ORIE 4580 Final Group Project

Vaccination Strategies

December 21, 2020

Executive Summary

Through various modeling techniques and parameter considerations, our modeling results suggest that a combination of social distancing, increased vaccine production, and prioritized distribution of vaccines for medical workers and high-risk individuals are effective in containing the spread of COVID-19 (number of infections as well as duration of outbreak). However, our models function under the assumption that local authorities (or any relevant governing body) and the persons vulnerable to the virus enforce and abide by certain protocol, respectively. This would include the ability to ensure consistent social distancing between individuals and the immediate self-reporting of symptomatic individuals who will then avoid contact with all other individuals aside from medical personnel.

Specifically, three different models were constructed and analyzed to evaluate the individual effects of 1) Social Distancing 2.) Vaccine Availability 3.) Vaccine Distribution on the predicted impact of the virus. The course of the COVID-19 epidemic is random and we modeled the spread as such. Hence, numerous simulations were performed to validate the significance of parameter alterations.

For the model analyzing social distancing policy, we find that decreasing meeting rates for the general population (non-medical workers) led to a rather counterintuitive result where the infected population percentage and the duration of the virus spread both increased. However, our findings show that the increase in infections can be attributed to the increased infections among medical workers while infection rates among the general population all decreased significantly.

In the second model focused on the scale of vaccine production and distribution volume, we find that increasing vaccine production and the consequent rate at which the population receives the vaccines decreases the total number of infected individuals as well as the duration of the virus

spread dramatically. While this may seem obvious, the importance of this analysis is to observe the rate of optimal production. There seems to be a steep improvement in virus control as production increases up to the point of producing and distributing vaccines for 10% of the population per day (at which point infection numbers and duration are both halved), but data indicates diminishing returns beyond that point.

The last model focused on distribution techniques among population clusters indicates the slight advantages of prioritizing vaccine distribution to medical personnel and high-risk individuals as opposed to even distribution. While both techniques lead to better results in controlling the virus spread, the difference in improvement between the two techniques is not significant enough to justify picking one of the other. However, in conjunction with our results from the first model, it would be ideal to prioritize vaccinations of medical workers as social distancing can already effectively reduce spread among non-medical workers while medical workers are the most prone.

For future analysis, it would be helpful to model and analyze scenarios including emergency shutdowns and periods of increased contact to help model the dynamic nature of human contact. Currently the models are rather static regarding meeting rates (social distancing or not), but in real-life school and work scenarios where contact rates vary based on seasonal holidays and ad-hoc policies, a dynamic model may be necessary to obtain results that better predict virus spread in the real world.

Modeling Approach, Assumptions, Parameters

The goal of our simulation is to create an accurate representation of a pandemic, and then determine a strategy that contains the pandemic as quickly as possible with as few infections as possible. To accomplish this goal, our model incorporates the following set of parameters:

- k_high - the average number of people a high-risk individual meets in a day
- k_low - the average number of people a low-risk individual meets in a day
- R0 - the reproduction rate of the virus. This is used in conjunction with k_high and k_low to determine the recovery rate of infected individuals
- n - population size
- Probability of being symptomatic - this is useful when calculating the spread of the infection. When an individual is symptomatic, they are only permitted to interact with medical personnel
- Probability of being vaccinated - this is used to determine the number of vaccines each class gets. We prioritize vaccinating essential medical staff over the 3 other classes
- gamma - the number of vaccines made available each day.

Additionally, our model is structured around the following assumptions:

I. Vaccine stock is replenished every day, and the same amount is made available each day. We figured that in a situation where a vaccine has been legalized and is being mass produced, they will be created at a constant rate

II. Asymptomatic people can spread the infection

III. When vaccines are made available, susceptible agents will immediately claim these vaccines before interacting with any other agents

IV. Symptomatic individuals will only interact with medical personnel, as instructed

V. In models with social distancing, people will obey social distancing guidelines

VI. Once an individual recovers or is vaccinated, they cannot be infected or spread the infection

VII. Meetings between agents and recovery time for infected agents are calculated using an exponential distribution

We decided on 3 distinct models to understand the spread of infection. Each model has a control group and additional permutations that showcase the effect certain vaccination strategies have. In our first model we examined how an infection spread in a population practicing social distancing without a vaccine. This serves as the control by which we measure the effectiveness of every other strategy. We then introduced a vaccine into this model, and varied the vaccine production/availability as a function of population size. This became the second model. Finally we changed the probability of being vaccinated between classes to see if prioritizing vaccinating a specific class would be more effective.

