How the U.S. Reacted to COVID-19

States' Responses to Alpha and Delta Variant

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November 8th, 2021

Contents

1 Introduction

1.1 Model Terminology

Ordinary Differential Equations

Epidemiology is the method used to find the causes of health outcomes and diseases in populations [6].

Infectious Disease is a clinically evident illness resulting from the presence of a pathogenic microbial agent, which can be bacterial, viral, fungal, parasitic, or toxic proteins [4].

Susceptible Individuals are the class of individuals who are healthy but can contract the disease [4].

Vaccinated Individuals are the class of individuals who have been vaccinated [4].

Exposed Individuals are the class of individuals who are vulnerable to contracting a disease that makes a potentially disease-transmitting contact. They may or may not develop the disease and are assumed not infectious [4].

Infected Individuals are the class of individuals who have contracted the disease and are now sick with it. It assumed that infected individuals are infectious [4].

Recovered Individuals are the class of individuals who have recovered and cannot contract the disease again [4].

1.2 Motivation

We were encouraged to learn more about the Coronavirus disease (COVID-19) after learning about statistical testing and ordinary-differential equations modeling. After looking at the proposed questions about COVID-19, we agreed to research and implement: "Modeling different US states' effectiveness of controlling the alpha and delta variant and the relationship between them (SEIR)." We are encouraged to produce epidemic models to illustrate how different U.S. states reacted to the delta variant versus the alpha. Specifically, this question was proposed after learning about the SIR model from Dr. Ledder's PowerPoint [16]. We hoped to reproduce a model that mimicked the SIR model presented in class. We kept susceptible individuals (S), infected individuals (I), and removed/recovered individuals (R). We were also motivated by Dr. Chayu Yang after his presentation about COVID-19 modeling, which ultimately provided us a backbone for our SEIR model, and this introduced another class of individuals: exposed individuals (E). With some minor background research and the information gathered from class lectures, we decided to use differential equations to model our project.

1.3 Goal and Methods

The SEIR model is abbreviated for susceptible, exposed, infectious, and removed individuals. To be as thorough as we could be in this research, we decided to focus our studies on four states. We wanted to study states that differentiated from each other significantly to study how governmental responses and other key factors relate to the growth and/or decline in COVID cases. We were motivated to use this modeling to numerically analyze how the states have chosen (California, Oregon, Tennessee, Vermont) compared to one another in the effectiveness of controlling the alpha and delta variants. One of the aims is to provide scientifically reasonable explanations for any increasing or decreasing trends among the states with COVID-19. To account for both variants is crucial in studying this epidemic as we hope to show how the four states performed with both variants. Our method of choice is to create a working code to visually graph the four individual classes for each variant of each state chosen. Our programming language of choice is MATLAB as we have had previous experience with it in class.

1.4 Significance

This research is significant by creating reliable illustrations given certain parameters, the model can be used to develop hypothetical graphs when studying infectious diseases. Also, this research will show the drastic differences between states that reacted quickly and effectively compared to states that were not as reactive. A component that we highly emphasized was studying not only the states' reaction to COVID-19 but states' initial response to the pandemic. For example, we specifically wanted to study how the states responded to the pandemic, but also if and how they changed their protocols from the initial wave of the pandemic to the second. We wanted to develop illustrations that not only explain why some states had a larger outbreak than others but also create a reliably precise model to estimate how states will be affected by certain parameters. With our MATLAB knowledge, we want to create a program that can estimate the number of cases throughout a long period with different numerical values for the parameters. Questions that we would want our model to answer are: If the vaccination rate was higher, how would the number of cases change throughout time? How does the graph of a state with a low infection rate compare to one with a high infection rate? If we changed any parameters, how does the state's graph change? This program will provide evidence for assumptions made concerning infectious diseases. For example, the assumption can be made that if the infection rate is higher, then the cases of infection will also increase. Our program will allow for that assumption to be studied and the graph to be constructed for further analysis. Not only do we want our research to create illustrations from our data, but to also create mathematical simulations. We want to see how changing the parameters affects each state's response to the alpha and delta variant.

1.5 Overview of Project

Our research was to determine what factors led to four different pandemic outcomes by comparing the states chosen. By using consensus, we chose a state for each of the following outcomes:

1. Vermont - (good alpha, poor delta).
2. Oregon – (good alpha, good delta).
3. California – (poor alpha, good delta).
4. Tennessee – (poor alpha, poor delta).

The first state we chose was Vermont; it is widely agreed upon that Vermont handled the pandemic well for the initial wave and the delta wave [3]. Despite being neighbors with Boston and New York, Vermont has the lowest total case and death count in the United States. Vermont put in place government restrictions early and has been slow to remove restrictions and to reopen its economy. Vermont has a low population density and has the second smallest population in the United States [5]. Another factor in Vermont's success in key metrics is that it leads the United States in vaccination rate [7].

Oregon's response to the first wave put it towards the top of the United States in cases and deaths, but the state's delta response has lagged in comparison. By mid-March of 2021, Oregon was in the bottom 5 states for cases and deaths [8] [9]. However, several factors contributed to a poor second response and hospitals reaching capacity during the delta wave. The early success of the state may have played a role due to the low exposure rate in the first wave. Low immunity rates coupled with a low vaccination rate in rural counties have contributed to much higher delta numbers. Oregon also has the second-lowest number of hospital beds in the country [18].

California was hit hard early in the pandemic and ranked very low for the first wave in cases and deaths. However, the state has been more successful during the second wave. Even with its large population and population density [5]. It also had some of the strictest government regulations in the United States [14]. The early struggles with California are most likely due to key factors such as its high population density, homeless population, and climate. Over half of Californians live in high-density areas. The high numbers early may have benefited from the delta surge due to a lower vulnerability rate among the population [15].

Lastly, we looked at Tennessee who has maintained a high caseload and high death rate throughout the entire pandemic[8] [9]. It left most of the government regulation to the local communities and never issued a statewide mask mandate. It also sits towards the bottom in a population vaccinated. The state has remained open for most of the pandemic [14].

The data we will be looking at for each state are cases, hospitalizations, and deaths per 100,000, population demographics, infected fatality rate, and government regulations and mandates. We will then compare that information across states for the first and second waves of the pandemic. By heavily relying on our MATLAB code, we will conclude and analyze our findings based on the graphs constructed from our code.

1.6 Summary

This report will ultimately reveal our conclusion regarding the impact of states' response to both the alpha and delta variants. Our original assumption was that states have four possible results when dealing with the COVID-19 pandemic. The possible outcomes for each state are either (1) good alpha and good delta, (2) good alpha, bad delta, (3) bad alpha, good delta, or (4) bad alpha, bad delta. We have chosen four states to thoroughly analyze to support our assumption. By using MATLAB and the parameters that are discussed in our methodology section, we will provide illustrations to accompany our claims. The states chosen (California, Oregon, Tennessee, and Vermont) will confirm our assumption by the simulations provided and analysis of the parameters. From government interference to infection rates, we will see how each contributing factor affects each state's SVEIR model in dealing with the alpha and delta variants of COVID-19.

1.7 Advantages

Ordinary differential equations are beneficial in studying how states are changing via their models. One benefit from using a model, compared to statistical testing to obtain a certain p-value, is that statistical testing determines if there is enough evidence that an alternative hypothesis is true, but not why. When we analyze changes in parameters, we can scientifically propose a hypothesis and change a parameter to see if our assumption was correct. The SVEIR model we chose can predict how likely a certain protocol is to be effective in a pandemic. For example, a mathematical model can predict and provide evidence to see if a lockdown protocol benefits the whole population based on previously developed models of infectious diseases.

2 Data

Table 1 on the next page shows the state demographic information for Vermont, Oregon, California, and Tennessee. The states vary widely on population density, with Oregon having the least and California the highest. The total population is also divided into risk categories for COVID-19, low risk, medium risk, and high risk. The low-risk category has the age range of 0-34, the medium risk is 35-64, and the high risk is age 65 and up. Table 1 shows the percentage of the population for each age group. One observation from this table is that Vermont and Oregon have the highest percentage of high-risk populations and the highest median age. However, Oregon still did the best in terms of cases and deaths for both the alpha wave and delta wave. When analyzing how each state dealt with COVID-19 we wanted to look at the demographics of each state to see if those played a role in how effective each state was.

Table 1: States demographic Information [5]

State	**Population Density**	**Median Age**	**Low Risk(0-34)**	**Medium Risk(35-64)**	**High Risk(65+)**
Vermont	69	43	38	40	22
Oregon	44	39	42	38	20
California	253	37	46	38	16
Tennessee	167	39	43	37	16

Tables 2, 3, and 4 show the data related to cases, hospitalizations, and deaths. These are broken down into cumulative, first wave, and second wave. It also shows the total percentage of the population vaccinated as of the beginning of October 2021 and the Infected Fatality Rate for each state. The numbers describe the trend mentioned in the overview with how states performed in each wave of the pandemic. These numbers were gathered to help with the creation of our model and to use as one metric of how each state performed during the pandemic. Also, to determine how preventative measures and demographics played a role in state outcomes.

Table 2: States Total COVID-19 Information (Oct. 1) [5] [8] [10] [9] [7]

State	**Population**	**Total Cases**	**Total Hospitalizations**	**Total Deaths**	**Percentage Vaccinated**
Vermont	645,077	5,349	238.11	50.07	67.49
Oregon	4,237,256	7,944	414.25	91.26	61.01
California	39,538,223	12,017	721.78	175.78	59.45
Tennessee	6,910,840	17,960	1054.72	222.80	45.47

Cases, Hospitalizations, and Deaths per 100,000

Table 3: First Wave (Alpha) [8] [10] [9]

State	**First Wave Length**	**Cases**	**Hospitalizations**	**Deaths**	**Case Fatality Rate**
Vermont	Jan. 1, 2020 - June 1, 2021	3,512.60	168.82	38.45	1.09
Oregon	Jan. 1, 2020 - June 1, 2021	4,758.95	231.92	63.11	1.33
California	Jan. 1, 2020 - April, 1 2021	7,441.23	528.75	156.14	1.65
Tennessee	Jan. 1, 2020 - May 1, 2021	12,233.81	698.06	176.91	1.45

Cases, Hospitalizations, and Deaths per 100,000

Table 4: Second Wave (Delta) [8] [10] [9]

State	**Second Wave Length**	**Cases**	**Hospitalizations**	**Deaths**	**Case Fatality Rate**
Vermont	July 1, 2021 - Current	1,483.23	99.06	9.77	0.66
Oregon	July 1, 2021 - Current	3,085.06	201.62	27.87	0.90
California	June 1, 2021 - Current	2,282.71	188.10	15.33	0.67
Tennessee	July 1, 2021 - Current	5,493.17	362.99	41.89	0.76

Cases, Hospitalizations, and Deaths per 100,000

Table 5 shows the measures that each state took due to the COVID-19 pandemic. The different measures being, state of emergency orders, stay at home orders, and mask mandates. The dates for each preventative measure are indicated in the table. Government intervention was another metric we wanted to use to see how it affected each state's performance. Vermont and Oregon had strict mandates at the beginning of the pandemic. Vermont has been cautious as it has tried to roll back on restrictions while Oregon removed most restrictions after the first wave. This could be one reason Oregon struggled during the delta wave. California has had the strictest measures and continues to have strict government-imposed mandates. Likely due to population density and climate, these mandates were less successful than Vermont and Oregon. Tennessee has been reluctant to impose mandates. This has probably led to higher numbers of cases and deaths, as well as a shorter wavelength during the first alpha wave as shown in Table 3.

