being let through by the mask. Then we divide by 100 as we are converting from a percentage from our slider variable.

Even though people are wearing masks, the infectiousness of the disease also matters because it combines with the effectiveness of the mask, together, to determine a likelihood of getting sick or not. Infectiousness represents how bad the disease spread can get, and, using the swiss cheese model, each mask (spreader and receiver) adds a layer of protection by reducing the infectiousness of the disease based on the effectiveness of each mask.

Visualization

We added several sliders to our model. The slider “number-of-masks” determines how many people in the model are wearing a mask. “Mask-effectiveness-receiver” sets how effective the mask that the receiver, or person in contact with someone that had the virus, is wearing. “Mask-effectiveness-spreader” is what sets how effective the mask a spreader, which is the person that already has the virus and is in contact with someone healthy, is wearing. The “immunity-duration” slider tells the model exactly how long of a time period a person or turtle can be immune from the virus after getting sick and recovering. Additionally, in our model, turtles shaped like people are people that are not wearing a mask and the turtles shaped as a circle are people that are wearing a mask. Turtles which are green represent healthy people, turtles which are red represent sick people, and turtles which are grey represent immune people.

We also added “watch-a-person.” This setting allows the user to track a specific person that has been randomly chosen. This way, we can see where the turtle has been. We can see where the turtle has been with a line that stays behind it and changes color when the turtle changes color as well, from having changed between being sick, healthy, or immune. These colors are reflected in the display graph that shows us the population of each state a turtle is at. There are four lines on the graph. A blue line shows the total number/population of turtles in the model. A red line represents the population of turtles that are sick, a green line represents the population of healthy turtles, and a gray line represents the population of turtles that are immune.

Limitations

In our model, at first we were only able to run the scenario with 300 people because we each only had access to our school-issued chromebooks. If we didn't set the model up to this limit, running the model would be slow and the chromebooks we used could have crashed because having that many turtles in the code can be too much for them to handle. Recently, we got a hold of a new desktop computer which works a lot better and faster. On this new computer, we are now able to run the scenario with up to 10,000 people. We were hoping to have a chance of trying out a supercomputer and running the scenario with lots more people so that it would be closer to the population of a small town and more like a real world scenario. Repetitions are basically how many times we could run scenarios from our model. We first gained access to an old computer, donated by our scientist's dad, which took about 2 minutes to complete a single run with 10,000 people, or about an hour and a half to run an experiment with 10,000 people at intervals of 250. In order to repeat the experiment to get a good set of 10 runs with that computer, it would have taken us about fifteen hours without repetitions to do so.

One good idea that we could have added to our model but would have been extra time-consuming is making individual people be able to wear different masks to see which are actually more effective. To add this, we would have had to make lots of new changes to the code. Instead, we decided to stick with the approximate results we get with our "mask-effectiveness" sliders. For example, N95 masks would be a higher effective mask category because they offer more protection than a medical mask does. So, if we wanted to show N95 masks on our model we would just set our "mask-effectiveness" sliders to the effectiveness that N95 masks are at. Adding another condition from the swiss cheese model, like social distancing or getting the vaccine, into our code would have also been really time-consuming for us because each one is a lot of different variables and would have also made the analysis too hard. We instead concentrated further on making more thorough results with the mask model we had already made rather than complicating the model further with other factors.

Problem Solving Method

Verification

We thought about the different possible meanings about infectiousness, and we figured out the infectiousness was the percentage between two people without masks and not the infectiousness of CoVID-19 itself. We set infectiousness in our model to 3% and ran our experiments in behavior space to get the RHO as close and accurate as possible to how it is in real life. We know that the herd immunity rate needed to not allow spread = 1 - 1/R_0 which means we would look for new cases to be 1/14 of current cases (because of the two week timeline set in our model). Ultimately, we used the equation R~= (new infections today)/(total current infectious population)*(length in days of average infection).

One of our experiments was set to zero people wearing masks. We did the experiments in order for our model to be able to calculate the RHO and figure out when it would be that we achieved herd immunity. We then put our results into graphs and counted as much as we could the amount of people that got sick or died and the amount of people that had recovered or stayed healthy. The graphs help us look more easily at how the RHO is affected and with them we can see when the virus dies out from herd immunity, with the amount of people that were still alive once it died out. We achieve herd immunity when you only have a chance of infecting one other person or less. So the threshold for herd immunity is when each person is expected to only infect one other person and if you can keep it under that then the virus dies out because of exponential decay. If one can still infect more than one person then there is still growth in the virus and we would need to do something else to mitigate.

Our model and experiments were set up to be as realistic and accurate to the real world as we could design them. Some extra factors in reality, like getting the vaccine, were not included in our model because it would have been too time consuming and complex for us to complete in the time we had left; however, the others that were included, like increasing the population, make it very close to the real world and the effect of RHO.

Validation

To validate our model, we went through the process of testing one variable at a time when adjusting code to make sure it worked, recording test parameters and results along the way. Below are a few samplings of our notes to ourselves when we were testing each thing we added to our model to make sure that our changes all worked before we moved on.

1/22/21

On this day, we were trying to adjust the ticks in the model. As the ticks went up when running the model, the time went up a year - we wanted to go up in days instead so it reflects CoVID-19 spread better. We needed to change duration and the time elapsed from weeks and years to both be days so we went To Set Up Constants and changed lifespan to 72 years, measured in days 72*365. We changed the mode to authoring to update the duration slider to reflect days (52 to 365) and changed the display mode to “days” as well so that every tick should be a day instead of a year.

