Distribution of the COVID-19 Vaccine to Minimize Cases in Chicago

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Executive Summary

COVID-19 is an infectious disease caused by SARS-CoV-2. In 2020 alone, the disease devastated the city of Chicago, causing more than 200,000 cases [9]. In December of 2020, the Moderna and Pfizer vaccines were approved by the U.S. Food and Drug Administration, allowing healthcare personnel, essential workers, people with high-risk medical conditions, and people 65 and older to be vaccinated [19]. Once the vaccination of these high risk populations is complete, Chicago will transition to the vaccination of the general public [13]. To understand how different vaccination plans will impact the number of cases Chicago will have in the future, our team seeks to provide scenarios supported by mathematical reasoning. A well thought out vaccination distribution plan can potentially decrease the number of COVID-19 cases by about 20,000 in the city of Chicago.

We created and analyzed two potential strategies for the distribution of the vaccine to the general public in Chicago. We compared the efficacy of a default Gridded Vaccine Distribution Plan (Gridded Model) against a Voronoi Vaccine Distribution Plan (Voronoi Model). In the Gridded Model, we divided the city of Chicago into square-shaped regions and placed a node in the center of each region. With each node representing a vaccine distribution site. In the Voronoi Model, we first mapped nodes on a map of Chicago using the population density data from the 2017 American Community Survey's 5 Year Estimates. We then used the Voronoi Model to divide the city of Chicago into polygonal regions, or Voronoi areas, each centered around a node. For both models, we ranked nodes in priority based on calculated case rates. These rates were calculated using data from the City of Chicago Data Portal.

Data outputted from both models allowed us to project the number of new COVID-19 cases in Chicago 20 weeks after general public vaccinations began. We compared each model output with logistic regression model results, which showed an estimated number of new cases without vaccine distribution. The logistic regression model projected 297,755 new cases at week 20. The Voronoi Model projected 22,599 new cases, and the Gridded Model projected 42,349 new cases at week 20. Additionally, based on simulation results for 66 operational nodes, we predicted that vaccinating the rest of the population with the Voronoi Model would finish vaccinations in 14 weeks while the Gridded Model would finish in 22 weeks.

We also identified various risks associated with vaccination plans in Chicago. Using a plan lacking efficiency and effectiveness could exacerbate health risks, including risks posed by existing racial disparities, long-term health conditions. An inefficient plan could also escalate economic risks, including higher rates of unemployment, business closures, and changes in consumer spending.

Based on our analysis of the risks of our distribution models, we proposed a set of government recommendations. We suggested that officials should focus on an equitable distribution of vaccines rather than an equal distribution of vaccines to areas across the city. Based on projections from our models, we recommend using the Voronoi Model in Chicago and other metropolitan areas around the United States.

As the U.S. progresses through the COVID-19 pandemic, we believe that our model and recommendations can be used in Chicago and adapted to fit other cities to ensure efficient and effective vaccine distribution to the general public.

Introduction and Background

Coronavirus disease 2019 (COVID-19) is an infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). SARS-CoV-2 first emerged in Wuhan, China in December of 2019. It has rapidly spread worldwide, and by March of 2020, COVID-19 was declared a pandemic. The virus is mainly spread from person to person via respiratory droplets. An infected individual can experience mild to severe symptoms, with some cases being fatal. Individuals 65 and older, healthcare workers, and individuals with pre-existing conditions are considered more vulnerable to be infected or to develop more severe symptoms [15,16].

The first US case of the virus spreading from person to person was reported in Chicago in January of 2020. In March of 2020, Governor Pritzker announced a stay-at-home order for all Illinois residents. Since then, cases and deaths in Chicago have risen and fallen in mainly two waves, described by figure 1 and figure 2.

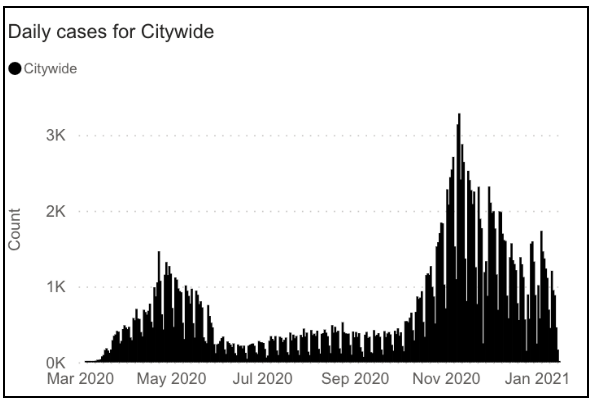

Figure 1. Daily COVID-19 cases [9].