Table 5: State Government Regulations [14]

State	**State of Emergency**	**Stay At Home Order**	**Statewide Mask Mandate**
Vermont	3/13/2020 - 6/15/2021	3/25/2020 - 5/16/2020	8/1/2020 - 6/14/2021
Oregon	3/2/2020 - Current	3/25/2020 - 5/20/2020	6/1/2020 - 6/30/2021 and 8/30/2021 - Current
California	3/4/2020 - Current	3/20/2020 - 6/15/2021	6/18/2020 - Current
Tennessee	3/12/2020 - Current	4/2/2020 - 4/30/2020	N/A

3 Methodology

3.1 Assumptions of the Model

Our model consists of 7 classes: Susceptible, Vaccinated, Exposed (alpha), Exposed (delta), Infected (alpha), Infected (delta), and Recovered. The susceptible class consists of anyone that has never gotten the virus or anyone that has lost natural immunity to the virus. The susceptible class has outward flows to both exposed classes and the vaccinated class, with an inward flow from the recovered class. We have split up the exposed and infected classes into two sub-classes. This is because the alpha and delta COVID variants have much different infection and incubation rates and therefore should be separated. Also, we are interested in seeing the connection between the two variants, and having a subclass that separates the two will allow for better analysis, specifically how early control of the virus affects the later stages of the pandemic. The inclusion of any exposed class allows for the model to account for the amount of time between exposure and actual infection of the virus, which affects the total time spent with the disease (either as latent or infectious).

The outward flow to the exposed class will account for anyone that has come in contact with the virus and has entered the incubation period. The flow to the vaccinated class accounts for anyone that has been fully vaccinated. The inward flow from the recovered class is meant to account for those individuals that have gotten the virus, however, their natural immunity fails to protect them. Both of the exposed classes have inward flows from the vaccinated and susceptible classes respectively and an outward flow to the infected classes. This means that both exposed classes will be populated with unvaccinated and vaccinated individuals that have come in contact with someone with COVID and are in the incubation period. The outward flows will account for those individuals that have passed the incubation period and are now infectious. The infected classes have one inward flow from the exposed class of the same variant and one outward flow towards the recovered class. The inward flow is the same as the outward flow of the exposed class, those individuals that have passed the incubation period and have contracted the virus. The outward flow represents those individuals that have fully recovered from the virus and are no longer infectious. The recovered class has two inward flows, one from each infected class, representing those that had the virus and are no longer infectious. The recovered class also has an outward flow that will represent those who had the virus, but their natural immunity has failed and they are susceptible to catching the virus once again. The vaccination class will not be implemented in the model until our start date for the delta variant, this is because the various vaccines were not available during the alpha variant waves.

3.2 Evaluation of Rates in Model

3.2.1 Infection Rate

Because the COVID 19 pandemic is ongoing, it is difficult to explicitly derive infection rates because there is no data on how many people escaped the virus. Therefore, we are using a collection of other models of infection rates and infection rates of other diseases to help build our infection rates. For models that maintain the basic structure of our model, ie. they follow an SEIR or SIR base model, they use visual analysis and trial and error methods to calculate infection rates. The reasoning behind this was the fact that other models that used predictive and best-fit methods produce results that do not follow the actual results as well as the trial and error methods. For our program, we also used visual analysis and trial and error methods to create our model.

An article published in the US National Library of Medicine gives models of China, South Korea, India, Australia, USA, Italy, and the State of Texas [2]. The inclusion of Texas provided an infection rate that could be used as a baseline for the states we are modeling. Using the CDC Covid Data Tracker to provide side by side comparison of infection data allowed for visual analysis and a better-informed trial and error process. The infection rate associated with Texas in the model created by Cooper, Mondal, and Antonopoulos was 0.130. Comparing that with the influenza infection rates derived from the case study at the school, where infection rates were in the range of 0.01 and 0.03, it appears that COVID is the more powerful virus, by a wide margin [2].

For our four cases/states, each will have a different infection rate for the alpha variant. Tennessee and California had an explosion of COVID cases at the forefront of the pandemic, therefore the infection rates of alpha, before the presence of the delta variant will be in the area of 0.130 and 0.140, seeing as these two states had similar alpha variant waves as Texas. California will be similar to Texas, mainly because of the length of the stay-at-home order issued by the state in tandem with the inspection of case rates per 100k on both the cumulative and logarithmic scale. Tennessee only had a very short stay-at-home order and also never had a statewide mask mandate in effect (moreover, very few Tennessee counties adopted a mask mandate). Inspection of Tennessee's case rate per 100k on the logarithmic and cumulative scale compared to Texas produced similar results as California, therefore they will be on the higher end of this range. Vermont and Oregon were consistently below average in terms of cases compared to the US average and therefore will have infection rates between 0.100 and 0.110. Vermont was the shining star in terms of case rate for the alpha variant, being consistently well below the US average, meaning Vermont will have an infection rate on the lower end of the range. Oregon was consistently slightly below the US average throughout the alpha variant wave and therefore will be more towards the higher end of the range. Inspection of case rates per 100k on the logarithmic and cumulative scale solidifies this assumption.

For the delta variant, Ashley Hagen states that the delta variant for COVID-19 is 40-60% more infectious than the alpha variant [13]. Once again the use of numerical analysis and trial and error will help further inform our infection rates for the delta variant. That being said, the use of a multiplier between 1.4 and 1.6 will be applied to produce the initial value, they will be adjusted based on infection data from the start of the delta variant as well as the use of preventative measures in each of the four states within the scope of this project.

3.2.2 Incubation Rate

The incubation rate is independent of the states, seeing as its disease-dependent. The mean incubation period for the alpha variant is about 5.6 days [17]. The technical range of possibilities is 2-14 days, with the higher limit of the range being more likely. However, we will be using the average time. For the delta variant, the incubation period is slightly smaller, maintaining an average of 4 days.

3.2.3 Recovery Rate

The CDC outlines that the typical amount of time from the end of the incubation period and the end of the infectious period is on average 10 days [11].

3.2.4 Loss of Immunity Rate

The loss of immunity rate depends on one factor, natural immunity. For the time pre-dating vaccines, natural immunity was the only protection available against COVID, outside of masks and other preventative measures (these preventative measures do not, however, provide immunity).

The World Health Organization states that those who have been infected with COVID will start to develop antibodies within two and four weeks post-infection and will eventually have robust levels of antibodies, regardless of whether they had symptoms or not. 80-90% of people that previously had the virus will avoid reinfection for up to seven months, with it being known that 94% of symptomatic people will avoid reinfection [19]. Using this data and numerical analysis/inspection, the loss of immunity rate will be 0.012.

3.2.5 Vaccination Rate

The vaccination rate will be based on the total population that is fully vaccinated to the current date. This ranges from 47% to 68%, depending on the state [20]. It was established in the COVID-19 model created by Thomas Usherwood, Zachary LaJoie, and Vikas Srivastava that a slow vaccination rollout accounted for 0.1% of the population, an average rollout of 0.3%, and a fast rollout of 0.5% [20]. Once again using numerical inspection and trial and error, 0.001 and 0.005 provided results that were on par with the total vaccinated percentage of each given state. 0.003 saw the vaccinated population increase to just under 50% of the population and 0.005 around 65%. These numbers are very much in line with the actual vaccination status of each of the states within the scope of this report.

3.2.6 Vaccination Immunity Rate

During the delta variant period, vaccines became available. According to Science Direct, 95% of individuals will avoid alpha variant infection [12]. Also, according to NEJM, those with the Pfizer or Moderna vaccines, which are the most common in the US by a wide margin, 88% will avoid delta variant infection [1]. For the individuals that go to the vaccinated class, it is still possible to contract the virus before going to the recovered class. Similar to the loss of immunity rate, the Pfizer and Moderna vaccines have 95% and 88% efficacy, respectively, against the alpha and delta variants. Therefore, 92% of the vaccination class will avoid reinfection. More people avoid reinfection with the vaccine than those who have contracted the virus. Thus the rate of infection for the alpha variant in the vaccinated population will be 0.006 and for the delta variant, 0.008, due to the delta variant being 40-60% more infectious.

3.3 Illustration of Model

Based on the assumptions of our model and the discussion of rates, we decided to construct a model as outlined in Figure 1.

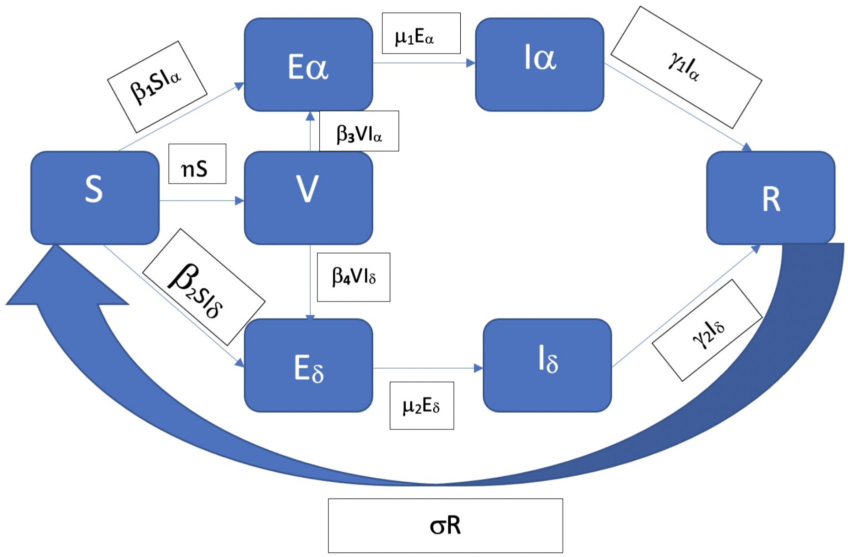

Figure 1: SVEIR model

The flow of our model has illustrated above. We have three outputs from the susceptible class: exposed alpha variant class, vaccinated class, and exposed delta variant class. At the end of each flow is the recovered class which returns to the susceptible class. In between, each class is the calculations needed to determine the value of the next class.

3.4 Parameters of the Model

Parameter	Description of Parameter	Range of Values
$\beta_1 > 0$	Infection Rate from Susceptible class to Exposed (alpha variant) class	0.1058 - 0.1300
$\beta_2 > 0$	Infection Rate from Susceptible class to Exposed (delta variant) class	0.1665 - 0.2000
$\beta_3 > 0$	Infection Rate from Vaccinated class to Exposed (alpha variant) class	0.0060
$\beta_4 > 0$	Infection Rate from Vaccinated class to Exposed (delta variant) class	0.0080
$\mu_1 > 0$	Incubation Rate from Exposed (alpha variant) class to Infected (alpha variant) class	0.18
$\mu_2 > 0$	Incubation Rate from Exposed (delta variant) class to Infected (delta variant) class	0.25
$\gamma_1 > 0$	Recovery Rate from Infected (alpha variant) class to Recovered class	0.10
$\sigma > 0$	Loss of Immunity Rate	0.0120
$\eta > 0$	Vaccination Rate	0.0030 - 0.0060

3.5 Differential Equations

$$S' = -\beta_1 S I_\alpha - \beta_2 S I_\delta + \sigma R - \eta S$$

$$E'_\alpha = \beta_1 S I_\alpha + \beta_3 V I_\alpha - \mu_1 E_\alpha$$

$$E'_\delta = \beta_2 S I_\delta + \beta_4 V I_\delta - \mu_2 E_\delta$$

$$V' = \eta S - \beta_3 V I_\alpha - \beta_4 V I_\delta$$

$$I'_\alpha = \mu_1 E_\alpha - \gamma_1 I_\alpha$$

$$I'_\delta = \mu_2 E_\delta - \gamma_2 I_\delta$$

$$R' = \gamma_1 I_\alpha + \gamma_2 I_\delta - \sigma R$$

4 Results and Analysis

4.1 Standard Vaccination Rate

Standard Vaccination Rate:

The use of a standardized vaccination rate is essential in determining if a proactive response to the alpha variant wave generates long term success. The vaccination rate is set at 0.0035 and will start after the first 365 days. This will create a vaccinated population of around 50% of the total population, depending on the state. This translates to a true medium-speed vaccination rollout. Infection rates will be state-specific, seeing as the four relevant cases are covered by each state within the scope of our project.