Test - set duration low to see if ticks move to a year at about 365, 34 ticks should be 34 days, 5 weeks, and ticks/days = years

Result - Showing days but displaying years >> need to go back to authoring and right click on days, in order to display days need to delete /365

With this result we went back to authoring mode and changed duration from weeks to days (the new units) and set the maximum to 365. We then ran another test.

Test - set duration at 14 days

Result -ticks matching but not doing anything from setting duration at 14

In considering this result, we asked, what is the duration slider representing? It represents the duration of the illness and decided to make it more specific in the slider label.

Test - set duration at 14 days

Result - ERROR (changed name of slider and needed to make code match)

Finally, we updated the line in the code to match duration of illness and our last test resulted in the ticks matching the days.

1/29/21

On this day, we were trying to determine which settings we needed for the model to produce good results and we went through the following process.

Test - set immunity-duration low, expected to see more red

Result - everybody went green, pretty fast, in two months (probably enough people died where the virus couldn't spread any longer)

Test - leave immunity-duration low, set masks at zero, put people as many as possible, infectiousness as high as possible (worst case), expect to see people get immune but stop being immune fairly quickly and then get reinfected

Result **-** immunity went up, came back down, then oscillated back and forth, and reinfection (loss of immunity) happening really quickly

Test **-** immunity-duration at 5 months (reflecting actual data), leaving population high, infectiousness high, and zero masks

Result - people got sick but they were immune so long that it died out so all went green - this is herd immunity

3/19/21

On this day, we were beginning to work with Behavior Space and were trying to design an experiment to look at the results from effectiveness of masks at various levels.

Test - (behavior space) mask receiver and spreader at 10, 20, 30… 90 at once, so 81 scenarios

Result - mask effectiveness receiver doesn't look like it should, not really changing anything - we expected increases in effectiveness to lead to less cases and less deaths but there wasn't a noticeable change as the mask effectiveness for receivers changed so we investigated that section of the code and found a problem with our equations.

Test - set both spreader and receiver effectiveness to zero so masks don't do anything

Result - does expected, lots get sick and a big spike, so after the fix, there was a steady decline in cases and deaths with more mask effectiveness which is what we expected.

Test - receiver set really high so no one should get sick if receiver effectiveness is 100%

Result - NOT as expected, something wrong, need to go in to check the code

Test - fixed Line 146 which had copy pasted but not updated and re-tested

Result - as expected and we were able to continue with Behavior Space experiments

Conclusion

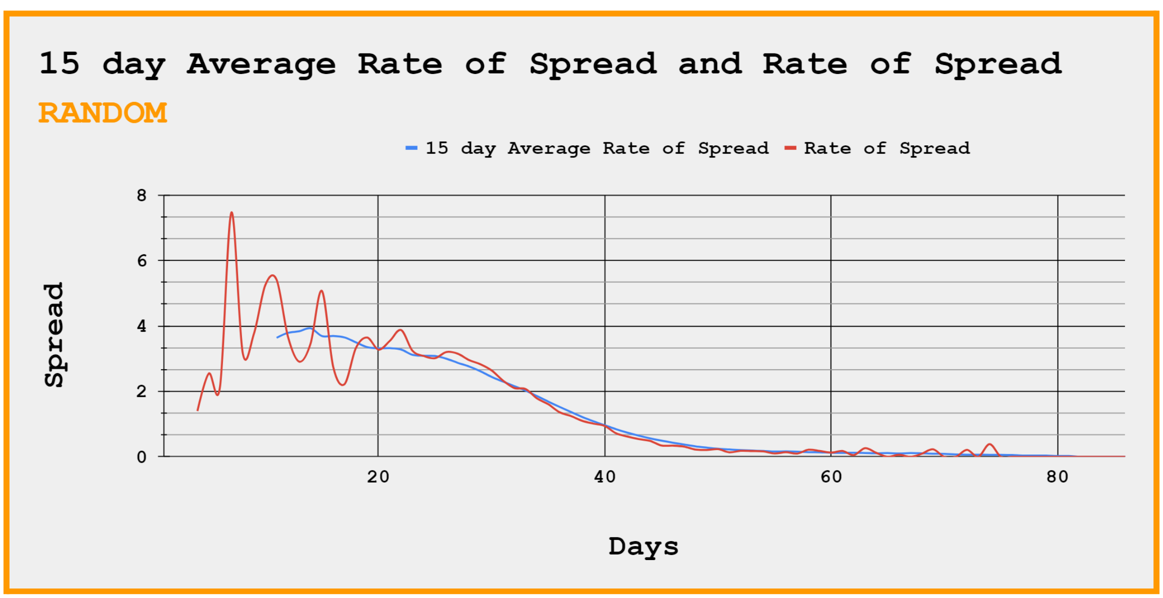
Results

At the suggestion of our interim judges, we ran several experiments using Behavior Space in order to get more data for results. This was a difficult endeavor at first because none of us had any devices except our school chromebooks. However, our scientist was able to get a donated computer which he wiped for us. This computer was still very slow but at least we could download NetLogo on it and begin experimenting. We had some luck, though, when someone dumped a computer in the construction dumpster at our teacher, Ms. Campbell's, house. Our scientist was also able to wipe that one for us to use and it turned out to be a much better and faster device which helped us to run several types of experiments with Behavior Space.