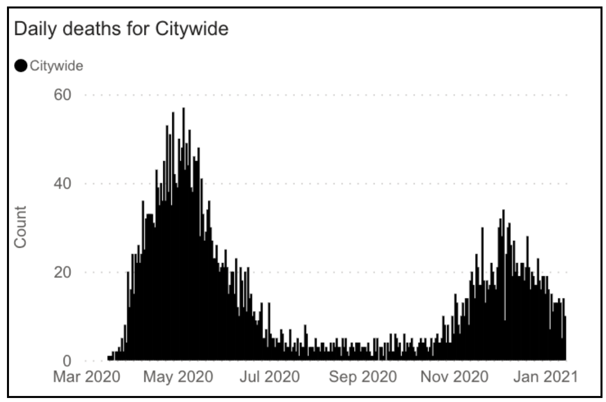

Figure 2. Daily COVID-19 deaths [9].

To mitigate future COVID-19 related deaths and infections, rapid development and distribution of vaccines to prevent the disease are crucial. As of December of 2020, two vaccines for the prevention of COVID-19 were authorized by the Food and Drug Administration (FDA) as Illinois officials outlined a distribution plan [19]. Phase 1, in which vaccines are distributed to critical populations, can be described in three sub-phases. In phase 1a, all healthcare personnel, long-term care facility staff, residents, and other identified congregate care staff and residents will receive the vaccine. In phase 1b, people aged 65 and older, essential frontline workers, and inmates will be vaccinated. In phase 1c, people aged 16-64 years old with high-risk medical conditions and other essential workers will be vaccinated. Once a large number of vaccines are available, Illinois will transition to phase 2, in which the general public will be vaccinated. In this project, we will develop and investigate a vaccine distribution method to present to the Chicago Department of Public Health for use in Phase 2.

Economic Effects of COVID-19

Unemployment

Businesses that rely on high-contact operations, including those in retail and dining industries, are at a higher risk of lost revenue as a result of the pandemic. Customers are either restricted from supporting these businesses due to social-distancing restrictions, or are wary of spreading or contracting the virus [1]. As their profits decrease, many of these businesses have resorted to laying off employees. As shown in figure 3 and according to data gathered from the US Department of Labor's Local Area Unemployment Statistics and Current Population survey, Chicago's unemployment rates have risen and remained higher than the national average since the beginning of the pandemic. This can be attributed to Chicago's strict COVID-19 based restrictions imposed throughout the pandemic that were used to control the spread of the virus through high-contact industries. As a result, the Chicago hospitality industry has been affected the most, with jobs dropping by about 27% from July 2019 to July 2020 [22].

