Quantitative Simulations to Study the Effect of Vaccination on Mitigating COVID-19

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1. Introduction

Since the outbreak of COVID-19, government across the globe has focused intensive resources on remedial actions. Among the grass-root and sustainable solutions is vaccination. To understand the statistical effect of vaccination on mitigating the situation of coronavirus in a community with infected individuals, this study discusses results generated by our simulation models with a population size of 42000 people. By comparing the total number of days the pandemic lasted, the maximum number of infected people, and the time to reach the maximum number of infected people per simulation across different vulnerable groups and vaccination rates, this study provides a quantitative perspective of how important vaccines are to our worldwide mission of stopping the formidable epidemic.

2. Methodology

The studying population size is 42000 people. There are three statuses a person might possibly have: susceptible, infected, and recovered. To simplify our study, a recovered person will be inoculated against the disease. Each simulation starts with patient Zero getting infected. As each day passes by, each infected person will interact with ten different random people and spread the virus. Once the person gets infected, it will take them 5 days to recover. The simulation stops when all infected people have recovered and no further individuals get infected.

Our goal is to answer three questions:

- *How does vaccination help reduce infections when all individuals have the same level of getting infected? At which vaccination rate will we achieve herd immunity?*
- *How does vaccination help reduce infections in different vulnerable groups?*
- *How does vaccination help reduce the death rate in different vulnerable groups?*

To answer the first question, we introduce a vaccine with a success rate of 90% to the population. We increment the proportion of the population that randomly receives vaccines to see the effect of vaccination in slowing down the infection. A person is classified as "vaccinated" if receives the vaccine. We report the results for five different scenarios where the proportion of the vaccinated population is 0%, 10%, 50%, 75%, and 95%.

For the second question, we randomly classify the population into three vulnerable categories: high-risk, medium-risk, and low-risk. Each different risk level coordinates with the chances of how likely a person will be infected. The higher the risk, the more a person is prone to infection. In the simulation, the infected rate is set at 10%, 15%, and 30% for low, medium, and high risk respectively. To simplify the study, all subjects in the population will be divided into the three mentioned groups, with an equal number of people across all vulnerable categories. We report the results for three different scenarios where the proportion of the vaccinated population is 0%, 50%, and 75%.

Using the same model built in question two, we introduce the "deceased" status in the next question. The death rate will be varied by vulnerable categories and is set at 5%, 8%, and 12% respectively for low, medium, and high risk. Once an infected person reaches their fifth day of being sick, they will be randomly considered either “recovered” or “deceased” the next day depending on the assigned death rate. Similar to question two, we report the results at 0%, 50%, and 75% vaccination rates.

It is noted that the simulation model of each question is built on one another. For each scenario under each question, one hundred simulations are run. Furthermore, since our focus is to understand the effect of vaccination in slowing down COVID-19 quantitatively, all other conditions are held constant, including the efficacy of the vaccines, number of interactions, and implicit demographic factors such as age, gender, location, and health condition. The variability of demographic factors is simplified and captured by the vulnerable categories. The risk of infection is also abstracted to capture the logic of how different vulnerability level reacts to the virus. No related sources have been used to back the assigned rates.

Since the efficacy of the vaccine, the number of interactions, and the number of days to recover are constant, the most important quantitative measure for this study will be the infection rate. In question one, for each simulation per scenario, we collect the total number of days the pandemic lasted, the number of days to reach the maximum number of people infected, and the maximum number of infected in the population. A similar approach is taken for question two, however, this time the results will be divided into different vulnerable categories. In question three, we look into the number of deceased across different vulnerable categories to understand the effect of vaccination, if any, on different groups.

3. Results

3.1. Question One: How does vaccination help reduce infections when all individuals have the same level of getting infected? At which vaccination rate will we achieve herd immunity?

In one random simulation of the homogenous population with no vaccination, the total number of days the pandemic lasts is 22 (Figure 1a). The peak number of infected people is on day 15, with 36768 people sick. The difference between a population without vaccination and with a vaccination rate of 10% is minimal: the vaccines apply to 10% of the population only slow down two days before reaching the peak of the number of people with infection compared to the population with no vaccines. Furthermore, the maximum of infected people between a 10% rate of vaccines and no vaccines is 1353 (Figure 1a). The difference becomes more visible with the increasing proportion of the population receiving vaccines. Table 1 shows the difference in mean of the total number of days the pandemic lasts, the maximum number of infections, and the number of days to reach the peak of infection in each scenario. The results show that the more people receive vaccines, the longer it takes for others to get infected. At a 95% vaccination rate, the length of the outbreak is significantly short due to the low number of new cases incurred (Figure 1b).