To begin, we wanted to calculate R_0 within our model to match our COVID-19 research. We did this by running experiments with zero masks. After some tests, we guessed to set the infectiousness setting to 3% . We then ran experiments to calculate the RHO as people got sick over time for verification. To do so, we looked at the rate of spread each day times the number of days for infection (14 days). This varied a lot, so we then averaged the rate of spread over a 15 day period. We analyzed the results by creating a chart where a random amount of people got sick for the experiment, followed by a chart with the highest number of people sick after the first thirty days, and then again followed with a chart of the lowest number of people sick after the first thirty days.

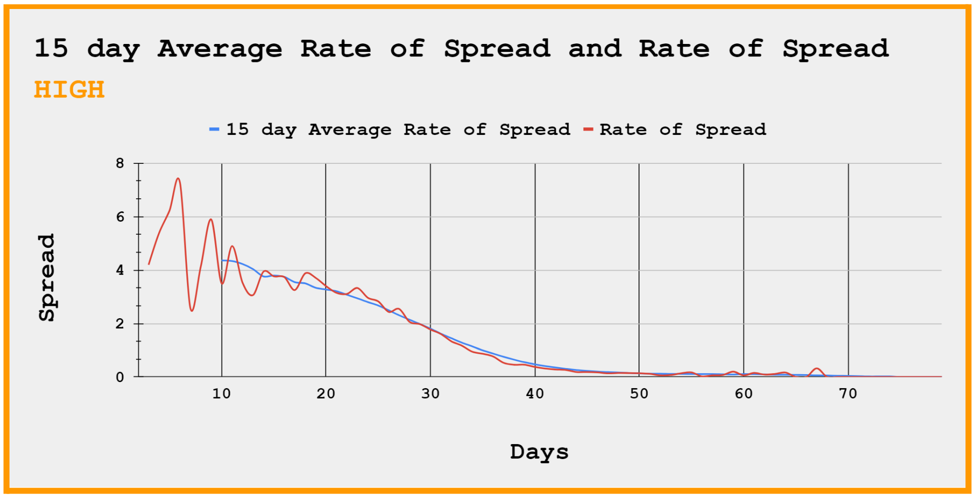
When we look at a randomly chosen experiment and the amount of people that got sick, the chart shows, with the red line, that on the second day of the experiment, there were already 10 people sick and there was one new infection. So, 1 new infection to 10 current infections for that day, and scaling that up for the length of the illness (14 days), means we estimate the RHO for day two is 1.4. We repeat this process for each day. Later, on the fourth day of the experiment, the graph spikes up, and again, on the twelfth day. This number fluctuates a lot, so we also made a line that averaged over 15 days (7 days before and after), which covers roughly one illness period. The rate of spread keeps going up and down until the twenty-third day of the experiment, where it now shows that fewer people are getting infected per sick person because the immune number of people keeps growing and the number of healthy people (who are not immune and are not sick) is going down. The rate at which the virus is spreading and growing lessens once we start achieving herd immunity. The average, as we can see with the blue line, shows a consistent pattern which pretty much sits at the middle of the day-to-day estimates. The blue line, as we move toward zero days looks like it is between 3.9 and 4 which means on this experiment the R_0 is between 3.9 and 4.

Figure 4 Average Rate of Spread and Rate of Spread, Random



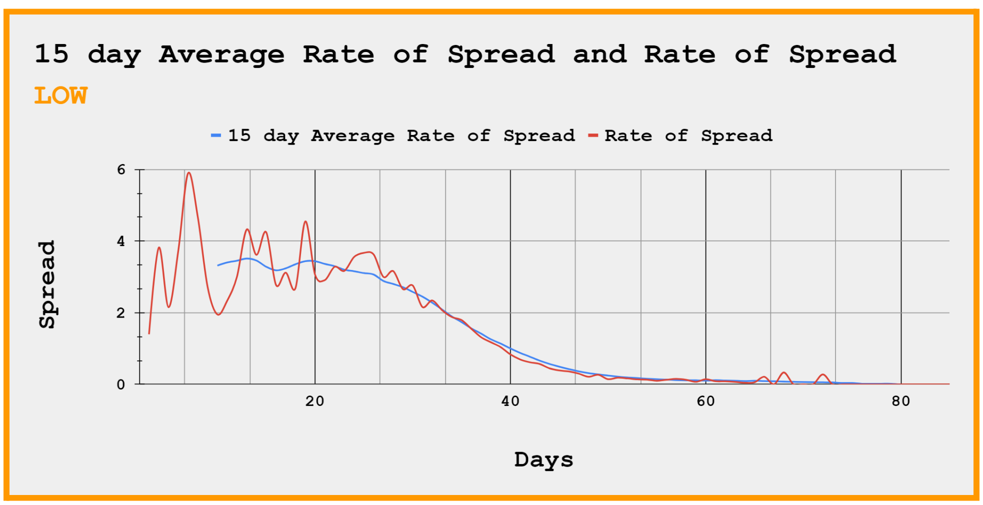
When we look at the chart for the highest number of people getting sick in an experiment, after thirty days, the pattern is similar to that of the random sampling, with an R_0 of 4.2.

Figure 5 Average Rate of Spread and Rate of Spread, High



When we look at the chart for a low amount of people getting sick we again got results very similar to the two prior graphs, with an R_0 of 3.6.

