Patient Zero

MATH435 Project

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Abstract

Imagine a vaccine that could distribute itself. No more appointments, no more shipping, no more expiration dates. This vaccine would be be created by making a variant of the disease that is highly infectious but less deadly. Then a Patient Zero, or many Patient Zeros, would be administered the vaccine and sent into the population to spread the vaccine. Unethical? Almost certainly. Interesting to study? Absolutely!

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1 Introduction

In this paper, we explore our hypothetical Patient Zero Vaccination Strategy and compare it to the Normal Vaccination Strategy, where there exists limitations in distribution, supply, and vaccine refusal. We describe both models and their impact on the population, comparing the outcomes of both strategies.

1.1 Motivation

There were two primary reasons why we chose to explore this topic. Firstly, we had an interest in modeling various scenarios. Using MATLAB allowed us to create our own model and test different values of our parameters. Thus, the possibilities were endless, and we could simulate our Patient Zero Strategy in numerous scenarios. Secondly, we knew that the creation of the Patient Zero strategy could have a real impact on the economy - eliminating the costs to distribute a vaccine and the costs to mass produce it. While the Patient Zero Vaccination strategy would certainly raise ethical concerns, it is something that could be used when a deadly virus is present.

1.2 Overview of the Project

The main goal of this paper is to compare the outcomes of the Normal Vaccination Strategy and the Patient Zero Vaccination Strategy. In Section 2, we discuss both models with flow diagrams, equations that describe the models, and the assumptions of the models. The constants and model parameters are also discussed in this section, as well as the methods of estimation of certain parameters of interests.

In Section 3, we discuss the outcomes of the Normal Vaccination Strategy and the Patient Zero Vaccination Strategy with a multiplier of 2 (the concept of multiplier is described in Section 2.2.3). We then explore the impact of varying the multiplier on hospitalization, deaths, the length of pandemic and the infected population.

1.3 Historical Context

The concept that the introduction of a disease variant can push out an existing strain isn't completely new nor hypothetical. For example, cowpox - a mild disease - was discovered to give humans immunity to smallpox, a much more deadly disease [6]. As a result, a vaccine was created based off of cowpox, and individuals would inoculate themselves in order to gain immunity to smallpox [6].

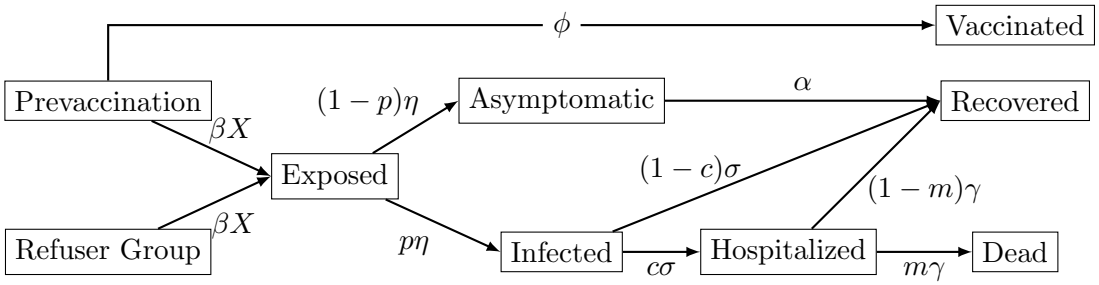
Furthermore, this concept is also seen in the case of Omicron and Delta. Data collected from South Africa during December 2021 shows that individuals who contracted Omicron (a more infectious but less deadly disease) demonstrated an increase in protection against the Delta variant, a deadlier disease [7]. Thus, due to Omicron's high infection rates, it pushed Delta out of the picture [7].

2 Methods

In this section, we provide an overview of the two vaccination models, namely the Normal Vaccination Strategy and the Patient Zero Vaccination Strategy. We provide the differential equations that describe

the models, the assumptions underlying the models, and the parameters of interest. We also describe how we estimated certain parameters from actual data to make our model more realistic.

2.1 Normal Vaccination Strategy



2.1.1 Equations Describing the Model

The dynamics of the epidemic is described as

$$P' = -\beta XP - \phi P \tag{1}$$

$$S' = \beta XS \tag{2}$$

$$E' = \beta X(P+S) - \eta E \tag{3}$$

$$A' = (1-p)\eta E - \alpha A \tag{4}$$

$$I' = p\eta E - \sigma I \tag{5}$$

$$H' = c\sigma I - \gamma H \tag{6}$$

$$D' = m\gamma H \tag{7}$$

$$R' = \alpha A + (1-c)\sigma I + (1-m)\gamma H \tag{8}$$

$$F' = \phi P \tag{9}$$

$$X = f_c(c_a A + c_i I) + \delta[f_a(1-c_a)A + (1-c_i)I] \tag{10}$$

And the vaccination effort is described as

$$W(0) = 1 - r \tag{11}$$

$$W' = \phi(W)W \tag{12}$$

$$\phi(W) = \frac{V(t)K}{K+W} \tag{13}$$

$$V = \min\left(\frac{V_1 t}{t_1}, V_1\right) \tag{14}$$

Notations for this model are as follows:

1. r is the percentage of the population that is unwilling to be vaccinated.
2. S is the refuser group, which is rN, where N is the total population.
3. $W(t)$ is the number of people who wants to be vaccinated at a given time, where
4. ϕ is the vaccination rate.
5. K is the W for which the rate is half of the maximum.
6. X is the effective transmitter population, where the infectivities of different classes and mitigation strategies are considered

The Limited Vaccine Distribution Model is based on lectures provided by Dr. Ledder [8]. This model includes realistic assumptions such as vaccine refusal, limited distribution, and limited supply. The model is based on the Michaelis-Menten kinetics.