Modeling Details

There are two major components to our model: the vaccinations and the general population consisting of four clusters. These four clusters are: medical workers, essential non-medical workers, non-essential high-risk, and non-essential low-risk. In our model each class contains the same number of people. The total population is thus split evenly amongst these four classes. Agents in a class can be in one of four states: Susceptible, Infected but Asymptomatic, Infected and Symptomatic, and Recovered. Here is a diagram of the markov chain:

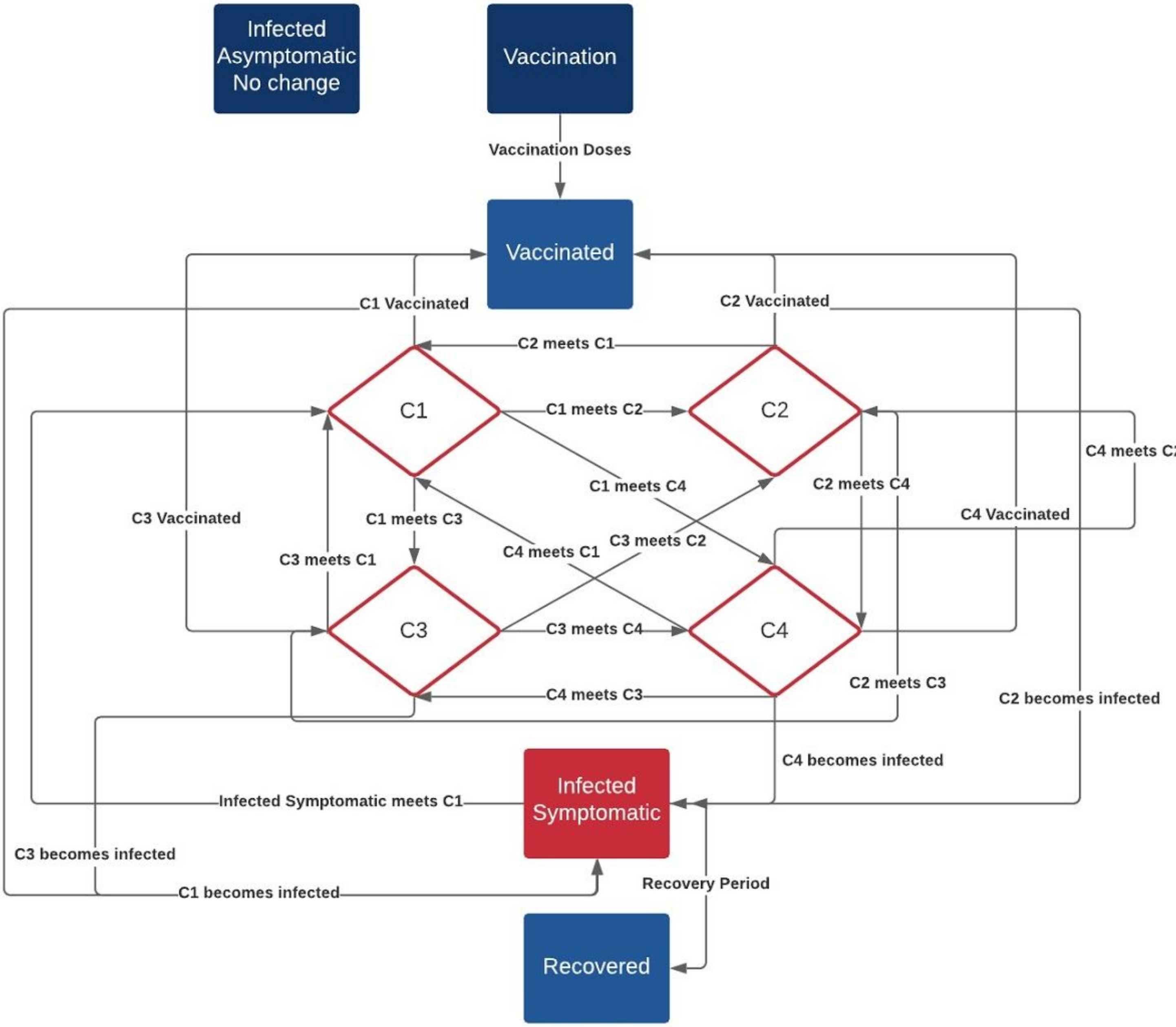


Figure. 1 Markov Chain Diagram for the SIR Epidemic Model

The interactions between every group are modeled as above. We know our model is correct at the end of the simulation, the number of total infected individuals has gone down to zero. Furthermore, class C1 is the class with the least number of people remaining. This makes complete sense as this class is all medical workers and they are exposed to all the infected symptomatic people the most.

Modeling Analysis

We wanted to study how the implementation of different vaccination strategies would affect 1) infection number and 2) the length of time it takes for the epidemic to be contained (which we defined as when there are no more susceptible individuals left in the population). By using the two aforementioned variables as metrics to evaluate effectiveness, we decided to use a simulation with no vaccination as a control group for baseline comparison and modify the following variables relevant to vaccination in order to assess which