Figure 6 Average Rate of Spread and Rate of Spread, Low

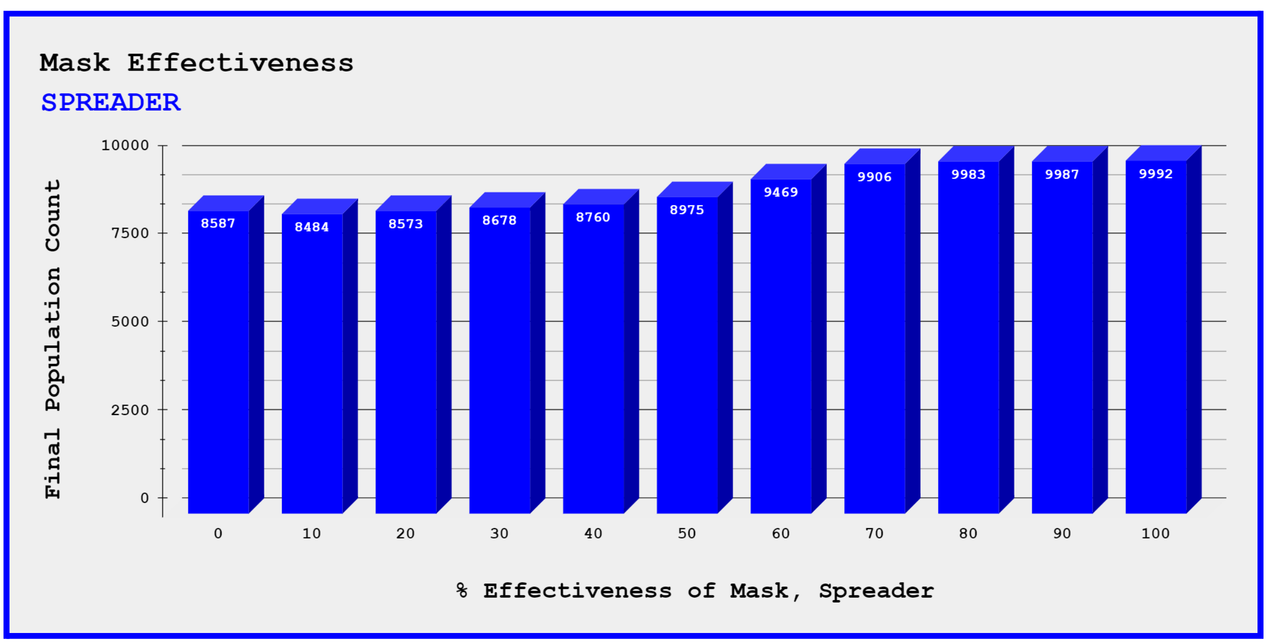


Taken together, with all three graphs showing similar findings within our expected range of about 4, the results of these three experiments do verify our decision to set infectiousness at 3% to simulate the RHO of CoVID-19.

Next, we looked at how different levels of effectiveness for masks gave different results for spreaders and receivers. For this experiment, we set up Behavior Space to do runs with 10,000 people and to look at the results with mask effectiveness of spreaders and receivers at intervals of 10%. We set infectiousness to 3% to mimic an R_0 of around 4 . We set the population to 10,000, immunity-duration to 90 days, chance-recover to 75%, number-of-masks to 10,000 (100%), and duration-of-illness to 14 days. This experiment looked at 121 scenarios and repeated 10 times for each scenario.

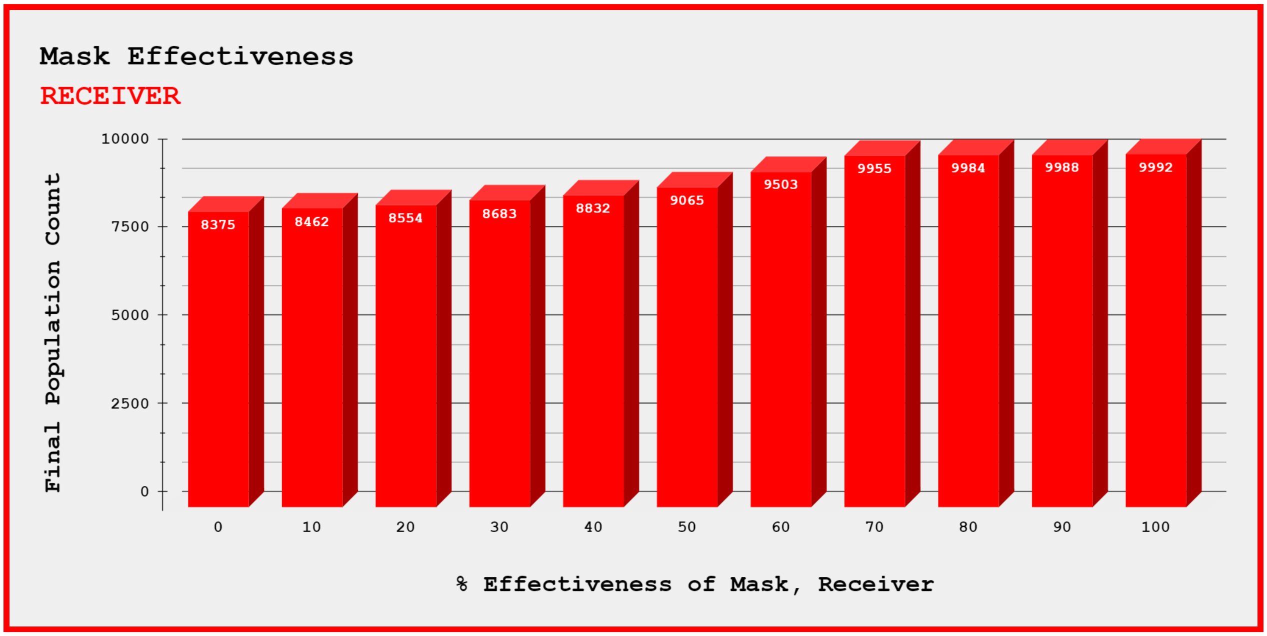
We analyzed our findings by first looking at the results for mask effectiveness of spreaders. We saw the biggest increase in survival from a spreader's mask was between the columns that represent 50 and 60 percent of mask effectiveness. Another increase in survival that was pretty close to the highest difference was between the columns that represent 60 and 70 percent of mask effectiveness. This analysis shows that the point where mask effectiveness for spreaders really has an impact in survival rate is between 50 and 70 percent.