2.1.2 Assumptions of the Model

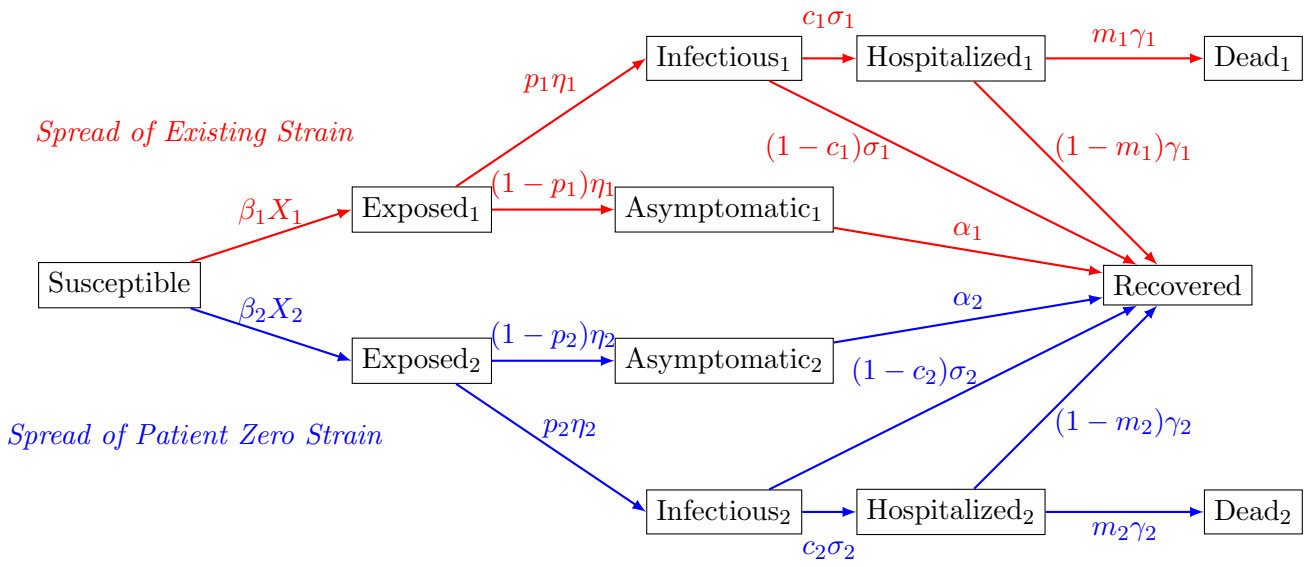
1. The virus does not mutate during the observation period.
2. The vaccine is 100% effective.
3. People in the hospital do not spread the virus.
4. Once a person has been infected, they are immune for the observation period.
5. Infected persons can only end up in two groups: recovered or dead. Long-term side effects are ignored.
6. People cannot change their minds about getting vaccination (r is a constant)
7. The recovered group are not vaccinated
8. Coronavirus restrictions are maintained

2.1.3 Constants & Model Parameters

The current parameters and constants used are displayed in Table 1 with accompanying references. The values are based on COVID-19 Data from December 14, 2020 as the roll-out of vaccination began in the United States.

The values of the parameters are based off of data from December 14 to make the model as realistic as possible. Because December 14 is the start of the vaccination in the United States, we can compare the Normal Vaccination Strategy to the true outcomes of the COVID-19 pandemic and ensure our parameters are realistic. Note that even though parameters of COVID-19 are used in this model, the model can be generalized for other diseases that satisfies the assumptions of the model relatively well.

2.2 Patient Zero Vaccination Strategy



2.2.1 Equations Describing the Model

$$S' = -\beta_1 X_1 S - \beta_2 X_2 S \tag{15}$$

$$E_1' = \beta_1 X_1 S - \eta_1 E_1 \tag{16}$$

$$E_2' = \beta_2 X_2 S - \eta_2 E_2 \tag{17}$$

$$A_1' = \eta_1(1-p_1)E_1 - \alpha_1 A_1 \tag{18}$$

$$A_2' = \eta_2(1-p_2)E_2 - \alpha_2 A_2 \tag{19}$$

$$I_1' = p_1\eta_1 E_1 - \sigma_1 I_1 \tag{20}$$

$$I_2' = p_2\eta_2 E_2 - \sigma_2 I_2 \tag{21}$$

$$H_1' = c_1\sigma_1 I_1 - \gamma_1 H_1 \tag{22}$$

$$H_2' = c_2\sigma_2 I_2 - \gamma_2 H_2 \tag{23}$$

$$D_1' = m_1\gamma_1 H_1 \tag{24}$$

$$D_2' = m_2\gamma_2 H_2 \tag{25}$$

$$R' = (1-m_1)\gamma_1 H_1 + (1-c_1)\sigma_1 I_1 + \alpha_1 A_1 + (1-m_2)\gamma_2 H_2 + (1-c_2)\sigma_2 I_2 + \alpha_2 A_2 \tag{26}$$

$$X_1 = f_{c_1}(c_{a_1} A_1 + c_{i_1} I_1) + \delta[f_{a_1}(1-c_{a_1}1)A_1 + (1-c_{i_1})I_1] \tag{27}$$

$$X_2 = f_{c_2}(c_{a_2} A_2 + c_{i_2} I_2) + \delta[f_{a_2}(1-c_{a_2})A_2 + (1-c_{i_2})I_2] \tag{28}$$