Tennessee was the worst in terms of early control of the alpha variant, reaching a maximum of 0.0314 infected between days 212.6 and 226.3. This caused the susceptible population to reach a minimum of 0.7368 between day 285.1 and 294.3 as well as causing the recovered class to reach a maximum of 0.2214 between day 301.8 and 306.7. The number of people within the alpha variant infected class after a year was 0.0232. The susceptible class ended the first year's simulation with a population of 0.7515, or 75% of the population, staggeringly low given that there is no vaccine to remove people from the susceptible population. The recovered class had 0.2125 within it at the end of the first year. The infected population closed the simulation out slowly decreasing, indicating that the peak of the alpha variant could have been reached, however, there are still enough infected people within the class that it is far from its end. It is worse to contract the virus than it is to not, but those that survive and enter the recovered class will gain natural immunities to decrease the likelihood of contracting the virus another time. Therefore, having 21.25% of the population end the first year with some form of immunity can be considered to be some form of control of the virus, albeit a very dangerous one.

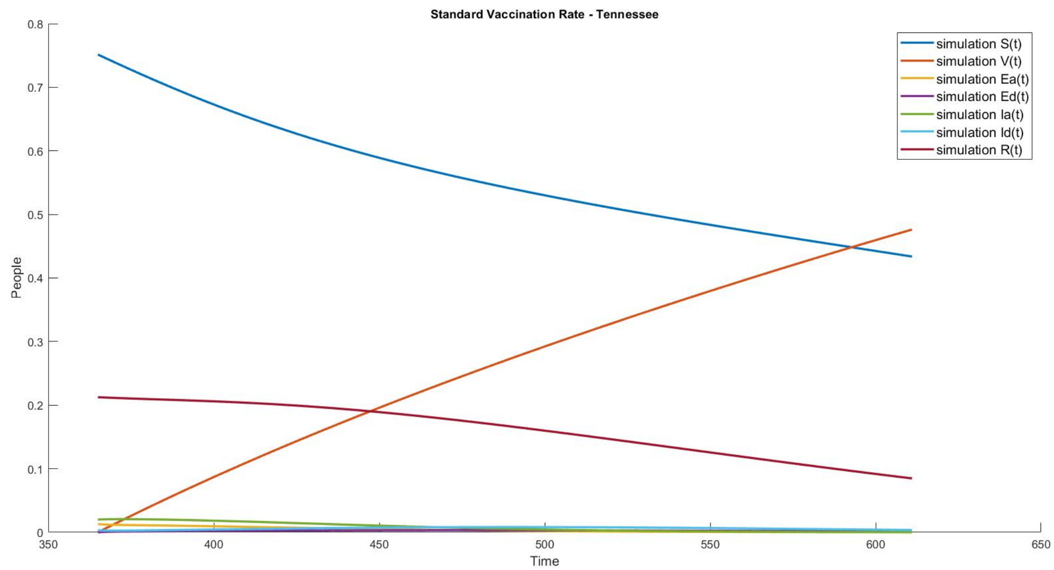

Figure 2: Tennessee Static Vaccination Rate

For the start of the second period, in which vaccinations and the delta variant were added, 13.7% of those infected with the alpha variant were switched to being infected with delta. This created a dynamic within the model where the alpha variant would be overtaken by the delta variant after around 100 days, a very similar timeline to that of the actual United States. Therefore, the initial value for the alpha infected class was set at 0.0200 and the delta variant infected class initial value was set at 0.0032. The alpha variant infected class reached a maximum of 0.0207 very early on in the second simulation, occurring between days 369.3 and 375.2. This was a marginal increase and it should be noted that it fell each day after that, eventually ending the simulation at 0.0003, effectively removing the worry of the alpha variant. Because the alpha variant reached its maximum number of infections so early on, the maximum number of total infected, those with either strain of COVID, reached its maximum value of 0.0235 between days 374.2 and 380.4. This is very early and it shows signs indicating a successful response to the breakout delta variant. That being said, the next data set to look at is that of the delta-infected class. This class reached a maximum of 0.0083 between day 484.2 and 495.9, a number that is substantially less than the maximum number of alpha infected during the first year, once again an indication that there was a successful response to the breakout delta variant. After the simulation, the vaccinated class grew to a population of 0.4762, or 47.62% of the population, and the susceptible population decreased to a population of 0.4337, or 43.37%. The number of alpha and delta-infected people on day 611 was 0.0003 and 0.0036, respectively. Both sit at values much less than the maximum and, specifically for the delta variant, reaching a number for which there is little concern. Overall, despite the dismal initial response to the alpha variant of COVID, the presence of a vaccine, with an extremely average rollout, was able to prevent a huge outbreak and therefore limit the damages that the more dangerous delta variant is capable of. That being said, it is important to note that while the delta wave was effectively controlled via the vaccine, the initial response endangered a large section of the population, which therefore somewhat cancels out the later success of the state. It is also important to note that these results were primarily attributed to the vaccination rate as we will discuss later when the actual vaccination rate for the state was used in the model.

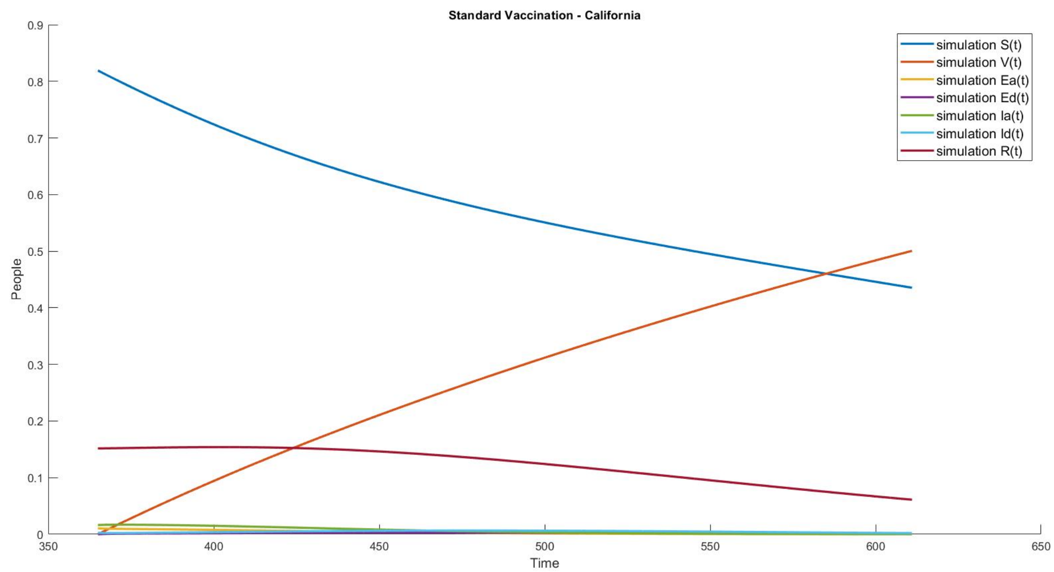

Figure 3: California Static Vaccination Rate

California is the next state to be put under the microscope of the model. Similar to Tennessee, the initial response to the alpha variant of COVID was poor relative to the rest of the US. Interestingly, California hit its critical values late within the simulation compared to Tennessee. The maximum alpha variant population was 0.0199 and occurred between days 288.2 and 293.3. Both the recovered class and the susceptible class reached their respective critical values on the final day of the simulation. The minimum for the susceptible being 0.8191 and the maximum for the recovered being 0.1516. The alpha-infected class ended the first year with a population of 0.0189. The slow reduction of those within the alpha variant infected class is a good sign that the brunt of the initial wave has passed. California ended up in a weird position after the first year in terms of those within the recovered and susceptible classes. 81.91% of the population will remain defenseless against COVID entering the second period, which is more than Tennessee but still less than the states with a successful response to the alpha variant wave. The recovered class reaching its maximum of 15.16% of the population on the final day indicates that it is still growing and that there will be even more people that will gain natural immunity before the delta variant hits its full stride during the second period.

As always, 13.7% of the alpha variant infected population was changed to delta variant due to the timeline for when the delta variant overtakes the alpha variant in terms of their respective class populations. Therefore, the alpha variant class started the second period with a population of 0.0163 and the delta variant class started with a population of 0.0026. The alpha variant marginally increased to 0.0169, hitting that mark between day 369.9 and 374.9. At the end of the simulation, the population of the alpha variant infected fell to 0.0002, a seemingly negligible value. The maximum delta variant population of 0.0066 occurred between days 472.6 and 484.9. A value that is much smaller than Tennessee, but that is to be expected considering the infection rates of both the alpha and delta variants for each respective state. Similar to Tennessee, the combined infected maximum occurred relatively early in the simulation for California. The value was 0.0192 and it occurred between day 374 and 385.6. This is encouraging seeing as the maximum total infected population just barely eclipsed the final alpha variant infected population of the first year simulation and also that a majority of the cases in this combined population is alpha variant cases and not delta variant cases. The maximum recovered class population is 0.1539 and also occurred relatively early in the simulation between day 397.7 and 406.1. This means that the amount of infected entering the recovered class slowed down enough for the outward flow of people back into the susceptible class to be larger, effectively creating a larger population to get vaccinated. The simulation finished with a susceptible population of 0.4354 coupled with a vaccinated population of 0.5006. The final values of the alpha and delta variant infected population were 0.0002 and 0.0020 respectively. This is very encouraging in the long run seeing as these are not worrying values for any time after day 611. Overall, the vaccine was able to save California from a delta-driven disaster, however, similarly to Tennessee, the initial response to COVID is a cause for concern. That being said, California was overall better than Tennessee throughout both simulations.

Oregon during the initial wave has staggeringly different results than both California and Tennessee. The state reached its maximum alpha infected population of 0.0076 between days 352.7 and 365, notably ending the simulation off at the maximum value. The minimum number of susceptibles also reached its critical value at the end of the simulation, establishing a minimum value of 0.9307. This is a very good result, seeing as 93.07% of the population avoided COVID infection going into the second period. However, this also presents some issues. If the suppression of the virus is not maintained throughout the delta variant wave, the state will have left a huge number of people vulnerable to the more dangerous virus. Unsurprisingly, the maximum recovered class population of 0.0574 was also found at the end of the first simulation. This is a low number of people that have natural immunity protection entering the delta variant wave. The maximum occurring at the end of the simulation suggests that the absolute maximum for the alpha variant infected population has yet to be reached, however, this is not as worrying as it would have been for a state like California or Tennessee. Based on the trend of the graph, it is doubtful the maximum would have reached a number much above 0.01, let alone 0.02.

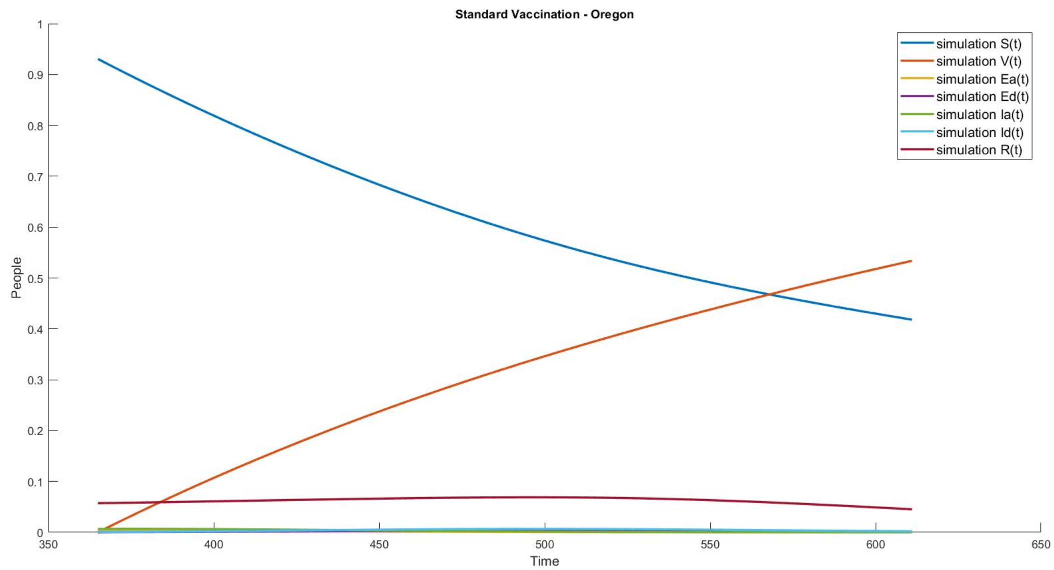

Figure 4: Oregon Static Vaccination Rate

Transitioning into the delta variant wave, Oregon found great success throughout as well. The maximum population of the delta variant infected class was 0.0068 and occurred between day 488.5 and 506.2, eventually regressing down to 0.0021 at the end of the simulation. These values are higher than that of California. This is primarily a result of the much higher susceptible class that resulted in Oregon, causing the delta variant to take hold quicker. The alpha variant had a similar trajectory in Oregon that it did in California and Tennessee, seeing a marginal bump from 0.0066 to 0.0069 on day 369.5. Similarly as well, the alpha variant infected class regressed throughout the rest of the second period, ending the simulation at 0.0000. Clearly showing that the alpha variant is a non-issue in the long run. The recovered class maximum was 0.0688 and occurred between day 488.5 and 503.6. This is a success seeing as the recovered class never exceeded 0.1 in either period. There were more susceptible people in Oregon, therefore the vaccinated class grew slightly larger than it did in California and Tennessee, reaching a final value of 0.5338. The susceptible population ended the simulation with 0.4181. Overall, Oregon found success through the delta variant wave, suppressing the amount of delta and alpha infected via the inclusion of the vaccine as well as the overall response from the state. This success is also compounded with the fact that Oregon was so successful during the alpha variant wave. 93% of the population entered the delta variant wave with no natural immunity and the recovered class still never eclipsed 10% of the population. An excellent showing from Oregon, setting the gold standard for other states to follow.