Figure 7 Mask Effectiveness, Spreader



We also analyzed the results by looking at the results for the effectiveness of receiver masks. Here, we saw that the biggest increase in survival was between 50 and 60 percent effectiveness of receiver masks, followed closely by the increase between 60 and 70 percent. Again, the analysis shows that the point where mask effectiveness for receiving really has an impact is between 50 and 70 percent.

Figure 8 Mask Effectiveness, Receiver



Additionally, we wanted to look at how the mask effectiveness of spreaders and receivers interacted so we once more analyzed the results but this time we combined the data for effectiveness of both spreader and receiver masks into one chart. We combined the effectiveness by using the equation [total effectiveness] =

100 - (100 - [mask-effectiveness-spreader]) * (100 - [mask-effectiveness-receiver])/100

Figure 9 Mask Effectiveness, Combined

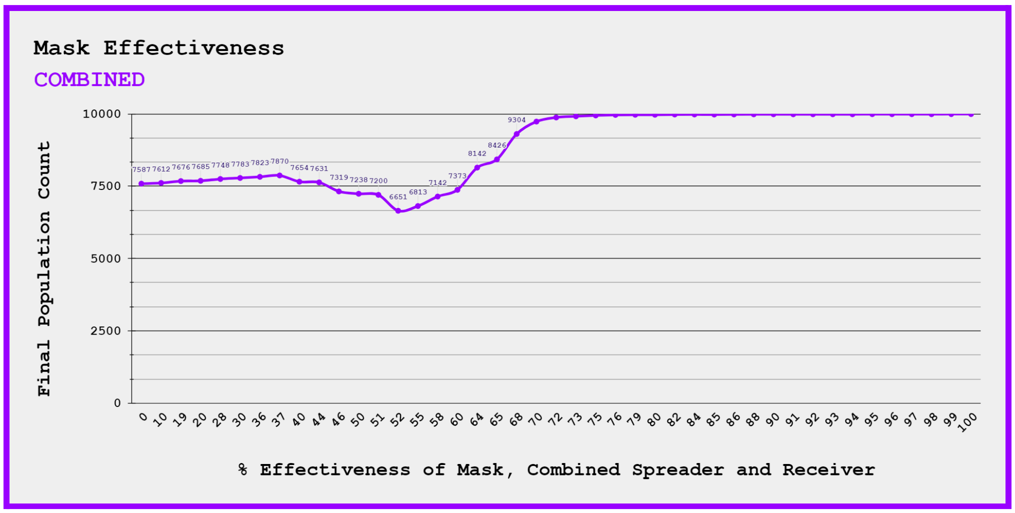
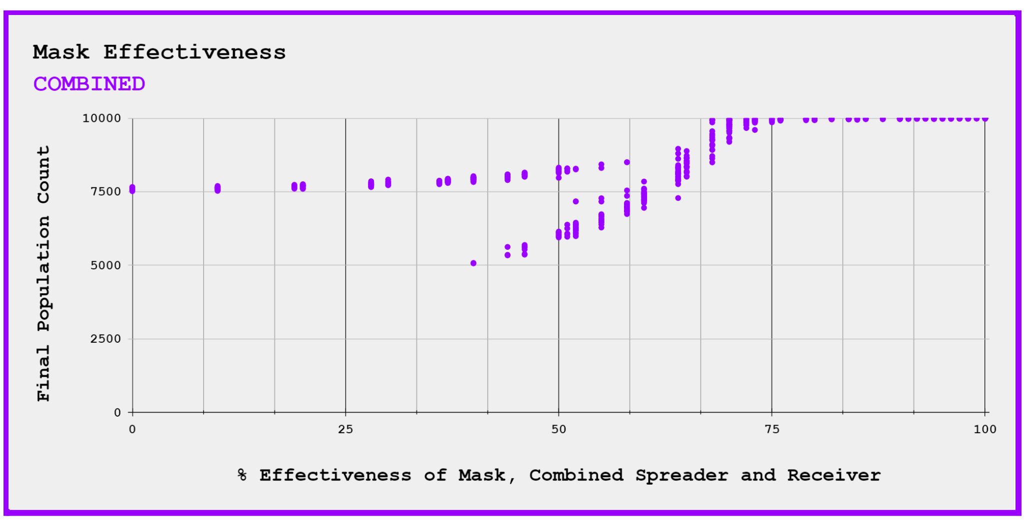


Figure 10 Mask Effectiveness Combined, Scatter



Looking at these results, specifically on the scatter graph, we see how after about 40 percent of mask effectiveness there can be two different scenarios that can come out of these results. In one scenario, the virus dies out completely as a result of having effective masks. In the second scenario, people keep getting sick because they are losing their immunity, get reinfected, and thus the virus never dies out, showing that it would be worse if we never reach a high prevention effectiveness threshold of 70-75% or better.