For all of the classes other than S' (susceptibles), we have

$$Y' = \sum_{i=1}^{2} Y_i' \tag{29}$$

2.2.2 Assumptions of Patient Zero Model

1. Neither the original virus nor our vaccine strain mutate during the time period we are examining.
2. Once a person has been infected with either the original strain of the virus or our vaccine strain, they cannot be reinfected with either strain. Nor can they get both at the same time.
3. People in the hospital do not spread the virus.
4. The vaccine we create has a larger infectivity rate and a lower severity factor. Part of the actual study is going to be looking at different magnitudes of difference.
5. Infected persons can only end up in two groups: recovered or dead. We are ignoring long-term side effects.

2.2.3 Constants & Parameters

The current parameters and constants that are used are stated in the following table with accompanying references. The parameters for the existing strain is the same for the Normal Vaccination Strategy as shown in Table 1. Table 2 shows the parameters of the Patient Zero strain.

In order to model the relative transmissibility and severity of the Patient Zero Strain as compared to the existing strain, we introduce M, which we refer to as the *multiplier*. We define the relationships of the parameters between the existing strain and Patient Zero strain as

$$\begin{aligned} \beta_2 &= M \cdot \beta_1 && \textit{Patient Zero Transmission Rate} \\ c_2 &= \frac{c_1}{M} && \textit{Patient Zero Hospitalization Proportion} \\ m_2 &= \frac{m_1}{M} && \textit{Patient Zero Death Proportion} \end{aligned}$$

With $M > 1$, the Patient Zero strain is M times more infectious as compared to the existing strain. At the same time, the Patient Zero strain reduces the proportion of deaths and hospitalization by a factor of M. Hence, the *multiplier* M can be interpreted as the 'efficacy' of the Patient Zero strain.

2.3 Estimation of Parameters

The parameters of the model that we have suggested are either estimated or obtained from publications about the COVID-19 pandemic to make the model realistic. As we ran the simulation of our results, we want to ensure that infection, hospitalizations and deaths correspond to the data for the COVID-19 pandemic in the period of observation.

Therefore, the following parameters are estimated and the methods of estimation are described below:

1. Transmission Rate β
2. Proportion of Hospitalized c
3. Proportion of Death m

2.3.1 Estimation of Transmission Rate

For the transmission rate β, our estimated value is 0.005. Our strategy for estimation is by minimizing the mean squared error of the simulation infections for a given time and reported infections based on the data provided by the New York Times [1].

$$\min_{\beta} \quad \frac{1}{N}\sum_{i=0}^{N}(I_{simulated} - I_{actual})^2$$

With $\beta = 0.005$, this is a relatively small value as compared to other estimates that we found online. A possible reason for this smaller estimate is because our simulation uses per million people for numeric stability, which affects the value of β.

2.3.2 Estimation of Proportion of Hospitalized and Death

Using the same method to estimate the proportion of hospitalized c and death m, the method described above did not work.

The observed period from December 14 2020 and the next 150 days were on a decline, which could not be emulated in our simulations for hospitalization. This is likely because newer methods for treatment are introduced during the period of observation which could have led to the decline of time spent in hospitals [13]. Hence, instead of trying to match every given point, we minimized the absolute difference between the maximum of simulated hospitalization and the maximum of the actual hospitalization.

$$\min_{c} \quad |\max(H_{simulated}) - \max(H_{actual})|$$

Using the method described, our estimate for the proportion of hospitalized was $c = 0.011$ based on the actual hospitalization data [11]. The reason why the maximum of actual hospitalization is used is because we are interested in how much hospital capacity is required for different vaccination strategies.

As for the proportion of death, we estimated $m = 0.176$. We used a similar method since using both mean squared error and mean absolute error yielded the final cumulative death that is approximately 200,000 deaths less than the actual cumulative death. Hence, applying the same method that was used for hospitalizations, we minimized the absolute difference between the maximum of simulated cumulative death and the maximum of the actual cumulative death.

$$\min_{m} \quad |\max(D_{simulated}) - \max(D_{actual})|$$

The results from the estimation, with the proportion of death at $m = 0.176$, is not too different from the data collected by the CDC for in-hospital mortality for COVID-19, with most of the data points in the range of 10% to 15% [4].

3 Results

In this section, we discuss the results of the simulations for both the Normal Vaccination Strategy and the Patient Zero Vaccination Strategy. We compare our main findings between the Normal Vaccination Strategy and the Patient Zero Vaccination Strategy with s multiplier of 2. Then, we compare the impact of the multiplier on the effectiveness of the Patient Zero Vaccination Strategy.