Vermont found early success against COVID, producing results that are very similar to that of Oregon. The first commonality is found when the critical values for each class occurred, being at the end of the simulation. The maximum for the alpha infected class was 0.0052 and occurred

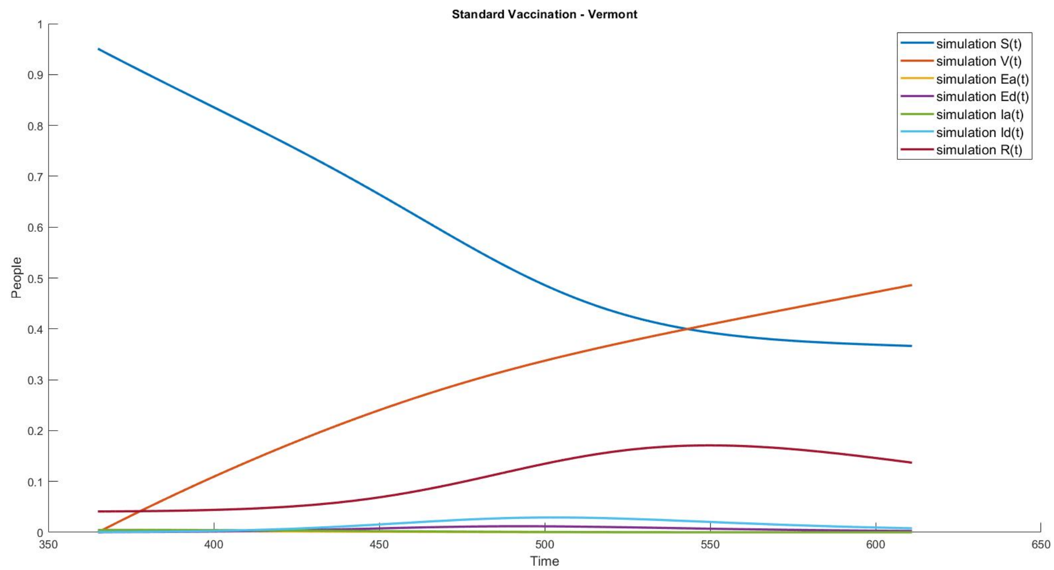

Figure 5: Vermont Static Vaccination Rate

between days 328.2 and 365. This is a remarkably low number of infected people. The maximum occurring at the end of the simulation does suggest that the amount of alpha-infected people is still increasing, however, it is increasing at a very low rate. The maximum for the recovered class was 0.0410 and occurred between days 362.8 and 365, translating to a minimum susceptible class of .9508. Similar to Oregon, this is both a positive and a negative for the state. The high amount of susceptibles shows that the state saw great success in repressing the original COVID strain, however, it also means that a large number of people are susceptible to entering the next phase of the virus, one that features a more dangerous virus.

Vermont is an interesting state when it comes to the delta variant wave. Initially, Vermont appeared to have the virus under control in a similar fashion to how the alpha variant was controlled, however, a late spike in cases resulted in a different opinion. Therefore, the infection rate for the delta variant for Vermont is massive. The Alpha variant behaved very similarly to every other state, becoming marginally larger before slowly decreasing throughout the rest of the simulation. The maximum was 0.0047 and occurred between days 369.1 and 382.4. The delta variant is a completely different story. The delta variant exploded in Vermont reaching a maximum value of 0.0291 between day 498.8 and 506.7. This is devastating for the success story of Vermont seeing as this is more than five times the number of alpha-infected people that occurred at one time during the first 365 days of the simulation. This explosion of delta cases caused the recovered class to reach a maximum value of 0.1709, reaching a value that slightly eclipsed the maximum in California. However the main difference is this was predominantly fueled by the delta variant, the more dangerous variant of the two accounted for in the simulation. Vermont ended the simulation with 0.3664 in the susceptible class and 0.4862 in the vaccinated class. The delta variant infected class was declining towards the end of the simulation and eventually landed on a value of 0.0078, an amount that is still enough to be slightly worrisome, however, it is far from the maximum value. In addition, it is important to note that they also had a much smaller amount of time at the peak of the delta variant. This is primarily due to the relationship between the vaccinated class and the susceptible class. The vaccinated class was drawing people out of the susceptible class so by the time the delta variant reached its max, the susceptible population had dropped enough that the effect of this maximum infected class was stymied. Overall, the medium-speed vaccination rollout presented some issues for Vermont. An incredible amount of people entered the second period as susceptible with very few having natural immunities. The condensed nature of the outbreak of delta, however, is what kept Vermont ahead of states like california and tennessee, seeing as these states had more prolonged outbreaks.

In Conclusion, if a state had a dismal response to the Alpha variant, even an average vaccination rollout will help them recover to an OK overall response to COVID. However, for a state that responded well to the Alpha variant, if there is only an average vaccination rollout, the state is in danger of having the more dangerous virus lay waste to the population, however it is in a more condensed manner, a better result than a prolonged outbreak.

4.2 Standard Infection Rate

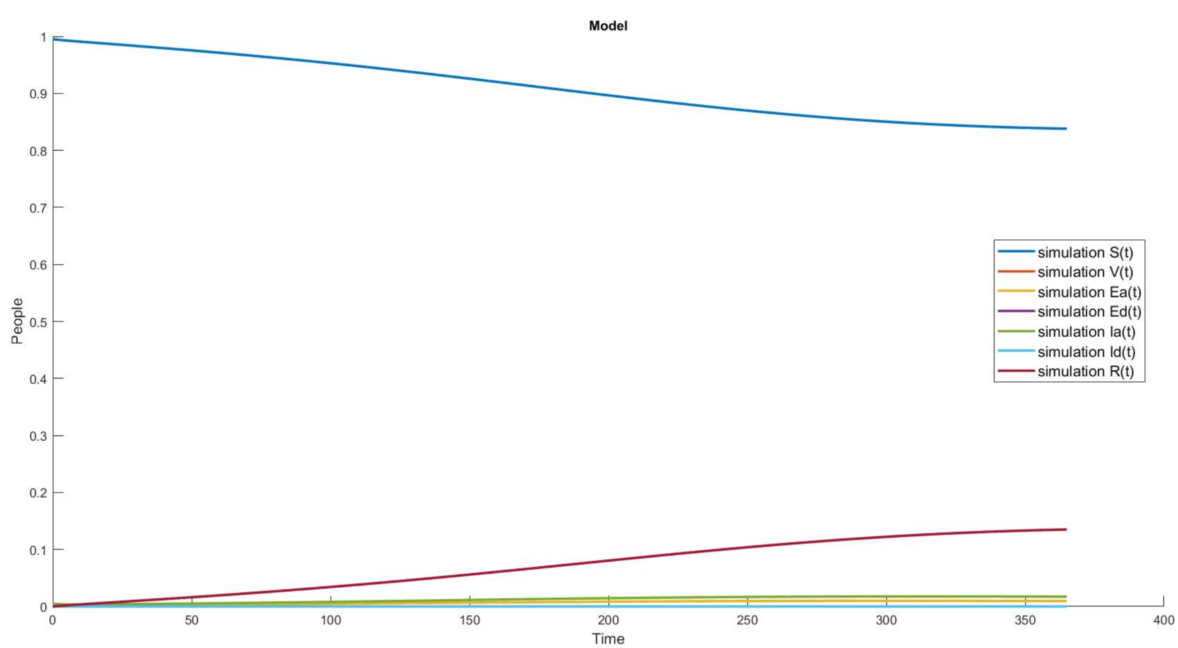

Figure 6: Static Infection Rate, Day 0-365

The infection rates used throughout figures 11, 13, 15, and 17 were reflective of the US average, that is, 0.118 was the infection rate for the alpha variant and 0.177 for the delta variant. During the alpha variant wave, or the first 365 days, the maximum amount of alpha infected at a time was 0.0177, or 1.77% of the population, maximum number of people in the recovered class was 0.1351, or 13.51% of the population, and the minimum number of people in the susceptible class at a time was 0.8379, or 83.79% of the population. The first 365 days have no one enter the Vaccinated class or contract the Delta Variant of COVID because neither were created/found during this time. From the data found via the WHO website, the United States had about 33.5 million cumulative positive tests for COVID, which translates to around 10% of the population. To account for those individuals that might have had COVID but did not get tested, the model was to produce a slightly larger infected population in comparison to the one measured in the US. The second time interval was between 365 and 611 (present-day) days and added in the Delta variant as well as a Vaccine. The initial value for the second period saw the alpha infected reduce to 0.0149 to give the delta variant 0.0024 infected. The delta variant took 13.7% of the alpha variant infected because this resulted in the delta variant becoming the more widespread variant after around 85 days in each simulation, which is very close to the amount of time it took to become the majority variant in the US. The model also needed to account for the mutation of the alpha variant. The overall goal for these simulations was to determine the effect of a proactive response to a vaccine being released.