After looking at results for mask effectiveness, we wanted to see what the model would show about the effect of more or less people wearing masks on the number of CoVID-19 deaths.

Figure 11 Survival Rate as related to Number of Masks

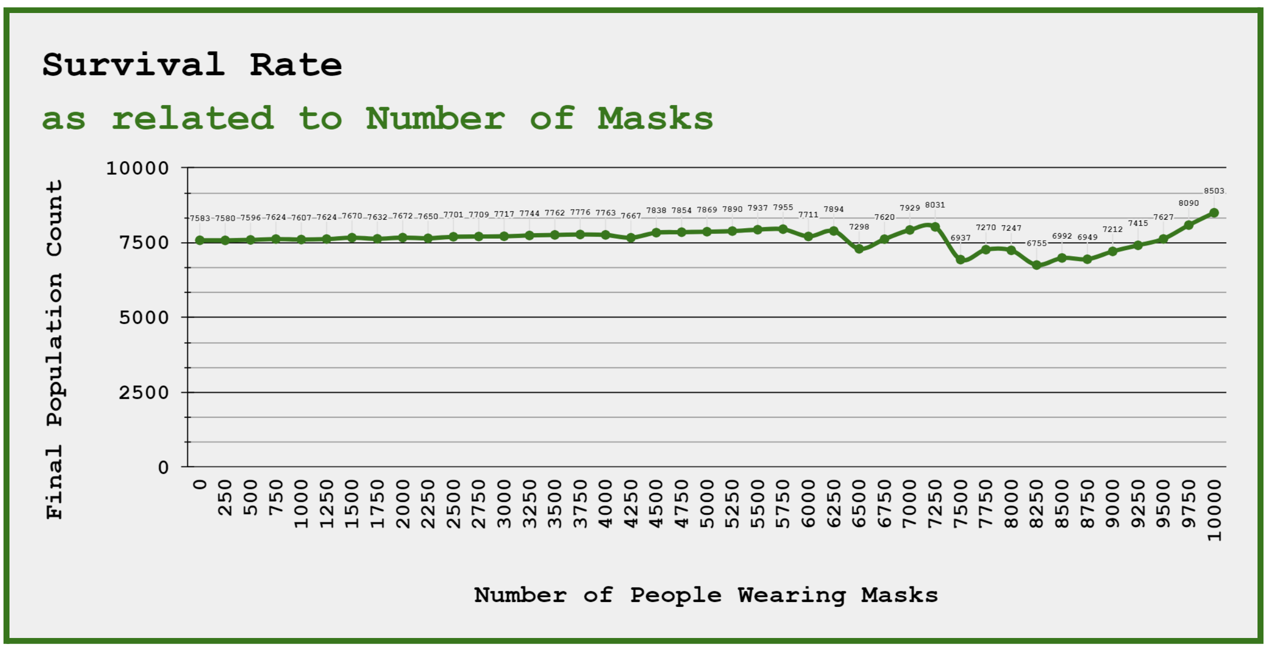
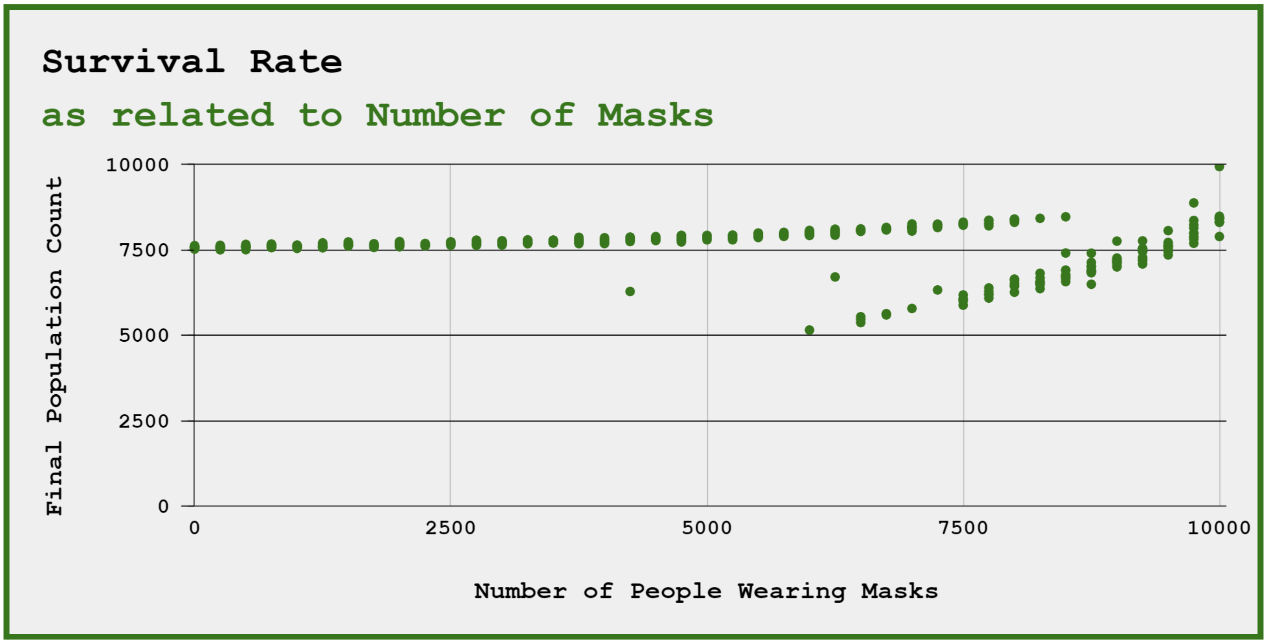


Figure 12 Survival Rate as related to Number of Masks, Scatter



These results also reflect the importance of having enough people, essentially everyone, actually wearing their masks in order to reach a level of protection where the loss of immunity does not begin the cycle all over again, resulting in even more deaths. Even if 90 percent of people wear a mask, that last 10 percent can have a drastic impact as more people die over time, as demonstrated in the chart when you look at 9,000 people wearing masks, and we still see an average of 7212 survival which is even lower than no one wearing a mask at 7583 at the projected end of the pandemic.