3.1 Normal Vaccination Strategy

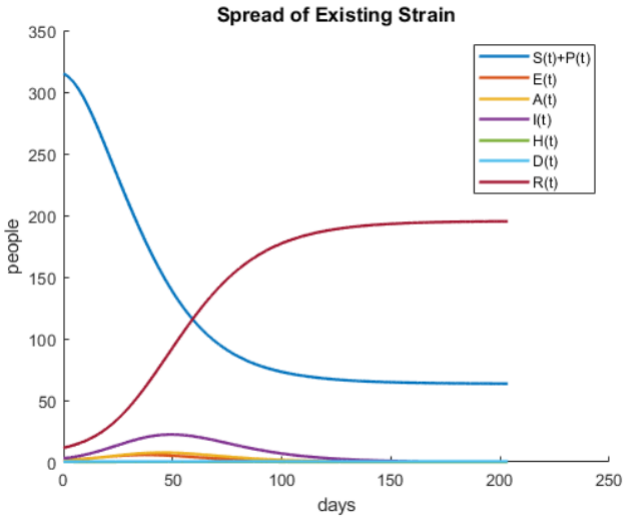


Figure 1: Spread of Strain under Normal Vaccination Strategy

Figure 1 shows the results of the simulation with the normal vaccination strategy. Based on our simulations, the pandemic lasted for 203 days and Table 3 shows the outcome of the pandemic after 203 days.

The overall results of the simulation under the Normal Vaccination Strategy serves as a 'benchmark' for the performance of the Patient Zero Vaccination Strategy. Specifically, we are interested in how a realistic scenario, which we used the COVID-19 Pandemic as the example, would compare against the Patient Zero Vaccination Model.

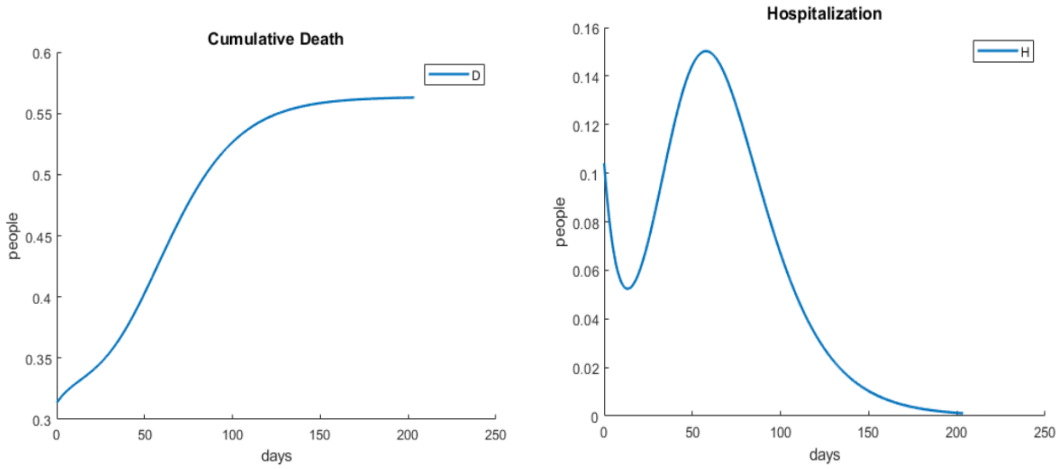


Figure 2: Cumulative Death and Hospitalization

3.1.1 Hospitalization and Cumulative Death

One of the most important outcomes to observe in a pandemic is the resulting cumulative deaths. On the left, Figure 2 shows the cumulative death of the pandemic with the Normal Vaccination Strategy over time. Using our estimated parameters, the actual and simulated cumulative deaths are relatively similar in the period of observation, which reached approximately 600,000 deaths after 203 days from December 14 2020.

As for hospitalizations, our estimation strategy led to a max hospitalization at any given time at around 150,000 patients. This is achieved as a result of our estimation strategy in Section 2.3.2. The resulting hospitalization curve does not perfectly match the actual COVID-19 data, but it does follow a relatively similar trend. Because both cumulative deaths and hospitalizations generally follow actual date, the parameters used in the models are more justified.

3.1.2 Vaccination

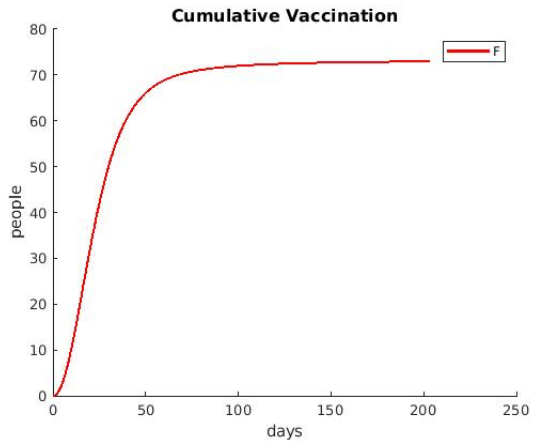


Figure 3: Cumulative Vaccination with Normal Vaccination Strategy

Figure 3 shows the total people vaccinated over the course of the pandemic. Note that the number is about half as small as the real-life number of people vaccinated. However, a plausible explanation is that our model assumes that those who recover from the disease do not get vaccinated, which is unlike the reality of the COVID-19 Pandemic.

Furthermore, the leveling out of the cumulative vaccination over time is realistic because susceptibles can refuse the vaccine. Vaccination is important when comparing the Patient Zero Vaccination Strategy and the Normal Vaccination Strategy because realities such as supply shortages, distribution costs, and vaccine refusal will negatively impact the Normal Vaccination Strategy.