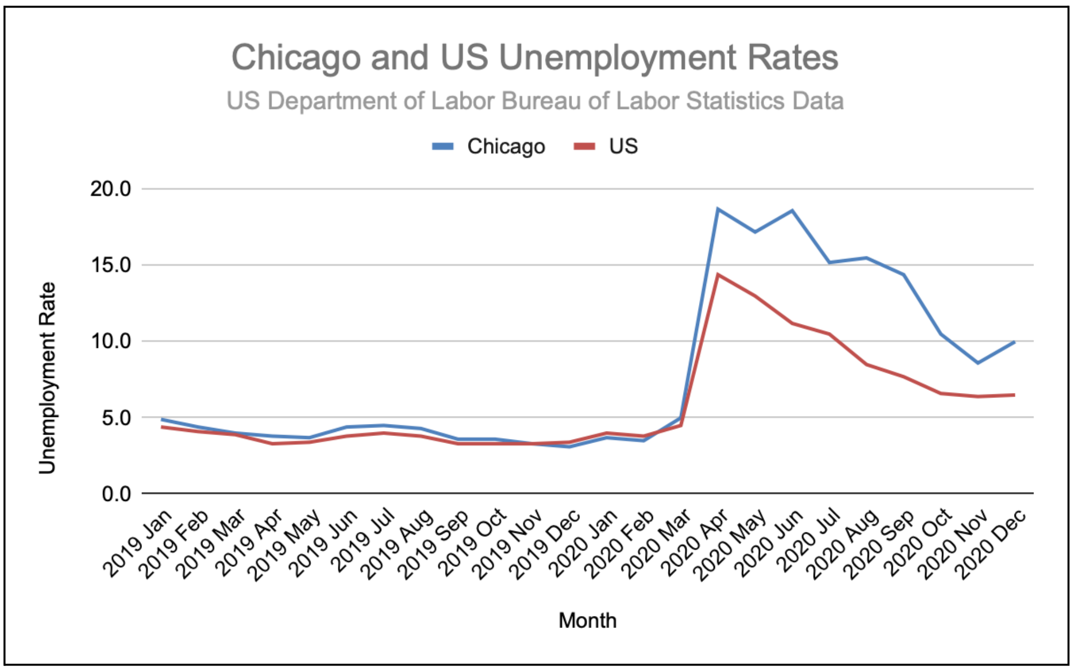

Figure 3. Unemployment rates in the Chicago metro area vs. US. Source: US Department of Labor BLS Data Local Area Unemployment Statistics (LAUS) and Current Population Survey (CPS) [2,3].

Chicago-area Business Closures

As COVID-19 related shutdowns arose throughout the pandemic, more businesses began to close permanently rather than temporarily. As shown in figure 4, out of the 5,000 business closures in Chicago from March to September of 2020, nearly 65% were permanent.

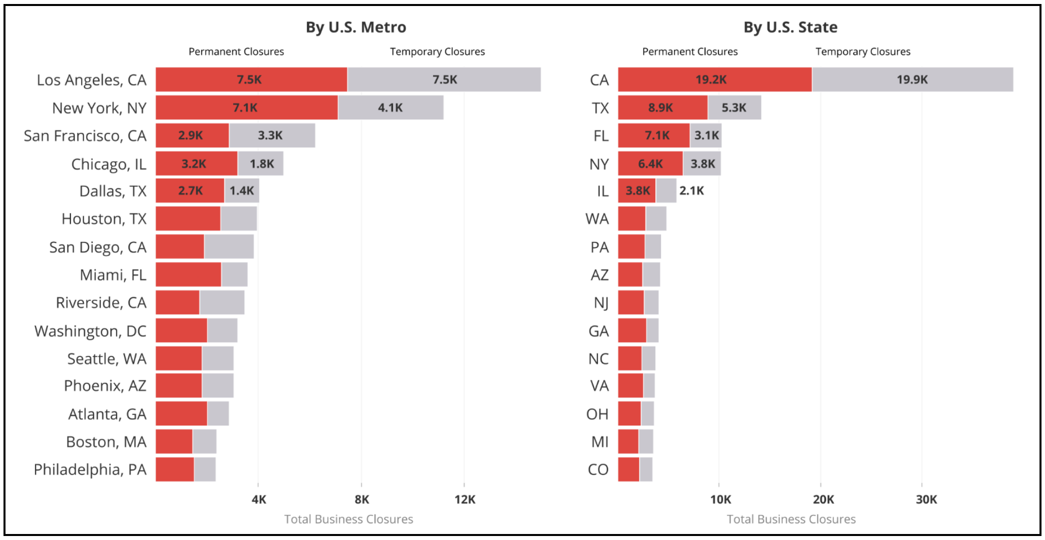

Figure 4. Geographic areas with the largest number of business closures from March 2020 to September 2020. Source: Yelp local economic impact report [29].

Additionally, according to research from the University of California Center for Risk and Economic Analysis of Terrorism Events (CREATE), overall effects of the COVID-19 pandemic are projected to cause net losses starting at $3.2 trillion and reaching as much as $4.8 trillion in U.S. real gross domestic product over the course of two years. The extent of the pandemic's economic impact is dependent on several factors, including the duration and extent of the business closures, the gradual reopening process, infection rates and fatalities, avoiding public places and pent-up consumer demand [27].

Insurance

Due to COVID-19, social security and private insurance will cost more. This is because general mortality rates have increased during the pandemic and there is a depressed earning history of beneficiaries, since many people have lost their jobs [18].

Change in Consumer Spending

Consumer spending, also referred to as personal consumption expenditures (PCE), is measured as the value of goods and services purchased by residents of the United States [14]. Additionally, PCE is thought to comprise nearly 70% of the US gross domestic product (GDP) [1]. Therefore, a drop in PCE often signals a drop in GDP and an economic downturn, as shown below in figure 5.