Discussion

Our results demonstrate a need to get above the 50-70 percent mask effectiveness level for both receivers and spreaders, and more importantly a combined effectiveness of 70-75%. If not everyone wears a mask, higher mask effectiveness is needed. We want to have almost everyone wearing effective masks or it could actually be even worse, with more deaths, than free-for-all, survival-of-the-fittest herd immunity; although this may not be realistic considering the other safety measures in place in many cases (Swiss Cheese model approach), and the likelihood that immunity lasts longer than 90 days. This means most people should wear masks and those masks should have a higher effectiveness, for example an N-95, KN-95 or other tested highly effective mask instead of a cotton mask. Ultimately, we would always want everyone wearing masks and for those masks to have an effectiveness of at least 70 percent with both masks.We think this analysis is the greatest achievement of the testing we did with our model.

Future Work

One thing we were not able to do because of time constraints was to demonstrate in the model how, after a period of time there is a percentage chance to retain immunity or lose immunity. Currently, when you set the immunity duration slider, all immune turtles are assigned the same immunity duration. In the future, we would like to add this consideration to the code because it would make our model more realistic because immunity loss would be more randomized.

Something else we could add to the model if time permitted is the effect of vaccination on the disease, including scenarios where more or less people are vaccinated, and the timeliness of vaccination. In the near future, we should be getting a lot of data from research on the effects of vaccination on the virus now that vaccines are more readily available to the wider population. It would also be interesting to include contact tracing and how effective or ineffective it would be with so many interactions that have such a small chance of spreading (3%).

Truly, it would be desirable to add as many as possible of the extra precautions of a Swiss Cheese model approach to mitigating the virus to our model. For example, adding testing to our model would let the code allow turtles to stay away from others, minimize contact, and wear better masks when they had to interact.

There are some issues with our model that are not realistic. For example, not everyone will wear their mask 100% of the time, especially around household members and close friends and family. Adding in factors when someone may have a small group (like a family pod) that do not wear masks would make it more realistic. Also, people may have reasons why they start or stop wearing masks, and having people always or never wear masks is not as realistic as we would like.

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References

1. Bates Ramirez, Vanessa. "What is R_0: Gauging Contagious Infections." *Healthline*. Healthline Media. San Francisco, California. April 20, 2020. https://www.healthline.com/health/r- nought-reproduction-number#meaning.
2. Centers for Disease Control and Prevention (cdc.gov). "COVID-19 Pandemic Planning Scenarios." *National Center for Immunization and Respiratory Diseases (NCIRD), Division of Viral Diseases*. March 19, 2021. https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html.
3. Griggs, Mary Beth. "A Swiss Cheese Approach to Pandemic Safety." *The Verge*. Vox Media. October 31, 2020. https://www.theverge.com/2020/10/31/21542207/swiss-cheese-infection-control-covid-19-antivirus.
4. Howard, Jeremy, *et al*. "An Evidence Review of Face Masks Against COVID-19." *Proceedings of the National Academy of Sciences of the United States of America*. National Academy of Sciences. Washington, D.C. January 26, 2021. https://www.pnas.org/content/118/4/ e2014564118.
5. Kushman, Rick. "Your Mask Cuts Own Risk by 65 Percent." *UC Davis Live*. Coronavirus Edition:Transmission. Davis, California. July 06, 2020. https://www.ucdavis.edu/coronavirus/news/your-mask-cuts-own-risk-65-percent/.
6. Reynolds, Sharon. "Lasting Immunity found after recovery from CoVID-19." *National Institutes of Health: Turning Discovery into Health*. NIH Research Matters. Bethesda, Maryland. January 26, 2021. https://www.nih.gov/news-events/nih-research-matters/lasting-immunity-found-after-recovery-covid-19.

7. Ueki, Hiroshi, *et al*. "Effectiveness of Face Masks in Preventing Airborne Transmission of SARS CoV-2. *mSphere*. American Society for Microbiology. Washington, D.C. October 2020. https://msphere.asm.org/content/5/5/e00637-20.
8. Wilensky, U. (1998). *NetLogo Virus - Alternative Visualization model*. http://ccl.northwestern. edu/netlogo/models/Virus-AlternativeVisualization. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.
9. Wilensky, U. (1999). *NetLogo*. http://ccl.northwestern.edu/netlogo/. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.