3.2 Patient Zero Vaccination Strategy (Multiplier of 2)

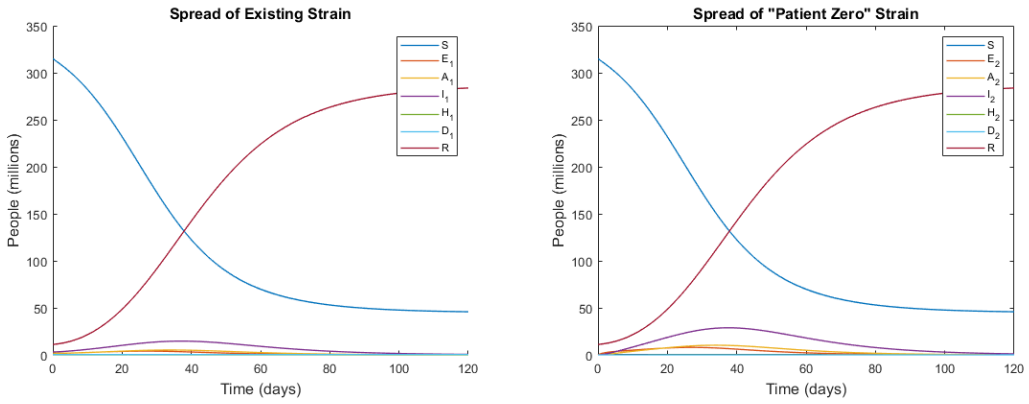


Figure 4: Spread of Both Strains with a Transmission and Infectivity Multiplier of 2

This section focuses on our Patient Zero Vaccination Strategy with a *multiplier* $M = 2$. Hence, the Patient Zero strain is twice as transmissible as compared to the existing stran $\beta_2 = 2\beta_1$ and half as severe, where the proportion of hospitalization is halved $c_2 = \frac{1}{2}c_1$ and the proportion of death is halved as well $m_2 = \frac{1}{2}m_1$.

Here, we based the parameters and initial values of the Existing Strain off of the Normal Vaccination Strategy. However, we increased the infectivity by a multiple of two and reduced the hospitalization and death rates by a multiple of two. As seen in Figure 4, by the end of 120 days there are still roughly 50 million people who are not infected. Table 4 summarizes the outcomes of the Patient Zero Vaccination Strategy with a multiplier of 2 at the end of the pandemic.

3.2.1 Cumulative Deaths

Figure 5 shows a cumulative death count of roughly 389,000 at the end of 120 days. Only 22,000 of those deaths were from the Patient Zero Strain and the deaths have generally leveled off. To put this into perspective, at 120 days there were 546,000 deaths and still increasing. However, these are just the final totals. The initial value of the total deaths was 313,000. So the number of deaths increased by 76,000 in the Patient Zero model and 233,000 in the Normal Vaccination model over 120 days. Therefore, the Patient Zero Vaccination "saved" at least 157,000 lives.

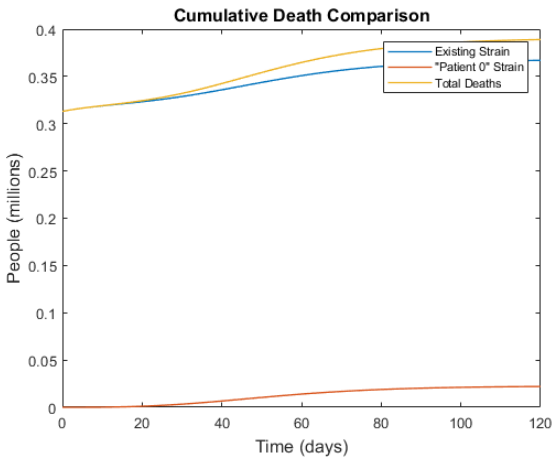


Figure 5: Cumulative Deaths of Existing and Patient Zero Strains with a Multiplier of 2

3.2.2 Hospitalization

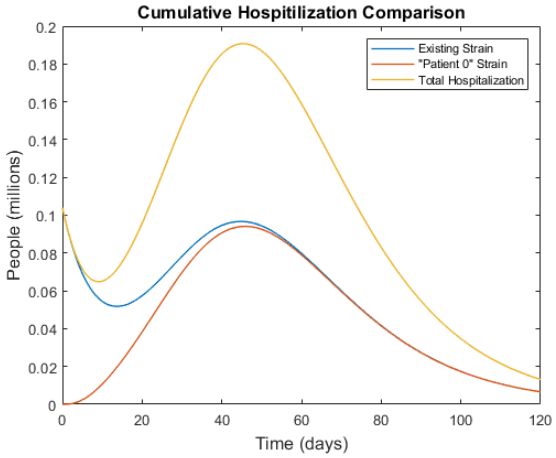


Figure 6: Hospitalization from Patient Zero Vaccination Strategy Multiplier of 2

In Figure 6, we can see the Patient Zero strain does significantly impact the hospitalization. The maximum number of hospitalizations at one time is 190,700. Roughly half of these hospitalizations are from the Patient Zero Strain. This is much higher than the Normal Vaccination Strategy, which peaks at 150,300. It's 40,400 more and this could potentially be too much for the hospital systems to survive.