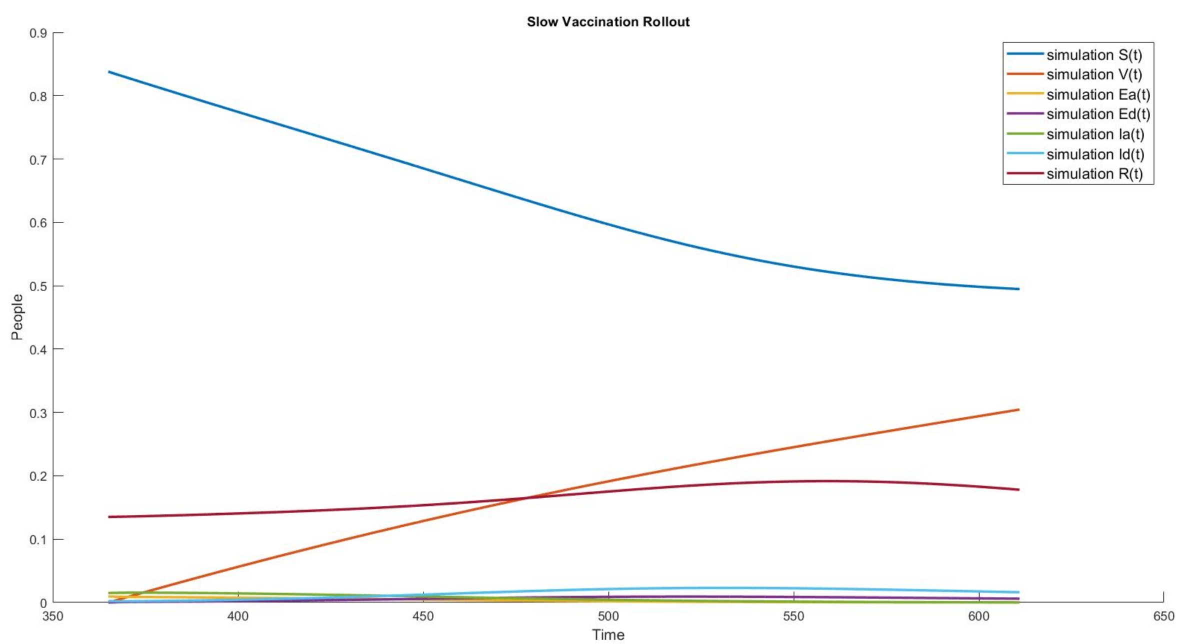

Figure 7: Static Infection Rate - Slow Vaccination Rate

To mimic a slow vaccination rollout, the vaccination rate was set at 0.002. This produced a vaccinated class of 0.3046 or 30.46% of the population. 49.48% of the population remained susceptible at the end of the simulation, which is much greater than the amount of those vaccinated. The slow vaccination rollout saw the highest number of people infected by the delta variant. The maximum amount of delta infected was 0.0231 which occurred between day 526.8 and 535.7. The population of delta infected finished the simulation at 0.0162. This was by far the most for the varying vaccination rates and only 0.0011 fewer than what the alpha variant ended at after the first year. The alpha variant was still present during the entire second-time interval, however reached its maximum of .0156 between day 372.3 and 374.7, then slowly decreased to 0.0003 at the end of the simulation. The maximum for the total number of infected, including both alpha and delta infected, was 0.0259 which occurred for the first time on day 508 and the final time on day 518.1. This was primarily driven by the outbreak of the delta variant, rather than it being a relatively healthy mix of both, a feature of the other 3 cases. The recovered class reached its peak of 0.1916 between days 556.8 and 561.7 and then slowly regressed down to 0.1779 at the end of the simulation. The biggest worry for this case is the number of people that remain susceptible at the end of the simulation coupled with the amount of those still infected with the delta variant. If another variant were to mutate similarly to the delta variant, over half of the population would be at high risk of contracting the new variant.

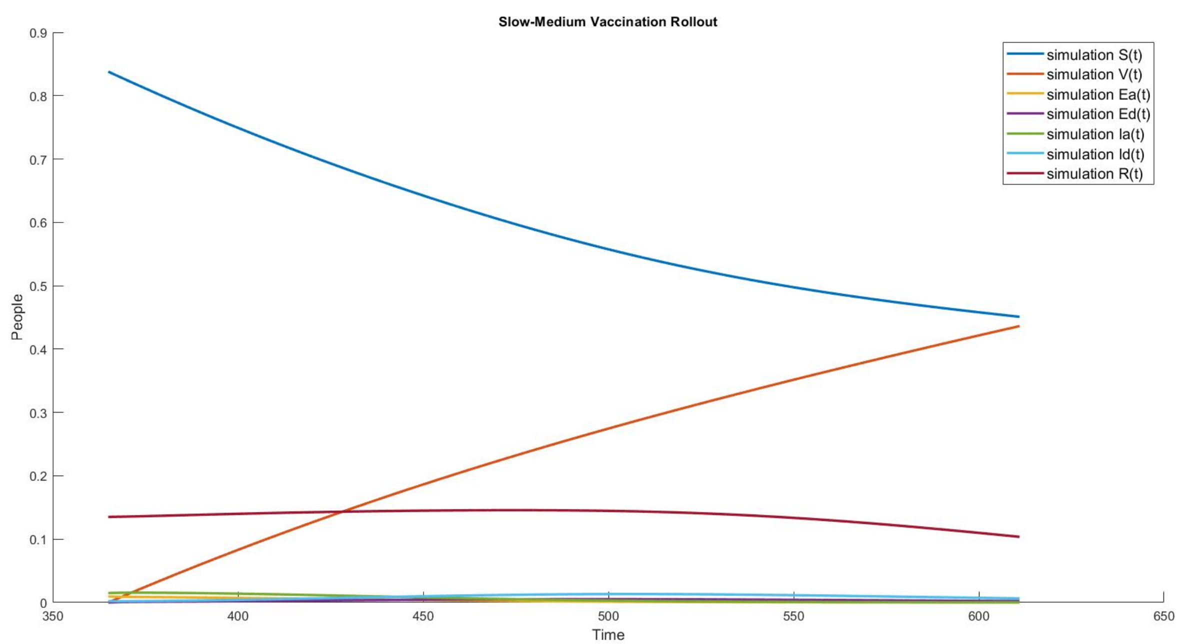

Figure 8: Static Infection Rate - Medium/Slow Vaccination Rate

To mimic a medium-slow vaccination rollout, the vaccination rate was set at 0.003. This resulted in 0.4363, or 43.63% of the population getting vaccinated at the end of the simulation. This is still behind the current mark of the US. 45.10% of the population remained in the susceptible class upon completion of the simulation. The peak of delta infections occurred between days 498.7 and 514.3

and was 0.0133, or 1.33% of the population. The final value for the delta infected was 0.0065. The alpha variant reached a similar maximum to the slow vaccination rollout, having 0.0155 between days 369.2 and 377.9. Akin to the slow vaccination rollout, the alpha variant slowly declined to 0.0001 on the final day of the simulation. For the combined infected, however, the maximum was reached fairly early on day 390.4, found for the last time at 433.5, and was 0.0182. The recovered class peaked between day 467 and 481.9 at a total of 0.1457, or 14.57% of the population, and finished the simulation at 0.1037. This case featured the longest recovered class peak of the four test cases. While this case has a similar problem with the remaining susceptible population at the end of the simulation, this case had a remaining delta-infected population of under 1%. This, however, only means that the population should not have many long-term issues with the Delta variant. Any other breakout variants could still present an issue.

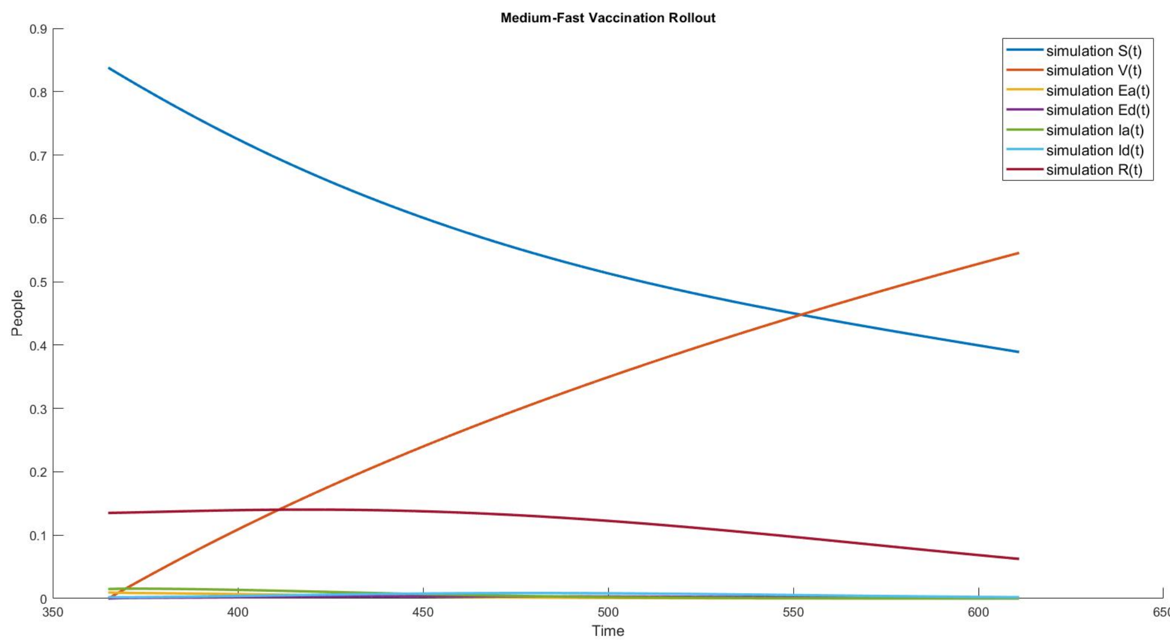

Figure 9: Static Infection Rate - Medium/Fast Vaccination Rate

For a medium-fast vaccination rollout, the vaccination rate was set at 0.004. At the end of the simulation, the resulting number in the vaccinated class was 0.5455 and for the first time the resulting susceptible population, 0.3891, was smaller than the vaccinated class. The maximum for the delta infections occurred between days 470.7 and 487.4 and was 0.0086, the first time the peak of the delta infected was fewer than 1% of the total population. The simulation finished with 0.0021 in the delta infected class. The alpha infected reached the same maximum in the medium-fast simulation that it did in the medium-slow simulation, that value being 0.0155. This was reached between days 369.3 and 376.7. While the value reached was the same, the duration of the maximum was marginally shorter. As is the case with the alpha variant in these simulations, it decreased until 0.0001 and ended the simulation with this value. As for the combined infected maximum value of 0.0179, that was reached for the first time on day 379.0 and the last on day 392.8. Finally, the recovered class peaked at 14.04% of the population, occurring between day 417 and 420.8, and finished the simulation with 0.0625.

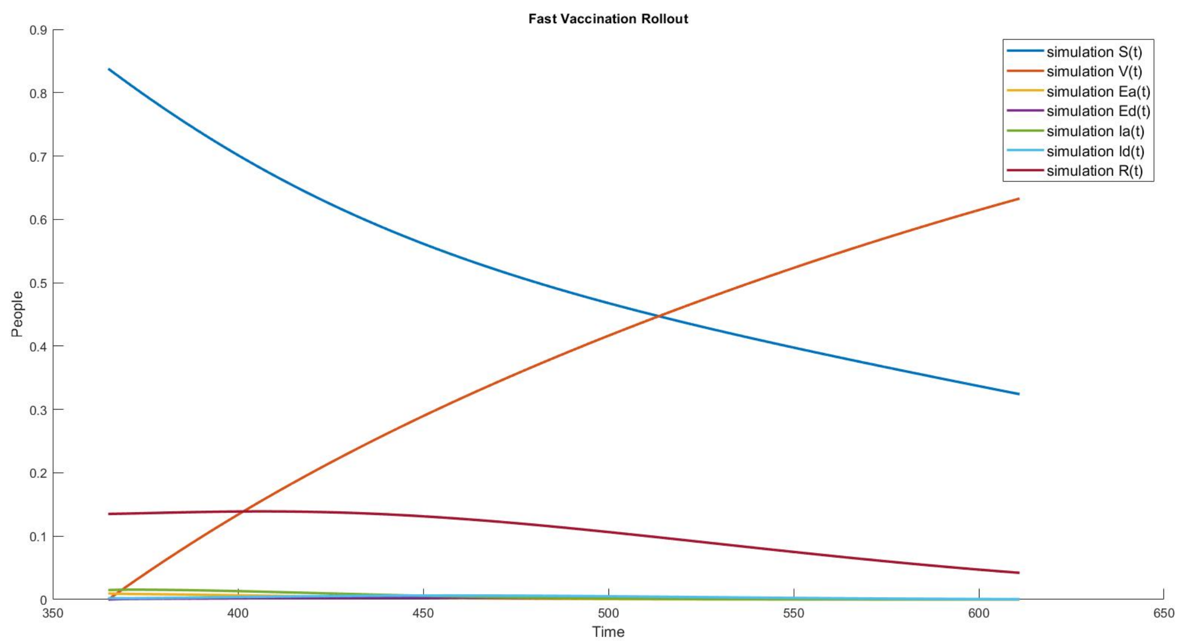

Figure 10: Static Infection Rate - Fast Vaccination Rate

The final test case for the static infection rate group is that of a fast vaccination rollout, which brings a vaccination rate of 0.005 with it. 63.28% of the total population were vaccinated, compared to 32.41% of the population remaining in the susceptible class. For the delta infected, the maximum value of 0.0063 began on day 447 and ended on day 468.3 eventually finishing the simulation at 0.0006. Similar to the two medium vaccination rollouts, the alpha variant peaked at 0.0155 between days 369.3 and 375.8. Uniquely, however, the alpha variant infected finished the simulation with a value of 0. The combined infected population maxed out at 0.0178 with the first occurrence being on day 377.6 and the final on day 385.3. Lastly, the recovered class peaked with 0.1391 between days 404.6 and 408.3, settling at 0.0421 upon completion of the simulation.