Appendix: Code

```
;; Sliders
turtles-own
  [ sick?               ;; if true, the turtle is infectious
    remaining-immunity  ;; how many days of immunity the turtle has left
    sick-time           ;; how long, in weeks, the turtle has been infectious
    wearing-mask        ;; if true, this person wears a mask
    age ]               ;; how many weeks old the turtle is
globals
  [ %infected           ;; what % of the population is infectious
    %immune             ;; what % of the population is immune
    lifespan            ;; the lifespan of a turtle
    chance-reproduce    ;; the probability of a turtle generating an offspring
each tick
    carrying-capacity   ;; the number of turtles that can be in the world at
one time
    number-dead         ;; the number of turtles that have died after getting
the virus
    ]  ;; how many days immunity lasts JACK JACK we deleted immunity-duration
from globals to get our sliders to work
;; The setup is divided into four procedures
to setup
  clear-all
  setup-constants
  setup-turtles
  update-global-variables
  update-display
  reset-ticks
end
;; We create a variable number of turtles of which 10 are infectious,
;; and distribute them randomly
to setup-turtles
  create-turtles number-people
    [ setxy random-xcor random-ycor
      set age random lifespan
      set sick-time 0
      set remaining-immunity 0
      set size 1.5  ;; easier to see
      set shape "person"
      set wearing-mask false
      get-healthy ]
  ask n-of 10 turtles
    [ get-sick ]
  ask n-of number-of-masks turtles    ;; want to change 20 to a slider value IN
FUTURE
    [ get-mask ]
end
to get-sick ;; turtle procedure
  set sick? true
  set remaining-immunity 0
end
to get-mask ;; turtle procedure
  set shape "circle"
  set wearing-mask true
end
```

```
to get-healthy ;; turtle procedure
  set sick? false
  set remaining-immunity 0
  set sick-time 0
end
to become-immune ;; turtle procedure
  set sick? false
  set sick-time 0
  set remaining-immunity immunity-duration
end
;; This sets up basic constants of the model.
to setup-constants
  set lifespan 72 * 365      ;; 72 times 365 day = 72 years = 26,280 days old
  set carrying-capacity 300
  set chance-reproduce 0    ;; previously was 1 now we made it 0
  set number-dead 0
  ;; set immunity-duration 152  ;; 152 days = 5 months ;; removed because it's
now a slider
end
to go
  ask turtles [
    get-older
    move
    if sick? [ recover-or-die ]
    ifelse sick? [ infect ] [ reproduce ]
  ]
  update-global-variables
  update-display
  tick
end
to update-global-variables
  if count turtles > 0
    [ set %infected (count turtles with [ sick? ] / count turtles) * 100
      set %immune (count turtles with [ immune? ] / count turtles) * 100 ]
end
to update-display
  ask turtles
    [ ;; if shape != turtle-shape [ set shape turtle-shape ]
      set color ifelse-value sick? [ red ] [ ifelse-value immune? [ grey ] [
green ] ] ]
   stop-inspecting-dead-agents
  if watch-a-person? and subject = nobody
    [ watch one-of turtles with [ not hidden? ]
      clear-drawing
      ask subject [ pen-down ]
      inspect subject ]
  if not watch-a-person? and subject != nobody
    [ stop-inspecting subject
      ask subject
        [ pen-up
          ask my-links [ die ] ]
      clear-drawing
      reset-perspective ]
end
;;Turtle counting variables are advanced.
to get-older ;; turtle procedure
  ;; Turtles die of old age once their age exceeds the
```

```
  ;; lifespan (set at 50 years in this model).
  set age age + 1
  if age > lifespan [
    set number-dead number-dead + 1
    die
  ]
  if immune? [ set remaining-immunity remaining-immunity - 1 ]
  if sick? [ set sick-time sick-time + 1 ]
end
;; Turtles move about at random.
to move ;; turtle procedure
  rt random 100
  lt random 100
  fd 1
end
;; If a turtle is sick, it infects other turtles on the same patch.
;; Immune turtles don't get sick.
to infect ;; turtle procedure
  let spreader-infectiousness infectiousness
  if wearing-mask [ set spreader-infectiousness infectiousness * ( 1 -
mask-effectiveness-spreader / 100 )]
  ;; if not wearing-mask [ let spreader-infectiousness infectiousness ] changed
it so default is not wearing mask with line 138
  ;; let spreader-infectiousness infectiousness * ( 1 -
mask-effectiveness-spreader * wearing-mask / 100 )
  ask other turtles-here with [ not sick? and not immune? ]
  [
    let receiver-infectiousness spreader-infectiousness
    if wearing-mask [ set receiver-infectiousness spreader-infectiousness * (1
- mask-effectiveness-receiver / 100 )]
    ;; if wearing-mask [set spreader-infectiousness infectiousness * (1-
mask-effectiveness-receiver/100)]
    ;; doesn't work as it doesn't change receiver infectiousness below
    if random-float 100 < receiver-infectiousness
      [ get-sick ] ]
end
;; Once the turtle has been sick long enough, it
;; either recovers (and becomes immune) or it dies.
to recover-or-die ;; turtle procedure
  if sick-time > duration-of-illness                        ;; If the turtle
has survived past the virus' duration, then
    [ ifelse random-float 100 < chance-recover   ;; either recover or die
      [ become-immune ]
      [
        set number-dead number-dead + 1
        die
      ] ]
end
;; If there are less turtles than the carrying-capacity
;; then turtles can reproduce.
to reproduce
  if count turtles < carrying-capacity and random-float 100 < chance-reproduce
    [ hatch 1
      [ set age 1
        lt 45 fd 1
        get-healthy ] ]
end
```

```
to-report immune?
  report remaining-immunity > 0
end
to startup
  setup-constants ;; so that carrying-capacity can be used as upper bound of
number-people slider
end
; Copyright 1998 Uri Wilensky.
```