3.3 Impact of the Multiplier on the Patient Zero Vaccination Strategy

Based on the results shown in Section 3.2, we observe that even though the cumulative death using the Patient Zero Vaccination Strategy is lower than that of the Normal Vaccination Strategy, the maximum hospitalization at a given time as a result of introducing the Patient Zero strain with a multiplier of 2 is significantly higher, with approximately 40,400 more patients hospitalized at its peak. However, this is with a multiplier of 2. This section will explore the impacts of increasing the multiplier all the way to 10 and investigating:

1. Cumulative Death
2. Maximum Hospitalization at a Given Time
3. Maximum Infected at a Given Time
4. Length of Pandemic

3.3.1 Cumulative Deaths

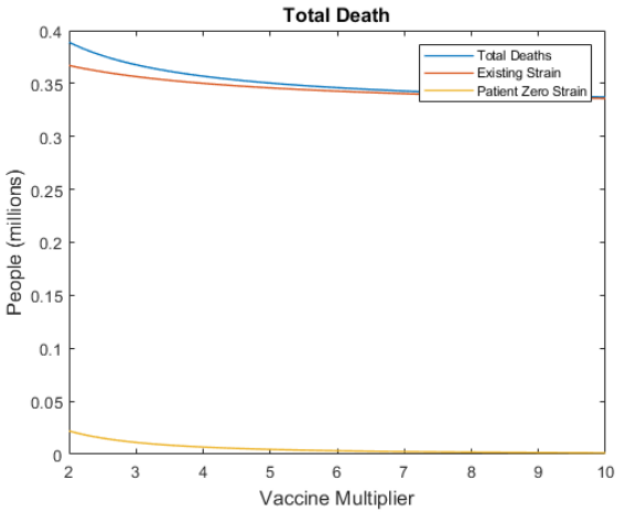


Figure 7: Cumulative Death with Multipliers 2 to 10

The cumulative death as a result of the pandemic is perhaps the most important and significant outcome that we observe. Ranging the multiplier from 2 to 10, we do see that that the total deaths over the course of the pandemic decreases. In fact, as the multiplier gets very large at around 10, the cumulative death of the pandemic is close to the initial death at around 313,501 people on December 14, 2020.

Figure 7 shows that as the multiplier increases, both the deaths caused by the Patient Zero strain and the existing strain decrease as a result. This is promising given that not only does the cumulative death caused by the Patient Zero strain decreases as a result of its reduced severity, but it also reduces the cumulative death of the existing strain since the Patient Zero strain dominates the existing strain and pushes it out.

This has important implications for diseases that have very high death rates, where the reduction of cumulative death can be more significant as compared to the COVID-19 pandemic.

3.3.2 Maximum Hospitalization

Based on Figure 8, the maximum hospitalization at any given time over the course of the pandemic also decreases as the multiplier increases. This is not surprising since the multiplier reduces c_2, the proportion of hospitalization of the Patient Zero strain.

We excluded the the maximum hospitalization caused by the existing strain $\max H_1$ in Figure 8. This is because the maximum hospitalization caused by the existing strain $\max H_1$ for any M in the range 2 to

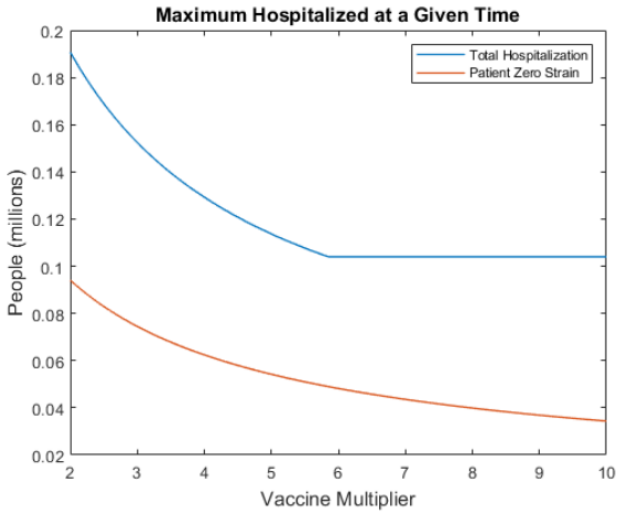


Figure 8: Maximum Hospitalization at a Given Time with Multipliers 2 to 10

10 is the initial hospitalization by the existing strain, or

$$\max H_1 = H_1(0) = 104,189$$

However, despite the fact that the release of the Patient Zero strain leads to reduction of hospitalization caused by the existing strain, it is important to note that for M between 2 to 3, the maximum total hospitalization at a given time is higher than the Normal Vaccination Strategy

$$\max H_1 + H_2 > \max H_{normal\ vaccination} \quad for\ M \in [2,3]$$

This is an important 'side effect' of Patient Zero Vaccination Strategy since with a low multiplier, the possibility of leading to high hospitalizations can overwhelm hospitals. In the event that hospitals are not able to treat all the infected patients that require hospitalization, a triage might be required and that can potentially lead to higher deaths as a result, which is not part of the consideration in our model. Furthermore, it is likely that those who are hospitalized could require further medical treatment as a result of long-term effects of the disease, which we do not model in this paper.

Note that with $M > 6$, the maximum total hospitalization plateaus. This is because if the multiplier is greater than 6, the maximum hospitalization over the course of the pandemic is the initial hospitalization at $H_1(0)$.

3.3.3 Maximum Infected

The maximum number of infected at a given time over the course of the pandemic as a the multiplier changes is shown in Figure 9. From the graph, we can see that $\max I_1 + I_2$ increases as M increases. This should make sense since as M increases, the transmission rate of the Patient Zero Strain β_2 increases, which leads to a high number of infected at a given time.