strategy was the most effective : 1) the number of vaccine doses available per day and 2) the number of doses distributed to each class (with the four classes being medical workers, non-medical essential workers, non-essential high-risk individuals and non-essential low-risk individuals). In addition, we also wanted to investigate whether social distancing or vaccination is more effective at containing the epidemic, with social distancing reflected in the model by having smaller meeting rates between each class.

We want to test the effect of social distancing policies (determined by meeting rate), the availability (determined by vaccine dosage), and the distribution of vaccines on total infections and pandemic lifetime. In order to prevent other variables from interfering with the test results, we set up 3 groups of models and within each group, one factor is altered while the other two factors are controlled. The effect of each strategy will be evaluated by comparing the level of reduction in infection rate and the percentage decrease in time to contain the virus. We will run 100 simulations for each model and compute the confidence bounds for the resulting infection rate and time. Note that we assume that when an individual is infected with COVID, s/he is symptomatic with probability p=0.8. We have outlined the models and the results in details below:

<u>Group 1</u>:

Change Social Distancing (Vaccine Distribution and Vaccine Dosage Kept Constant)

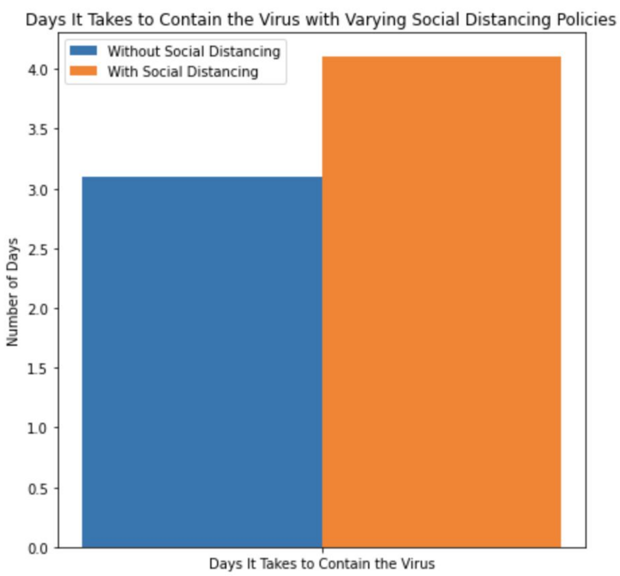
(Initially Infected Population: 500 medical, 2500 essential, 2500 high risk and 2500 low risk)