Results of one hundred simulations for each vaccination scenario reveal that the larger the portion of the population vaccinated, the more visible the difference between the average total of days, the average maximum number of infections, and the average number of days to reach the maximum infection (Figure 2). Compared to the population with a zero vaccination policy, the population with a 10% vaccination rate has 3.46% less of average maximum infection cases (Table 2). Such a number will even more significant with 50% and 75% vaccination rates: 18.83% and 27.87% reduction respectively compared to no vaccination. The infection reduction rate, in essence, is not proportionate to the increase in vaccination rate.

To eliminate the need of running multiple one-hundred simulations for all possible scenarios, we collect the standard deviation in total days, the maximum number of infections, and the number of days to reach the maximum of infections (Table 3). Results show that the increases in vaccination rate will lower the standard deviation in the maximum number of infections. The standard deviation is also very insignificant to the true mean. Such information about the standard deviation is helpful for future simulations of large adjustments and requires huge computing capacity. The standard deviation also justifies reasons why we can eliminate the need to generate simulations for other vaccination rates and give us context to interpret values achieved from one simulation.

3.2. Question Two: How does vaccination help reduce infections in different vulnerable groups?

The difference in the average number of days to reach the maximum number of infections are huge across different vaccination rates, with the mean of 6 days different. The difference in the average maximum number of infections across 0%, 50%, and 75% vaccination rates, however, is less significant, with an average of 2000 cases different. When comparing the results between groups, the difference is even less noticeable: an average of 0.5 difference in the number of days to reach the peak of the outbreak, and an average of 200 cases difference in the maximum number of infected subjects.

3.3. Question Three: How does vaccination help reduce the death rate in different vulnerable groups?

The difference in deceased cases is only noticeable between different vulnerable categories, though almost seems to stay constant across different vaccination rates.

4. Discussion

4.1. Question One: How does vaccination help reduce infections when all individuals have the same level of getting infected? At which vaccination rate will we achieve herd immunity?

Incrementing vaccination rate shows that the more people receive vaccines, the slower the infection rate and the lower number of infected people. Furthermore, at the vaccination rate of 95%, a substantially small number of people are infected compared to the entire population. In other words, herd immunity can be achieved by having 95% of the population vaccinated.

4.2. Question Two: How does vaccination help reduce infections in different vulnerable groups?

The larger the proportion of the population vaccinated, the slower it takes to reach the maximum number of infections across vulnerable categories. The difference between all vulnerable categories versus 0%, 50%, and 75% vaccination rates is relatively significant, however, either the difference in the maximum number of infections or the number of days to reach the maximum infections are insignificant between high, medium, and low-risk groups. It is concluded that the increase in vaccination rates has clear positive effects in reducing the number of transmitted cases in the overall population. Across different vulnerable groups, the positive effects of vaccines are also observed but with less significant differences.

4.3. Question Three: How does vaccination help reduce the death rate in different vulnerable groups?

We observe that different vaccination rates do not have a huge effect on the death rate in different vulnerable categories. Such a phenomenon is explainable. Based on the results from question two, the difference in the number of infected people across vulnerable categories is only relatively significant, which results in an even less significant difference in deceased cases when the number of deceased is randomized proportionally with the vulnerable groups. Based solely on the generated numbers, there is no substantial evidence showing how different the death rates are across vulnerable groups with and without the presence of vaccination.

4.4. Implicit Factors and the Length of the Pandemic

Simulations show that the larger the proportion of the population vaccinated, the longer the pandemic lasts unless the vaccination rate reached herd immunity. In reality, there are accompanying factors that help reduce infection rates along with vaccination. For instance, social distancing, isolation, and medical assistance are those that can be listed. By delaying the number of days to reach the peak of infections and lowering the maximum number of infected people, vaccination provides a certain amount of necessary protection for susceptible individuals and extra time for other remedial actions to take place which eventually cut down the length of the pandemic.