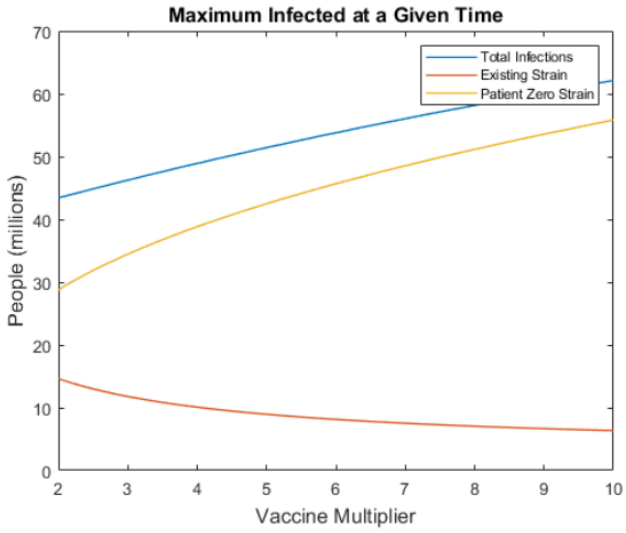


Figure 9: Maximum Infected at a Given Time with Multipliers 2 to 10

However, an interesting result is that even though $\max I_1$ (the infected class as a result of the existing strain) decreases as M increases, the $\max I_2$ (the infected class caused by the Patient Zero strain) increases significantly as M increases. This leads to the total maximum infected increases as M increases.

This observation is important since with a multiplier at $M = 10$, the maximum number of infected, which is defined as those who experience symptoms reach around 60 million people. This can be potentially harmful if a approximately one fifth of the population is not able to work as a result of the infection.

3.3.4 Length of Pandemic

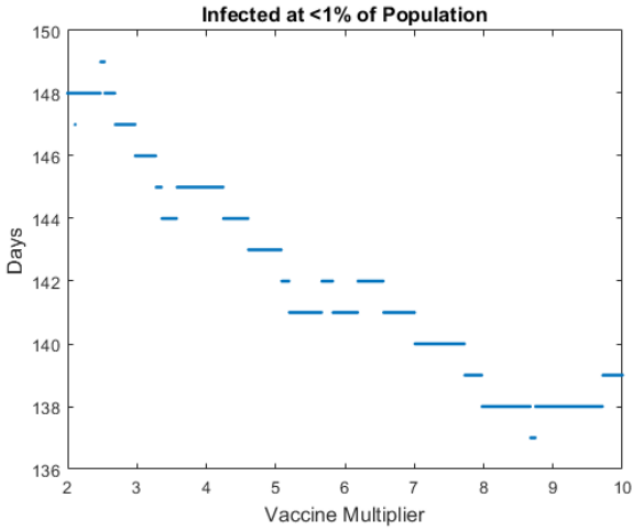


Figure 10: Length of Pandemic with Multipliers 2 to 10

The length of the pandemic as a result of the increasing M is shown in Figure 10. We define the length of

the pandemic as when the number of total infected $I_1 + I_2$ is less than 1% of the total population. As we can see in Figure 10, the number of days required to reach a less than 1% infected population decreases as M increases, albeit not uniformly.

With a higher multiplier M, we are able to reduce the length of the pandemic which can have important economic and social benefits. This is because the reduction in the length of the pandemic means that restrictions on social and economic activities can be lifted earlier, which reduces the costs of lockdowns, school closures etc.

4 Conclusion

4.1 Straightforward Conclusions

The results of our Patient Zero Vaccination Strategy provided significant evidence that this strategy may be viable. Even with a multiplier of 2, the Patient Zero Strategy saved 157,000 lives. Increasing our multiplier up to 10 decreased the final death total even more. Our Patient Zero Strategy also shortened the length of the pandemic. With a multiplier of 2, only 22,000 death resulted from the Patient Zero Strain. This means that roughly 7 lives were saved for every life lost to the Patient Zero Strain. There are quite a few limitations to our project, however, each limitation provides an opportunity for an additional study.

4.2 Limitations and Future Studies

The first limitation of the study is simple: we still don't know if our Patient Zero Strategy is "better". Although we "saved" 157,000 lives, we also put significantly more people into the hospital. The hospitals in the United States cannot hold an infinite amount of people, nor do they have infinite resources. Are the lives saved and a shortened pandemic worth the cost of those hospitalizations? This is a question that a future study could explore. The most straightforward, but still complicated, way of calculation the best strategy is through economics. Calculate the economic costs of deaths, hospitalizations, infections, pandemic length, vaccine distribution, etc. and then generate the final cost of each strategy.

The second limitation is the parameters for our Normal Vaccination Strategy and the Existing Strain. The results of the Normal Vaccination Strategy were sufficiently similar to real life for us to use them for our models. However, they could be made more precise, especially the hospitalization parameters. A future study with better parameters would be important and interesting.

The third limitation is immunity. In the Normal Vaccination Strategy, we assume that vaccinated individuals and recovered individuals cannot get the virus again. In the Patient Zero Vaccination Strategy, we assume that individuals infected by either strain cannot be infected again. Over such a small window of time, these assumptions seem reasonable. It is possible that our Patient Zero Strain would not provide enough immunity, even in that short time frame. A future study could explore partial immunity.