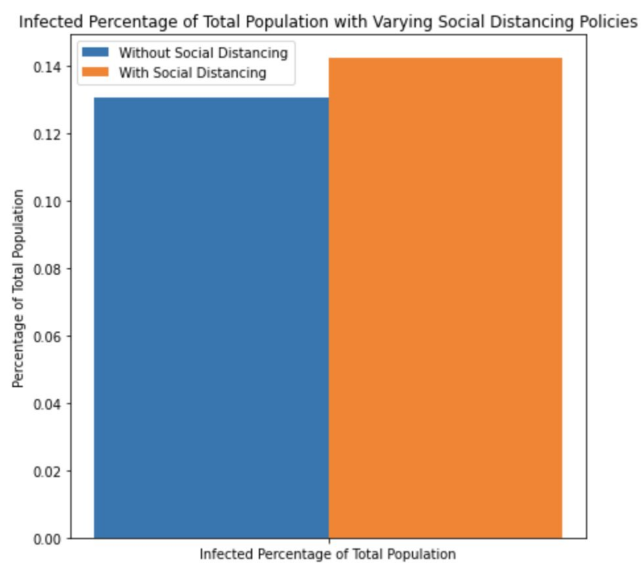
a. *Table showing parameters used in each model*

Parameters	Model # 1 (Without	Model #2 (With Social

	Social Distancing)	Distancing)
Medical worker meeting rate	10	10
Non-medical worker meeting rate	4	1.5
Total population	100000	100000
Reproduction number	1.5	1.5
Probability of infected but asymptomatic for each class (in the order of medical, essential, high risk and low risk)	[0.8,0.8,0.8,0.8]	[0.8,0.8,0.8,0.8]
Vaccine distribution of each class	[0.25,0.25,0.25,0.25]	[0.25,0.25,0.25,0.25]
Vaccine daily dosage availability	0.01	0.01

b. *Visualizations:* plots showing infection rates and days to contain the virus



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The 95% CI for percentage of infected individual in total population without social distancing is ( 0.1297 ,  0.1316 )
The 95% CI for percentage of infected individual in total population with social distancing is ( 0.1409 ,  0.1439 )

The 95% CI for the number of days it takes to contain the virus without social distancing is( 2.9141 ,  3.2859 )
The 95% CI for the number of days it takes to contain the virus with social distancing is( 3.6661 ,  4.5339 )
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Figure. 2 Group 1 Simulation Results

c. Result Interpretations

From the histograms above, we see that when social distancing policy is included in the model (by decreasing the meeting rates for non-medical workers), not only did the infected percentage of the total population increase, but the number of days it takes to contain the virus also increased. This may seem counterintuitive upon first glance, but diving deeper into the infection number, we see that the increase in total infected individuals are entirely attributed to the increase in infected (and later recovered) medical workers and that the infection numbers for essential workers, high-risk and low-risk individuals (all of whom adhered to social distancing and met up with others less frequently) all decreased.

This is due to the fact that when there is social distancing, although the meeting taking place amongst non-medical people decreased, the number of meetings taking place between susceptible medical workers and infected individuals of all classes (essential workers, high and low risk individuals) increased dramatically at least by 1000 for each category, which ultimately contributed to the increase in infected medical workers and resulted in a longer containment time period.

<u>Group 2</u>: Change Vaccine Dosage Availability
(Vaccine Distribution and Social Distancing Kept Constant)

a. Table showing the parameters used in each model

Parameters	Model # 1	Model #2	Model #3	Model #4	Model #5
Vaccine daily dosage availability	0.01	0.05	0.10	0.15	0.20

the parameters are kept constant across all three models (with varying vaccine distributions:

Medical worker meeting rate	10	Total population	100000
Non-medical worker meeting rate	1.5	Reproduction number	1.5
Probability of infected but asymptomatic for each class	[0.8,0.8, 0.8,0.8]	Vaccine distribution of each class	[0.25,0.25,0.25,0.25]

b. Visualizations: Line plots showing average infection rates and days to contain the virus