Ultimately, a faster vaccination rollout resulted in fewer people contracting the delta variant. This is primarily due to the faster outward flow of people from the susceptible class. This has lasting effects on the final values of the delta-infected population. For the fastest vaccination rollout, 0.06% of the population ended the simulation infected with the delta variant, a seemingly negligible amount of people. The two medium vaccination rollouts had a resulting delta-infected class that was under 1% being 0.6% and 0.2%. These are still smaller than the slow vaccination rollout by more than half. This will ultimately make the pandemic last longer. Also, with a higher vaccination rate, the quicker the recovered and susceptible classes shrink. This indicates that the influx of people from the infected classes is outweighed by those returning to the susceptible class, another indicator that the pandemic is reaching the latter stages. A smaller susceptible population brings fewer individuals who are not protected from the virus. Overall, being proactive in administering the vaccine not only reduces the number of infected people at one time but also reduces the number of unprotected individuals. Thus, resulting in a shorter pandemic.

4.3 California

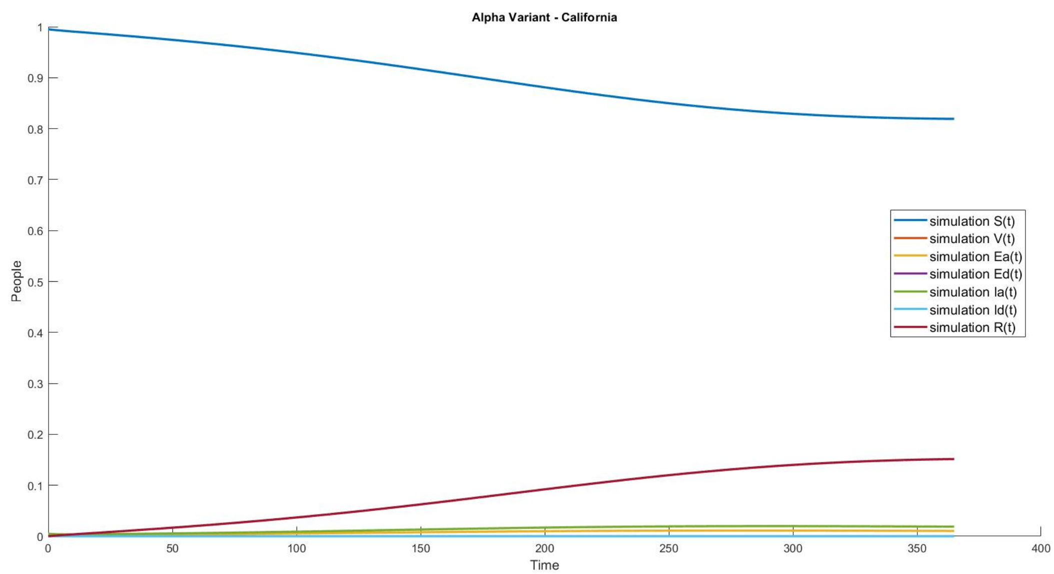

Figure 11: California Alpha Variant Wave, 365 Days

Figure 11 illustrates California's alpha variant wave and the development for this graph is covered in the analysis section of the static infection rate.

Figure 12 shows California's illustration from the delta variant. The time frame used in creating this simulation was 246 days. As mentioned earlier, we estimated California's alpha variant infection rate to be 0.120. However, we also discussed that the delta variant for COVID-19 would increase each infection rate by 40-60 percent. Thus, this would cause California's delta variant infection rate to be 0.168. Some major noticeable differences from California's delta variant from the alpha variant wave (in Figure 11) are the transformation of the vaccination curve, the declining trend in recovered individuals, and the large decrease in the proportion of susceptible individuals. We see the susceptible class line intersect with the vaccinated class in this graph where we see a trend: as the vaccination class increases, the susceptible class decreases. Towards the end of the delta variant wave, we see the vaccinated class continuing an upward trend. This ended up being the catalyst to the success of California during the delta variant wave. As we saw from the standard

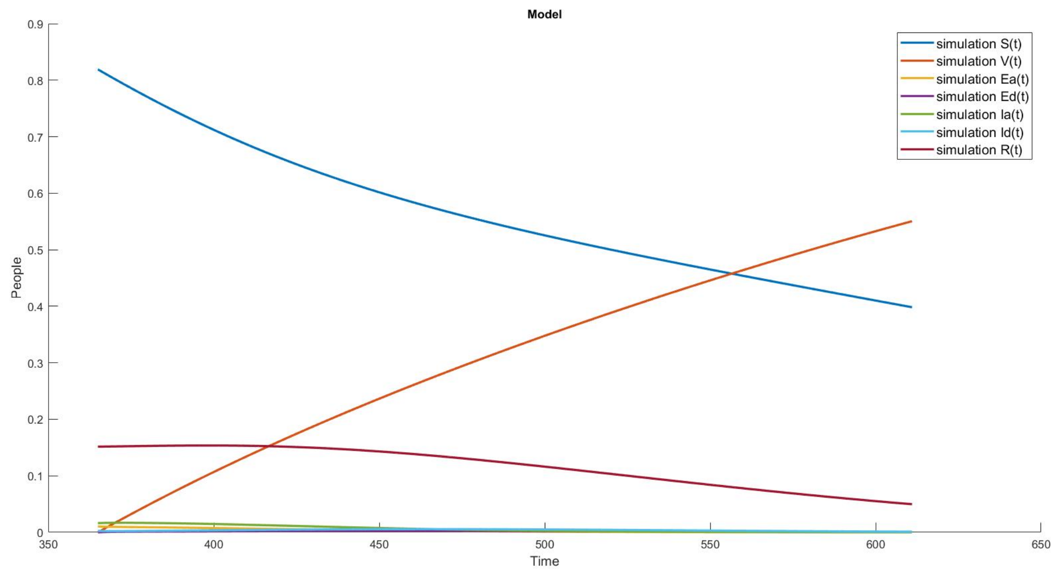

Figure 12: California Delta Variant Wave, 246 Days

infection rate simulations, the faster the vaccinated class grows, the faster the susceptible population drops and therefore causing the delta variant to be suppressed faster. For the actual critical values of this simulation, the delta variant infected class only reached 0.0056 as its maximum, the combined infected class reached a maximum of 0.0192, but this is mainly due to the alpha variant infected class, not the delta. The recovered classes maximum occurred right at the beginning of the simulation, reaching a value of 0.1536, eventually ending the simulation at 0.0497. Finally, the susceptible class and the vaccinated class reached a their critical values of 0.3983 and 0.5505 respectively at the end of the simulation. The success of California could be caused for several reasons: (1) They still have a statewide mask mandate, (2) they are still in a state of emergency, (3) they were the last state (from the four chosen) to end the stay at home order. The simulation, however, also suggests that their proactive vaccination rollout has a large hand in the success of the state. This is why we made California our prime state to represent a "poor alpha, but good delta" variant response.

4.4 Oregon

Figure 13 illustrates Oregon's alpha variant wave and the development for this graph is covered in the analysis section of the static infection rate.

Figure 14 shows Oregon's delta variant wave. Similar to California, we see a significant increase with the number of people in the vaccinated class come the end of the simulation, reaching a maximum of 0.6137 on the final day of the simulation. Seeing as the susceptible class and the vaccinated class have a large effect on one another, the susceptible class reached a minimum value

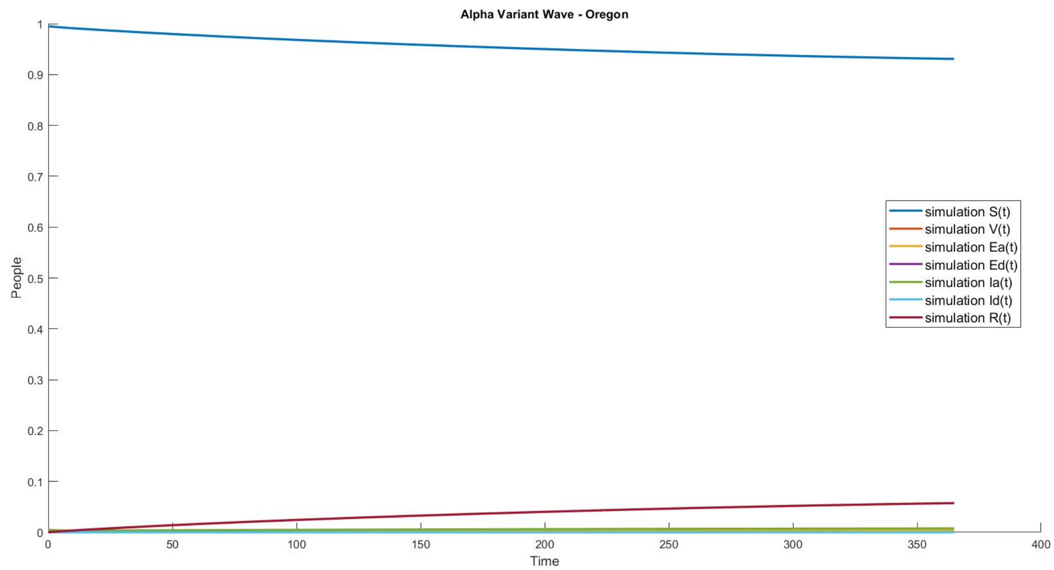

Figure 13: Oregon Alpha Variant Wave, 365 Days

of 0.3568 at the end of the simulation. Another important thing to note is the behavior of the recovered class. Much similar to the alpha variant wave in Oregon, the recovered class never eclipsed a value of 10% of the population, reaching a maximum of 0.0632, eventually ending the simulation at 0.0286. The plateauing nature of the recovered class during the first half of the second wave is representative of the brilliant response of Oregon. They were able to keep their high number of susceptible people safe from the more dangerous virus while also vaccinating a large portion of their population. The delta and combined infected classes also are indicative of this, seeing a maximum of 0.0047 and 0.0083 respectively. The delta variant infected class ended off the simulation with a value of 0.0007. This is practically negligible, showing the delta variant is a non issue after day 611. Overall, Oregon was able to keep their infection rate low via prolonged mask mandates as well as stay at home orders. Compounding that with the proactive vaccination rollout, Oregon produced fantastic long term results.We see this from both figure 11 and figure 12. Thus, Oregon in our research represents a "good alpha, good delta" response state.