Long-term side effects are another limitation. COVID can effect people weeks after the symptoms are gone and we are releasing a whole new strain. If the new strain adds a large amount of long-term side

effects, the benefits of our strategy will be reduced. A new study could calculate the percentage of people with long-term side effects and work that into a new model.

Mutations are another significant limitation. COVID mutated many times, with the most well-known mutations being Delta and Omicron. If our Patient Zero Strain mutated into something more deadly, that may ruin all the benefits. Research should be done on mutations and hopefully that could be worked into a new model.

The final limitation relates to the ethics of our strategy. We are intentionally infecting people with a man-made virus. The ethics of this don't limit the modeling or the numbers, but it does limit the real-world applications of the study. How could ethics be worked into a study? Recall that the multiplier of 2 produced 7 lives saved for every Patient Zero death. Perhaps a new study could set a ratio threshold, for example 30 lives saved for every death caused, that when reached would force the public to overcome their ethical concerns. With a fixed multiplier, the severity and transmission of could be varied until that goal was reached.

Clearly, this study has many potential avenues of study.

4.3 Acknowledgements

We would like to thank:

Dr. Ledder for inspiring our idea and allowing us to base our Normal Vaccination Model off of his. He assisted us greatly with parameters and the inclusion of COVID response measures. His input allowed us to be confident that we were preceding correctly.

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5 Appendix

Code for Simulation

The code for the simulations can be found in https://github.com/justinhjy1004/Patient_V

Parameter		**Value**	**Reference**
Initial Time	$T_0 = 0$	December 14 2020	[5]
Population	N	331,750,000	[12]
Initial Hospitalization	H_0	104,189	[3]
Initial Death	D_0	313,501	[3]
Initial Infected	I_0	3,120,708	[9] [10]
Initial Asymptomatic	A_0	1,786,907	[9] [10]
Initial Recovered	R_0	11,410,801	[3]
Initial Susceptible	S_0	315,064,317	[3]
Initial Exposure	E_0	680,786	[3]
Proportion that Becomes Infectious	p	0.65	[10]
Proportion of Hospitalized	c	0.011	Estimated
Proportion of Death	m	0.1760	Estimated
Transmission Rate	β	0.05	Estimated
1 / Avg Time in Hospital	γ	0.1163	[10]
1 / Avg Time in Exposed	η	0.5	[2]
1 / Avg Time in Infected	α	0.125	[2]
1 / Avg Time in Hospitalization	σ	0.0746	[2]
Fraction of Infectivity Upon Isolation	f_c	0.1	[8]
Proportion of Asymptomatic without Isolation	f_c	0.6	[8]
Percentage of Detected Asymptomatic Infectives	c_a	0.4	[8]
Percentage of Detected Infectious Infectives	c_i	0.8	[8]
Mitigation Factor	δ	0.2	[8]

Table 1: Parameters for Normal Vaccination Strategy

Parameter		**Value**	**Reference**
Initial Hospitalization	H_0	0	-
Initial Death	D_0	0	-
Initial Infected	I_0	10000	-
Initial Asymptomatic	A_0	0	-
Initial Recovered	R_0	0	-
Initial Exposure	E_0	0	-
Proportion that Becomes Infectious	p_2	0.65	[10]
Proportion of Hospitalized	c_2	c_1/M	Estimated
Proportion of Death	m_2	m_1/M	Estimated
Transmission Rate	β_2	$\beta_1 \cdot M$	Estimated
1 / Avg Time in Hospital	γ_2	0.1163	[10]
1 / Avg Time in Exposed	η_2	0.5	[2]
1 / Avg Time in Infected	α_2	0.125	[2]
1 / Avg Time in Hospitalization	σ_2	0.0746	[2]
Fraction of Infectivity Upon Isolation	f_c	0.1	[8]
Proportion of Asymptomatic without Isolation	f_c	0.6	[8]
Percentage of Detected Asymptomatic Infectives	c_a	0.4	[8]
Percentage of Detected Infectious Infectives	c_i	0.8	[8]
Mitigation Factor	δ	0.2	[8]

Table 2: Parameters for the Vaccine Strain

Class		**Value**
Susceptibles + Prevaccinated	$S_{203} + P_{203}$	63.5195 million
Exposed	E_{203}	0.0100 million
Asymptomatic	A_{203}	0.0212 million
Infected	I_{203}	0.1003 million
Hospitalized	H_{203}	0.0033 million
Deaths	D_{203}	0.5629 million
Recovered	R_{203}	195.1462 million

Table 3: Number of People in Each Class After 203 Days for Normal Vaccine Strategy

Class	**Strain**		**Value**
Susceptibles	-	S_{120}	45.83 million
Exposed	Existing	E_{120}	0.03815 million
Asymptomatic	Existing	A_{120}	0.09363 million
Infected	Existing	I_{120}	0.5324 million
Exposed	Patient Zero	E_{120}	0.07629 million
Asymptomatic	Patient Zero	A_{120}	0.1873 million
Infected	Patient Zero	I_{120}	1.064 million
Hospitalized Total	-	H_{120}	0.01314 million
Death Total	-	D_{120}	0.389 million
Recovered	-	R_{120}	283.8 million

Table 4: Number of People in Each Class After 120 Days for Patient Zero Vaccine Strategy (M = 2)