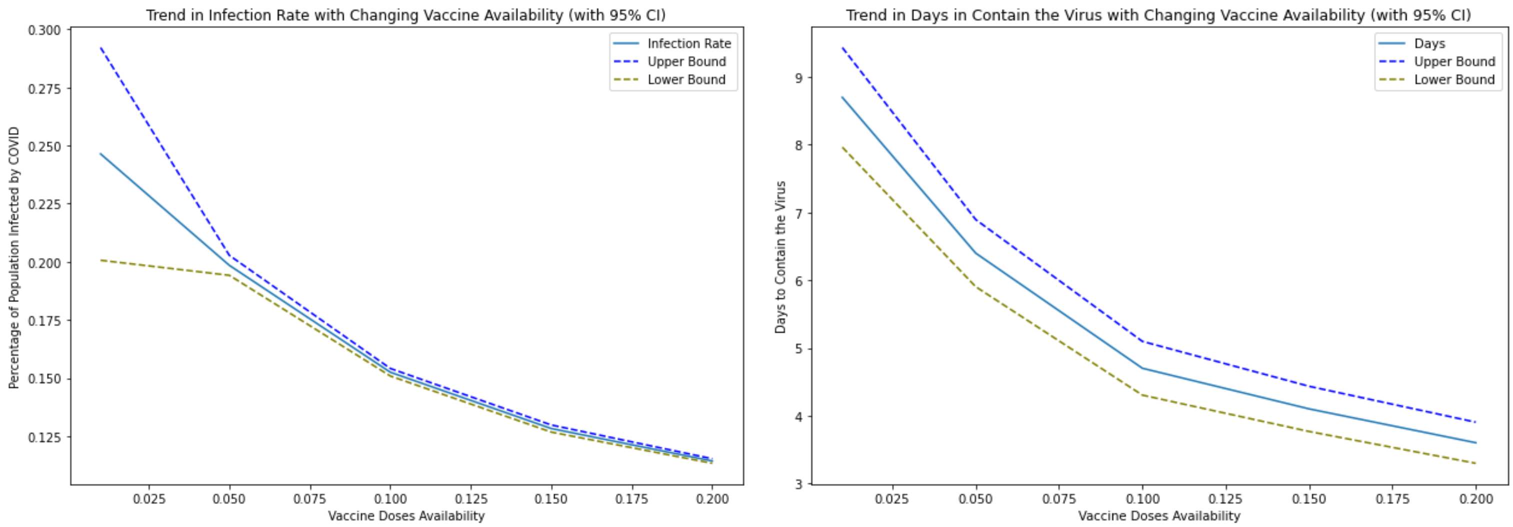

Figure. 3 Group 2 Simulation Results

c. Result Interpretations

This group of simulations aims at testing the effect of vaccine doses availability on the spread of virus. We ran 10 simulations at each vaccine dosage level; the average infection rate at each level is shown by the downward sloping green line in Figure 3, while the 95% confidence bounds at each dosage level are given by the blue and olive colored dashed lines. It is within expectation that as the vaccine availability in the population increases, the proportion of population infected decreases since when more vaccines are made available, the difference between the rate at which susceptible individuals enter the infected and vaccinated subclasses decreases. We also observed that the rate at which the increase in vaccine availability improves infection rate, slows down as we move towards the higher end. A similar trend is observed in the number of days, with the trend line becoming less steep at dosage level=0.10.

Group 3: Change Vaccine Distribution

(Vaccine Doses Availability and Social Distancing Kept Constant)

a. Parameters used in each model

Parameters	Model # 1	Model #2	Model #3
Vaccine distribution	[0.25,0.25,0.25,0.25]	[0.4,0.2,0.2,0.2]	[0.2,0.4,0.2,0.2]

of each class			

Other metrics are kept constant across all three models (with varying vaccine distributions:

Medical worker meeting rate	10	Total population	100000
Non-medical worker meeting rate	1.5	Reproduction number	1.5
Probability of infected but asymptomatic for each class	[0.8,0.8, 0.8,0.8]	Vaccine daily dosage availability	0.05