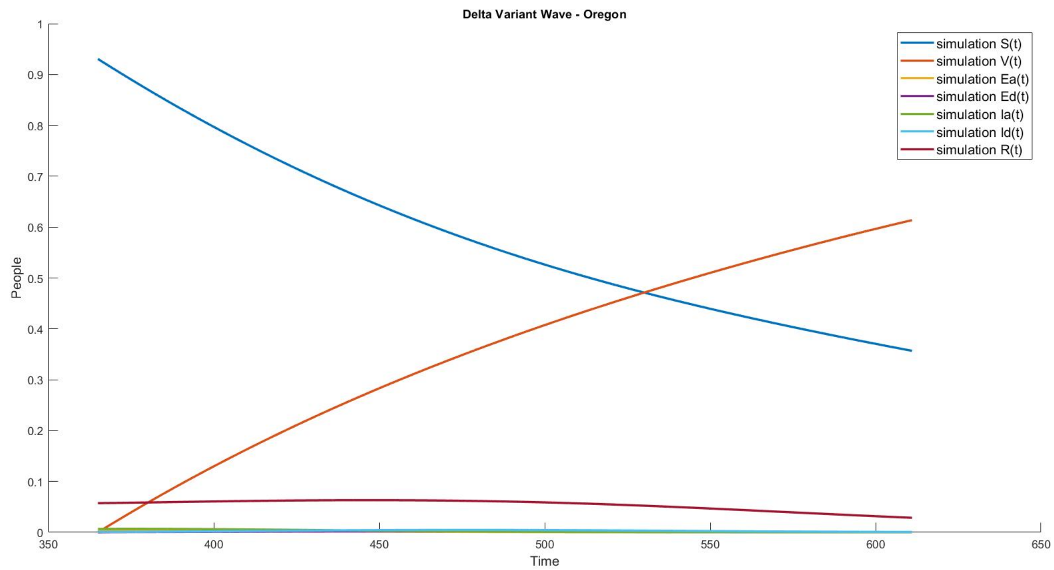

Figure 14: Oregon Delta Variant Wave, 246 Days

4.5 Tennessee

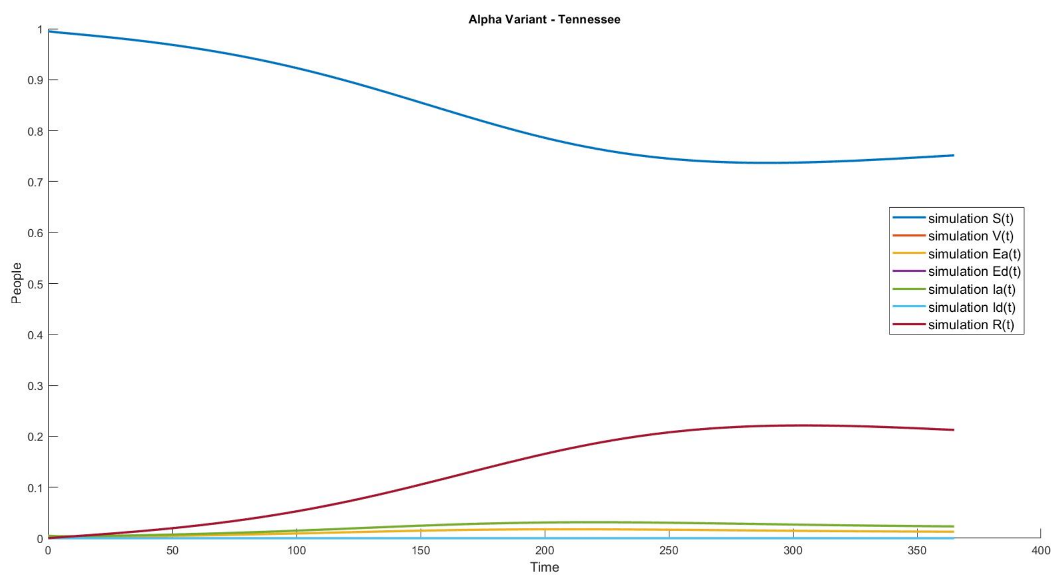

Figure 15: Tennessee Alpha Variant Wave, 365 Days

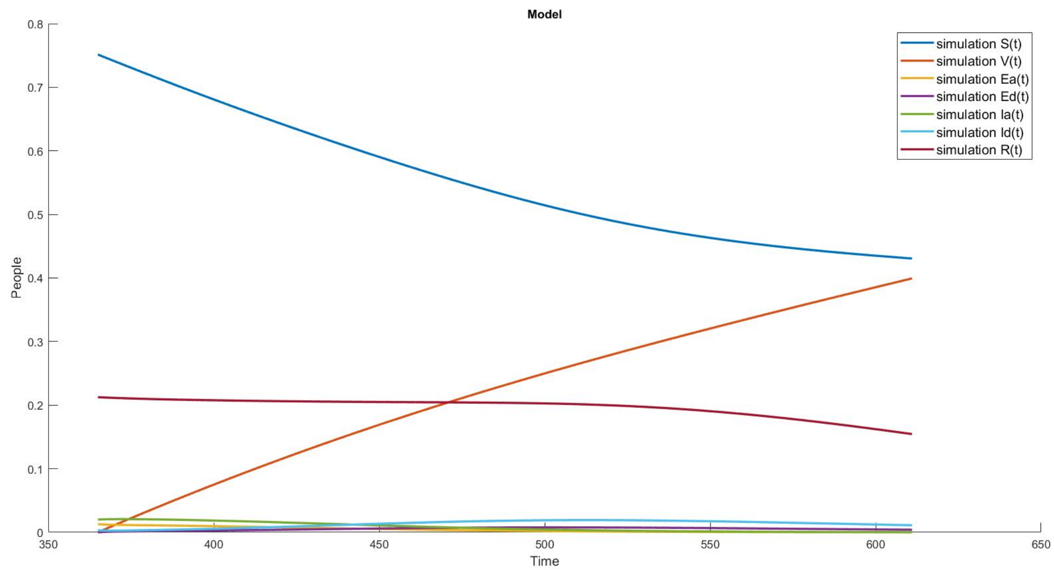

Figure 16: Tennessee Delta Variant Wave, 246 Days

Figure 15 illustrates Tennessee's alpha variant wave and the development for this graph is covered in the analysis section of the static infection rate.

Figure 16 is Tennessee's graph of their response to the delta variant wave. We see the result of the lack of government interference displayed fully here. Tennessee never had a statewide mask mandate which is a catalyst to why their infection rates were so high. Compounding that with the fact that they had the lowest vaccination rate among the four states chosen caused the delta variant to present an issue in the state. The delta variant and combined infected classes had a maximum of 0.0103 and 0.0235, with the delta class finishing the simulation with a value of 0.0062. Not only was the maximum for the delta and combined infected classes relatively high, the delta class was able to maintain a robust nature for a prolonged amount of time due to the slow vaccination rollout. In fact, the vaccinated class only reached a value of 0.4209, notably lower than the amount of susceptibles, 0.4634, at the end of the simulation. Overall, the poor response to the alpha variant was not able to generate long term success and in fact, due to a poor response to the delta variant, no amount of success was achieved during the duration of the simulation. Thus, Tennessee was chosen to be the state that displayed the most appropriate "poor alpha, poor delta" evidence.

4.6 Vermont

Figure 17 is Vermont's simulation for the alpha variant wave and the details behind the development of this graph is covered in the analysis section of the static infection rate.

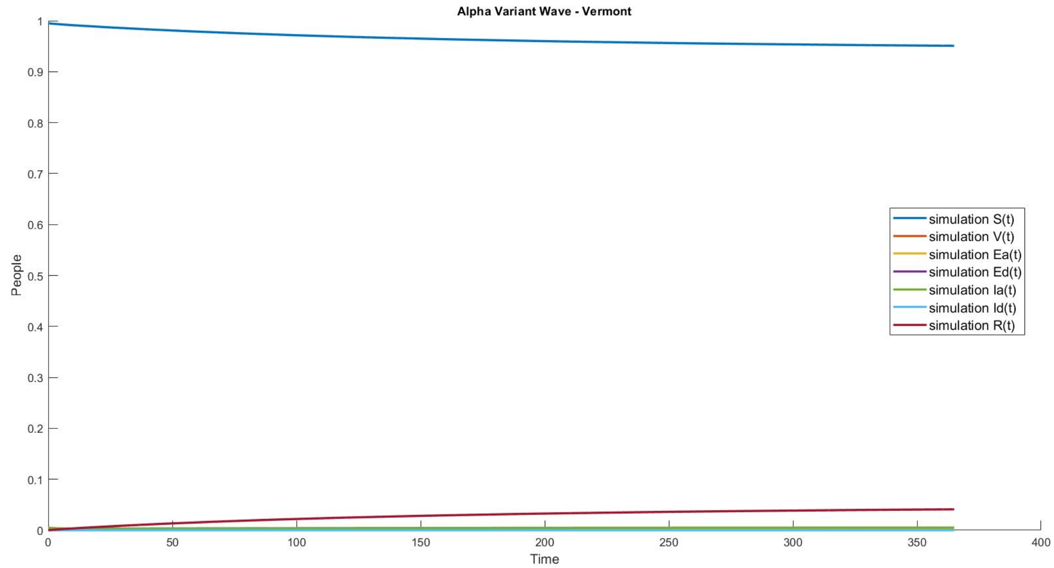

Figure 17: Vermont Alpha Variant Wave, 365 Days

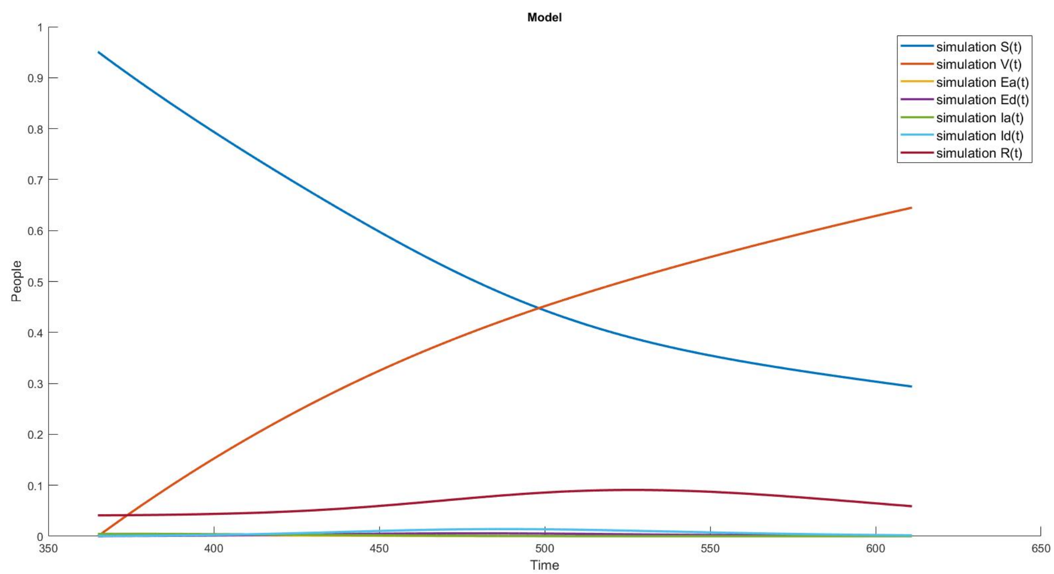

Figure 18: Vermont Delta Variant Wave, 246 Days

Figure 18 is Vermont's simulation for the delta variant wave. Compared to the standard vaccination simulation, Vermont had a much faster vaccination rollout. This proved crucial for the states long term success, seeing as the isolated spike of delta variant cases had a much smaller maximum value of 0.0090. The loss of a mask mandate too early caused the infection rate to be massive, but, as we saw during the standard infection rate simulations, the vaccine rollout was able to mitigate the effects of the delta variant. Not only did the delta variant nor combined infected class maximum never eclipse 1% of the population, the final value for the delta variant infected class was 0.0005, a seemingly negligible value. The aforementioned vaccinated class grew to a massive value of 72.38% of the population, and as a result the susceptible population ended the simulation with a value of 0.2418. Finally, the recovered class never eclipsed 10% of the population, having a maximum and final value of 0.0652 and 0.0337 respectively. Overall, the initial response to the alpha variant wave setup Vermont with the possibility of obtaining long term success, while also presenting the scary scenario of a massive delta variant boom. However, via the help of the vaccine, Vermont was able to achieve long term success.

5 Conclusions

Our original hypothesis was that a proactive response to COVID, both at the very beginning of the virus and at the start of any breakout case waves, would positively affect long term results. We wanted to dive deeper to show that states either respond good or bad to the alpha variant and delta variants. Thus, we concluded that there are four possibilities that a state could experience: good alpha and delta response, good alpha and bad delta, bad alpha and good delta, or bad alpha and delta response. We began our studies and chose states based on state rankings for handling COVID-19. We then dove further to see what type of government interventions were initiated during the pandemic and how the simulations created would provided sufficient evidence to show or explain the trend of COVID within each state. The goal of this report was to show the effects of different contributing factors among COVID-19 and how they interact with long term success. However, we also found out there is a large number of factors, therefore we had to redirect our focus on the most important few. We investigated what happens when a state ends a mask mandate or stay-at-home order too early and when a state responds well to one variant, but poorly to another, etc. From the simulations created and information gathered, we have seen sufficient evidence to suggest that governmental intervention affects how a state responds to COVID-19 immensely and that the response dictates long term results. Ultimately concluding that the more proactive the response was to either the alpha or delta variant waves, the better the long term results. We also concluded that our original assumptions of the four states chosen: California, Oregon, Tennessee, and Vermont were not all correct. We initially believed that Vermont was the state that performed well through both variants. However, after careful examination and analysis, we saw that Oregon displayed more affirmation in being the state that performed well with the alpha and delta variant. Some recommendations that we have based on our results are simplifying the scope covered, focusing on two major states, and proposing a question that was dependent on the time frame chosen. For example, our project had to be extra careful in our sources and make sure the time stamps on the sources match the numerical data we were displaying. Some possibilities of future work related to this report could be updating the report when and if more variants of COVID-19 arise (for example:

the Omicron variant). Then the number of combinations of performance further increases. We could have a state perform a good alpha, good delta, good omicron than a state that performs bad alpha, bad delta, good omicron, and furthermore. In that case, not only would there be more factors to consider, the entire model would have to change to consider all the new variables. We would have more classes of individuals. Some other future possibilities include using the same concept, but applying the focus to different countries, applying the concept to cities within a state, etc.