4.5. Un-random Randomization: The Necessary Bias?

The results yielded in question two for the vaccination rate of 75% are interesting: the number of infected people in the medium-risk group, in fact, is 290 higher compared to that of a high-risk group. Such unexpected results can be explained by how the program systematically picks random numbers in its computational process. Pertaining the fact that the random numbers in the program are not “random” – they are a result of an organized list of numbers that have been pre-built in the system. Due to such reasons, introducing different infection rates means introducing biases to our process due to the built-in frequency of how numbers are “randomized”. To what extent such a bias violate our interpretation of results is an unsolved question, similar to how people in life are born differently though all classified as “human being”.

5. Further Study

5.1. Diversify Scenarios

Further customizations can be made to the simulation to diversify our questions and study scenarios. Below are some, but not limited to, idea suggestions:

- Introduce multiple vaccine shots
- Adjust rates (efficacy rate, recovery rate, infection rate, and death rate)
- Adjust the number of interactions
- Introduce more demographic variables
- Adjust population size

5.2. Accompanied Research

Accompanied research is encouraged to unlock further potentials of the simulating models.

6. Conclusion

From the quantitative perspective, we can conclude that vaccination plays a critical role in mitigating the pandemic. The larger the proportion of the population vaccinated, the longer it takes to reach the peak of the pandemic and the lower the maximum number of people transmitting the disease. The power of vaccination, therefore, is not only to provide necessary protection for susceptible subjects but also to allow more time for medical actions to take place. It is advisable that policymakers and leaders across organizations encourage vaccination within the community to help stop the outbreak. Accompanied research is simultaneously encouraged to enhance the simulating models and unlock prediction capability.

7. Source Code

Vivian Bui (2022) COVID-19 Simulation (Version 1.0) https://github.com/vivibui/COVID-Simulation.git

8. Appendix

Figure 1a. SIR Model from One Random Simulation

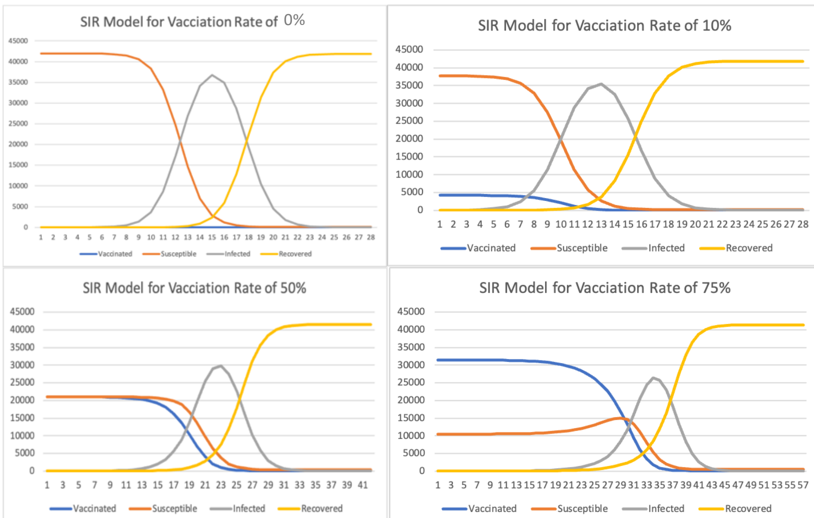


Figure 1b. Number of Infected People with the Vaccination Rate of 95% from one random simulation

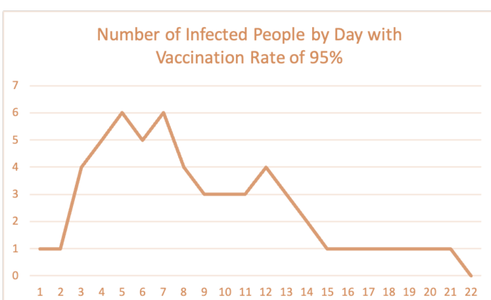


Table 1. The difference in Mean of Total Days, Maximum Number of Infected People, and Number of Days to reach the Maximum Number of Infection across Different Vaccination Rates compared with No Vaccination in One Random Simulation

	DiM Total Days	DiM Max Infection	DiM Day to Max Infection
10% Vaccination	0	-9.2142857	-2
50% Vaccination	7	-2785.3452	8
75% Vaccination	14.5	-4231.735	19
95% Vaccination	-3	-8226.3019	-8