b. Visualizations: Plots showing infection rates and days to contain the virus

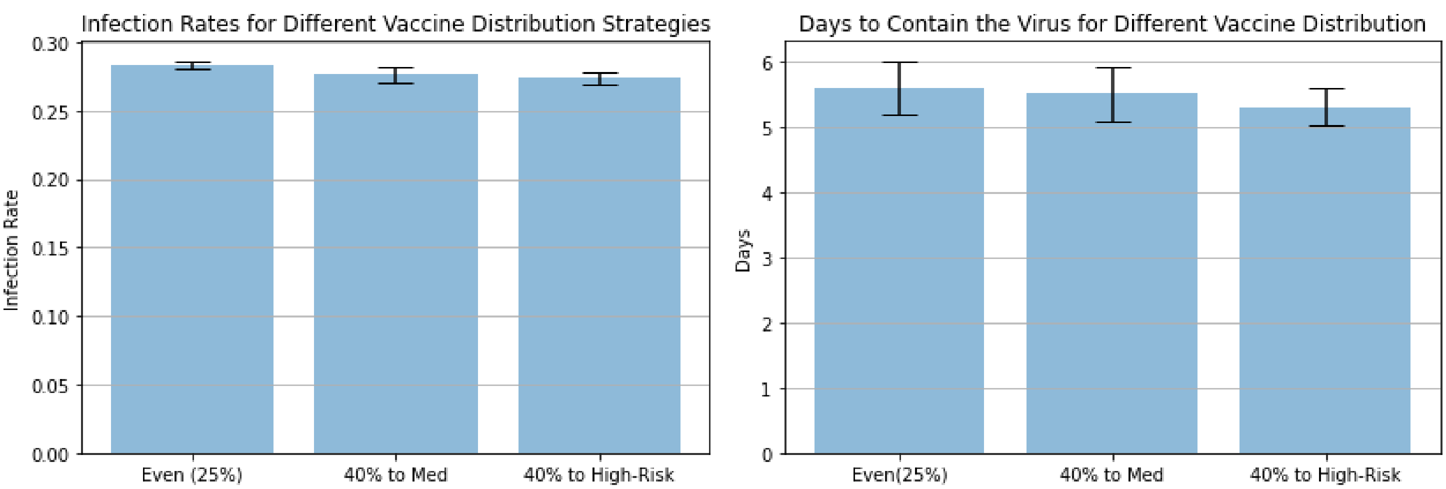

Figure. 4 Group 3 Simulation Results

c. Result Interpretations

As shown in Figure 4, each bar represents the infection rate resulting from implementing one of the three specified vaccination distribution strategies. We want to explore how the proportion of population infected changes with different distributions. We proposed the following three strategies: 1) evenly distributing the vaccines across all four classes (25% each); 2) assigning more vaccines (40%) to medical workers (since their meeting rates are high); 3) assigning more vaccines (40%) to high-risk personnels. We expect the infection rate and the time taken to contain the virus to be shorter if a higher proportion of the available vaccines is first given to groups that more frequently meet with both symptomatic and asymptomatic people. This is supported by our simulations, as we can see that by assigning 15% more vaccines to non-essential high-risk individuals, the infection rate dropped from 0.285 to 0.265, while the days to contain the virus dropped from around 5.6 to 5.15 days. However, the improvements are not significant as we can see in the diagram on the right, the 95% confidence intervals for the number of days to contain the virus when 40% of vaccines are given to high-risk personnels largely overlap with that when vaccines are evenly distributed across all classes.

Conclusions

From our simulation outputs above, we can conclude that the availability of vaccine dosage has a significant positive impact on the containment of the virus as well as the infection spread within the population, yet the rate of improvement decreases as we continue to increase the vaccine availability. Meanwhile, the distribution of vaccines among the different classes (more towards medical workers vs. more towards high risk individuals) did not result in a difference that is significant enough to be considered.

Therefore, under the assumptions of our epidemic model, the vaccination strategy that we would recommend is one where the number of doses made available should be maximized while distributing more of the vaccine for either medical workers or high-risk individuals as there was no significant difference in terms of how effective one was over the other.

Technical Appendix

- R0, the reproduction rate of the virus was chosen to be 1.5 in accordance with previous modeling assignments concerning the SIR pandemic. This value can be interpreted as the expected number of cases directly generated by one infected individual in a population where all other individuals are susceptible. As such, this number is different for different viruses.
- We set k_high = 10 and k_low = 4, and when modeling with social distancing set k_low = 1.5. We figured that even with social distancing, high-risk individuals such as essential medical workers would still have to interact with the same number of people on average.
- Infection recovery rate (Beta) was calculated as Beta = ((k_high + k_low)/2) / R0. Since we had two separate values for the average number of meetings a day per person, we took the arithmetic average of the values. Our high risk and low risk classes contain equal numbers of individuals, and this function preserved that quality.

- Within our models we had two different parameters governing when meetings occurred, h and l. h = k_high/(n-1), l = k_low/(n-1). These are used along with beta to compute the rate events occur, and we calculate inter-event times using an exponential random variable distribution.