6 Appendix

1. The code to the original program.

```
function results=Judy1(betaA,betaD,betaVA,betaVD,muA,muD,
eta,gamma,sigma,S0,V0,Ea0,Ed0,Ia0,Id0,R0,target,T0,Tmax)



%% DATA

% total population
N = S0 + V0 + Ea0 + Ed0 + Ia0 + Id0 + R0;

%% INITIALIZATION

% output results is a matrix with columns [t S V Ea Ed Ia Id R]
dt = 0.1;
N_Iter = ceil((Tmax-T0)/dt);
dt = (Tmax-T0)/N_Iter;
results = zeros(N_Iter+1,8);
results(1,:) = [T0,S0, V0, Ea0, Ed0, Ia0, Id0, R0];
results(:,1) = [T0:dt:Tmax]';

%% COMPUTATION

for i=1:N_Iter
    % y is a column vector [S_old ; I_old]
    y = results(i,2:8)';
    V_old = y(2);
    Ea_old = y(3); Ed_old = y(4);
```

```
    Ia_old = y(5); Id_old = y(6);
    R_old = y(7);
    t = results(i,1);
    y = RK4(t,dt,y);
    results(i+1,2:8) = y';
    if (y(5)+y(6))/N < target
        % pandemic ends or is stable
        results = results(1:(i+1),:);
        break;
    end
end


%% FUNCTION FOR 4th order Runge-Kutta

    function y=RK4(t,dt,y0)
        % y0 is a column vector of initial conditions at t
        % y is a column vector of values at t+dt
        k1 = yprime(t,y0);
        k2 = yprime(t+0.5*dt,y0+0.5*dt*k1);
        k3 = yprime(t+0.5*dt,y0+0.5*dt*k2);
        k4 = yprime(t+dt,y0+dt*k3);
        y = y0+dt*(k1+2*k2+2*k3+k4)/6;
    end


%% FUNCTION FOR THE DIFFERENTIAL EQUATION

    function yp=yprime(t,y)
    % split out components
        S = y(1);
        V = y(2);
        Ea = y(3);
        Ed = y(4);
        Ia = y(5);
        Id = y(6);
        R = y(7);
```

```
    % compute derivatives
        Sp = -betaA*S*Ia + -betaD*S*Id + -eta*S + sigma*R;
        Eap = betaA*S*Ia + betaVA*V*Ia + -muA*Ea;
        Edp = betaD*S*Id + betaVD*V*Id + -muD*Ed;
        Vp = eta*S + -betaVD*V*Id + -betaVA*V*Ia;
        Iap = muA*Ea + -gamma*Ia;
        Idp = muD*Ed + -gamma*Id;
        Rp = gamma*Id + gamma*Ia + -sigma*R;
    % assemble derivative
        yp = [Sp;Vp;Eap;Edp;Iap;Idp;Rp];
    end


end
```

```
%% SIR Model
%% RK4 Numerical Method

clear all
close all
clc

%% Observe the data from the problem



%% Numerically solve SIR model


%Transmission alpha
betaA = .130;
%Transmission delta
betaD = .195;
%Transmission (vax) alpha
betaVA = 0.006; % .006;
%Transmission (vax) delta
betaVD = 0.008; % .008;
```

```
%Incubation alpha
muA = 1/5.6;
%Incubation delta
muD = 1/4; % 1/4;
%Vaccination
eta = 0.003; %.003;
%Recovery (alpha and delta)
gamma = 1/10;
%Loss of Immunity
sigma = .012;
S0 = .995; % initial value of S
V0 = 0;
Ea0 = 0.0;
Ed0 = 0;
Ia0 = .005; % initial value of I
Id0 = 0.00;
R0 = 0.0;
T0 = 0; % initial time
Tmax = 365; % maximum time for the simulation

% target is the infected fraction used as the
%end condition of the pandemic
target = 0.001;

% computation using RK4
% output: results = [time S I];
results = KevinAaronJudy1(betaA,betaD,betaVA,betaVD,muA,muD,
eta,gamma,sigma,S0,V0,Ea0,Ed0,Ia0,Id0,R0,target,T0,Tmax);
sim_t = results(:,1);
sim_S = results(:,2);
sim_V = results(:,3);
sim_Ea = results(:,4);
sim_Ed = results(:,5);
sim_Ia = results(:,6);
sim_Id = results(:,7);
sim_R = results(:,8);
```

```
% plot the data and the simulation results
figure; hold on;
% plot(data_t, data_I,'o');
plot(sim_t, sim_S, 'linewidth',2);
plot(sim_t, sim_V, 'linewidth',2);
plot(sim_t, sim_Ea, 'linewidth',2);
plot(sim_t, sim_Ed, 'linewidth',2);
plot(sim_t, sim_Ia, 'linewidth',2);
plot(sim_t, sim_Id, 'linewidth',2);
plot(sim_t, sim_R, 'linewidth',2);
legend({'simulation S(t)','simulation V(t)','simulation Ea(t)',
'simulation Ed(t)', 'simulation Ia(t)', 'simulation Id(t)',
'simulation R(t)'},'FontSize',12)
xlabel('Time','FontSize',12);
ylabel('People','FontSize',12);
title('Model')
```

```
%% SIR Model
%% RK4 Numerical Method

clear all
close all
clc

%% Observe the data from the problem



%% Numerically solve SIR model


%Transmission alpha
betaA = .130;
%Transmission delta
betaD = .195;
%Transmission (vax) alpha
betaVA = 0.006; % .006;
```

```
%Transmission (vax) delta
betaVD = 0.008; % .008;
%Incubation alpha
muA = 1/5.6;
%Incubation delta
muD = 1/4; % 1/4;
%Vaccination
eta = 0.003; %.003;
%Recovery (alpha and delta)
gamma = 1/10;
%Loss of Immunity
sigma = .012;
S0 = .7515; % initial value of S
V0 = 0;
Ea0 = 0.0128;
Ed0 = 0;
Ia0 = .02; % initial value of I
Id0 = 0.0032;
R0 = 0.2125;
T0 = 365; % initial time
Tmax = 611; % maximum time for the simulation

% target is the infected fraction used as the
%end condition of the pandemic
target = 0.001;

% computation using RK4
% output: results = [time S I];
results = KevinAaronJudy1(betaA,betaD,betaVA,betaVD,muA,muD,
eta,gamma,sigma,S0,V0,Ea0,Ed0,Ia0,Id0,R0,target,T0,Tmax);
sim_t = results(:,1);
sim_S = results(:,2);
sim_V = results(:,3);
sim_Ea = results(:,4);
sim_Ed = results(:,5);
sim_Ia = results(:,6);
sim_Id = results(:,7);
```

```
sim_R = results(:,8);

% plot the data and the simulation results
figure; hold on;
% plot(data_t, data_I,'o');
plot(sim_t, sim_S, 'linewidth',2);
plot(sim_t, sim_V, 'linewidth',2);
plot(sim_t, sim_Ea, 'linewidth',2);
plot(sim_t, sim_Ed, 'linewidth',2);
plot(sim_t, sim_Ia, 'linewidth',2);
plot(sim_t, sim_Id, 'linewidth',2);
plot(sim_t, sim_R, 'linewidth',2);
legend({'simulation S(t)','simulation V(t)',
'simulation Ea(t)', 'simulation Ed(t)', 'simulation Ia(t)',
'simulation Id(t)', 'simulation R(t)'},'FontSize',12)
xlabel('Time','FontSize',12);
ylabel('People','FontSize',12);
title('Model')
```

[?]

References

[1] Jamie Bernal. Effectiveness of covid-19 vaccines against the b.1.617.2 (delta) variant. https://www.nejm.org/doi/full/10.1056/nejmoa2108891.

[2] Ian Cooper. A sir model assumption for the spread of covid-19 in different communities. *Chaos, Solitions, and Fractals*, 139, 2020.

[3] Meredith Deliso. How vermont became a 'model for the country' in responding to the coronavirus pandemic. https://abcnews.go.com/US/vermont-model-country-responding-coronavirus-pandemic/story?id=73057030.

[4] Huijing Du. Mathematical Modeling of Epidemiology [powerpoint presentation]. file:///Users/judytruong/Desktop/Part2_1_SIR%20(2).pdf.

[5] KFF State Health Facts. Population and Distribution. https://www.kff.org/other/state-indicator/distribution-by-age/?dataView=1&currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D.

[6] Centers for Disease Control, U.S. Department of Health Prevention, and Human Services. Using Principles of Epidemiology. https://www.cdc.gov/csels/dsepd/ss1978/index.html.

[7] National Center for Disease Control. Covid and Data and Tracker. https://covid.cdc.gov/covid-data-tracker/#vaccinations_vacc-total-admin-rate-total.

[8] National Center for Disease Control. Covid and Data and Tracker. https://covid.cdc.gov/covid-data-tracker/#cases_casesper100klast7days.

[9] National Center for Disease Control. Covid and Data and Tracker. https://covid.cdc.gov/covid-data-tracker/#cases_deathsper100klast7days.

[10] National Center for Disease Control. Covid and Data and Tracker. https://covid.cdc.gov/covid-data-tracker/#new-hospital-admissions.

[11] National Center for Immunization and Division of Viral Diseases Respiratory Diseases. Quarantine and Isolation. https://www.cdc.gov/coronavirus/2019-ncov/your-health/quarantine-isolation.html?CDC_AA_refVal=https%3A%2F%2Fwww.cdc.gov%2Fcoronavirus%2F2019-ncov%2Fif-you-are-sick%2Fquarantine.html/.

[12] Eric Haas. Impact and effectiveness of mrna bnt162b2 vaccine against sars-cov-2 infections and covid-19 cases, hospitalisations, and deaths following a nationwide vaccination campaign in israel: an observational study using national surveillance data. https://www.sciencedirect.com/science/article/pii/S0140673621009478.

[13] Ashley Hagen. How dangerous is the delta variant (b.1.617.2)? *American Society of Microbiology*, 2021.

[14] Kaia Hubbard. These states have covid-19 mask mandates. `https://www.usnews.com/news/best-states/articles/these-are-the-states-with-mask-mandates#tenn`.

[15] Lin Rong-Gong Karlamangla, Soumya. California vs. florida: Who handled covid-19 better? `https://www.latimes.com/california/story/2021-03-09/florida-vs-california-who-had-better-covid-response`.

[16] Glenn Ledder. SIR model Powerpoint. `file:///Users/judytruong/Desktop/Part2_1_SIR.pdf`.

[17] J.A. Quesada. Incubation period of covid-19: A systematic review and meta-analysis. *Revista Clínica Española*, 221, 2021.

[18] Cline Sara Selsky, Andrew. Oregon, once a covid-19 success story, struggles with delta surge. `https://www.registerguard.com/story/news/coronavirus/2021/08/25/oregon-once-covid-19-success-story-struggles-delta-variant-surge/5573457001/`.

[19] Lorenzo Subissi. Covid-19 natural immunity. `https://apps.who.int/iris/bitstream/handle/10665/341241/WHO-2019-nCoV-Sci-Brief-Natural-immunity-2021.1-eng.pdf`.

[20] Thomas Usherwood. A model and predictions for covid-19 considering population behavior and vaccination. `https://www.nature.com/articles/s41598-021-91514-7#citeas`.