Figure 2. Average Total Days, Maximum Day, and Maximum Number of Infected People by Vaccination Rate

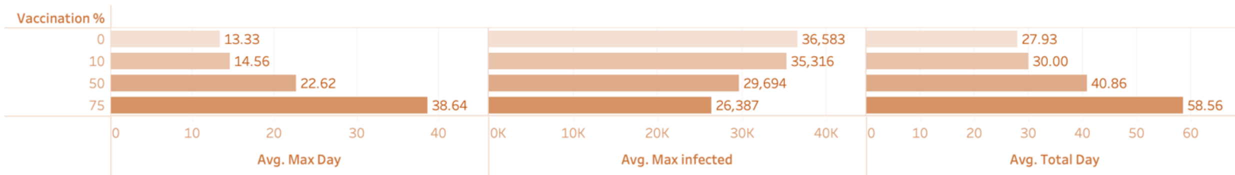


Table 2. The Percentage Difference in Mean of Total Days, Maximum Number of Infected People, and Number of Days to reach the Maximum Number of Infection across Different Vaccination Rates compared with No Vaccination in One Hundred Simulation

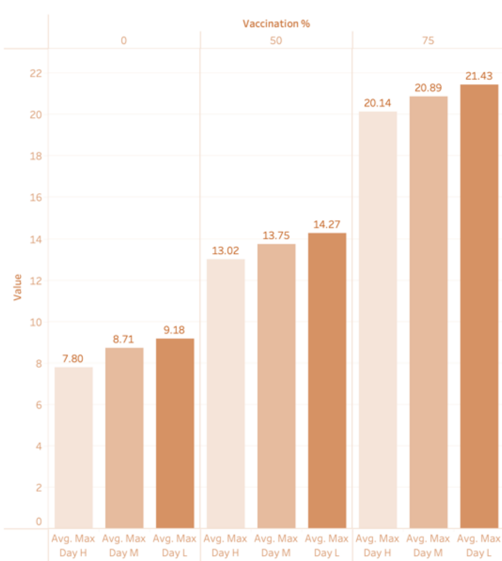
	% Difference of Total Day	% Difference of Max Infection	% Difference of Day to Max Infection
10% Vaccination	7.41%	-3.46%	9.23%
50% Vaccination	46.29%	-18.83%	69.69%
75% Vaccination	109.67%	-27.87%	189.87%

Table 3. Standard Deviation in Total Days, Maximum Number of Infected People, and Number of Days to reach the Maximum Number of Infection between One Random Simulation and the Average calculated from One Hundred Simulations

	Total Day	Max Infection	Day to Max Infection
No Vaccination	1.870856	179.1745323	1.28751
10% Vaccination	1.927997	165.5823574	1.25786
50% Vaccination	2.792559	165.1336416	2.36891
75% Vaccination	5.81415896	139.4810653	5.48923648

Figure 3. ***(left)*** Average Number of Days to reach the Maximum Number of Infected People for Three Vulnerable Groups across Different Vaccination Rates

Figure 4. ***(right)*** Average Maximum Number of Infected People for Three Vulnerable Groups across Different Vaccination Rates



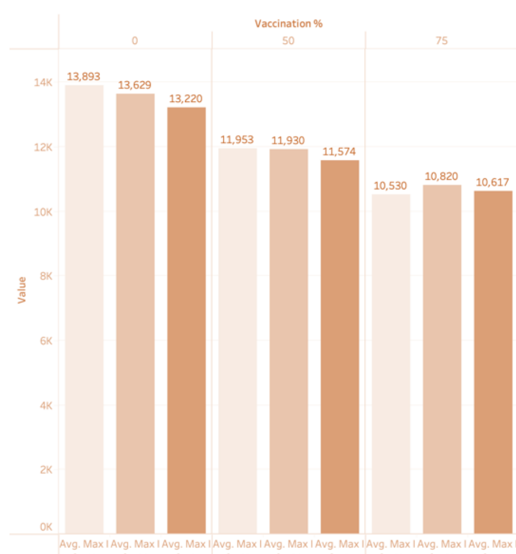


Figure 5. Average Number of Deceased People for Three Vulnerable Groups across Different Vaccination Rates