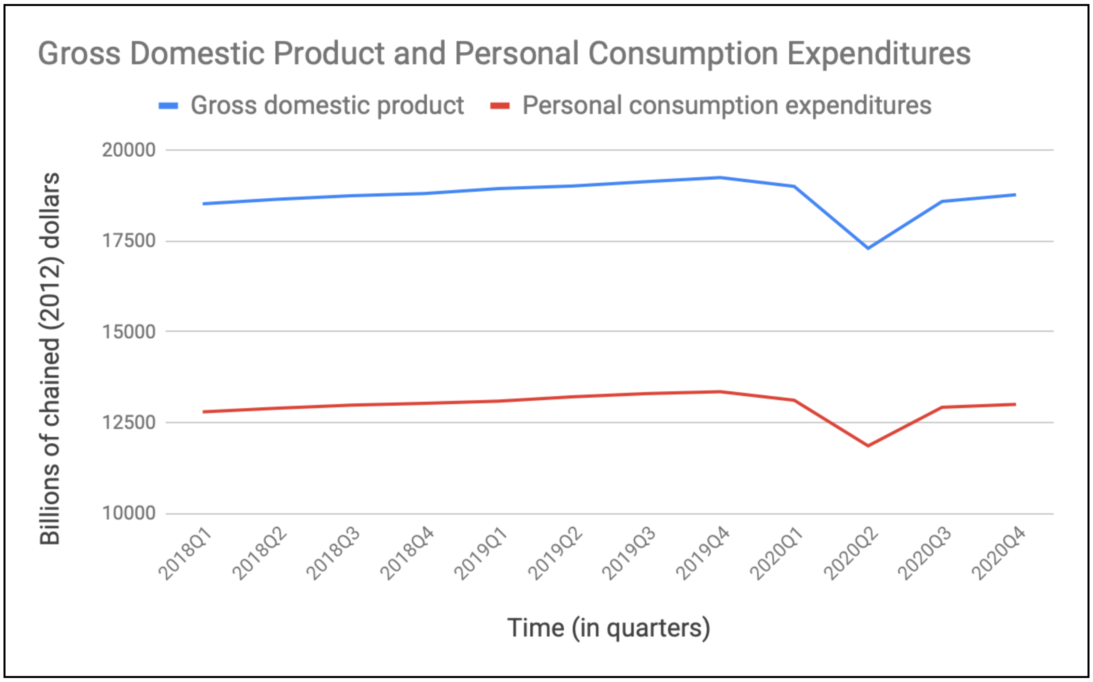

Figure 5. US GDP and PCE 2018-2020 seasonally adjusted at annual rates. Source: US Bureau of Economic Analysis [4].

In March of 2020, nearly every industry in Chicago saw extreme drops in consumer spending. As shown below in figure 6, consumer spending in Chicago dropped by 5.3% from January of 2020 to February of 2020. Industries hit hardest in the city included the restaurant hotel industry as well as the entertainment and rec industry.

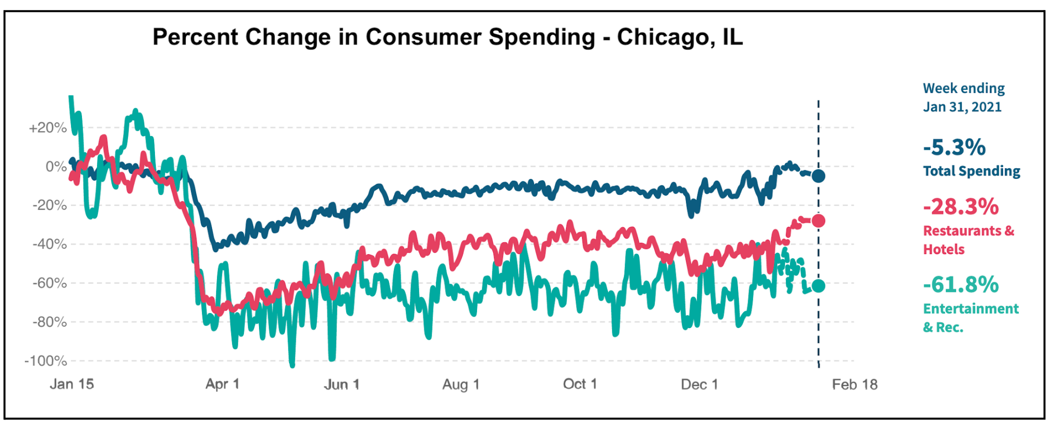

Figure 6. Percent change in total consumer spending, restaurants & hotels spending, and entertainment & recreation spending in Chicago, IL [24].

Problem Statement

During the COVID-19 pandemic, the people of Chicago are at risk of becoming infected COVID-19. A high number of cases can heighten health and economic risks among the general public. Potential risk mitigation strategies include implementing mass vaccination plans based on area or vaccinations based on population density.

Model Development

Data Methodology

The first database we used is from the Census's 2017 American Community Survey's (ACS) 5 Year Estimates, where we collected data of population density by square mile per census tract in Chicago. This data was used to predict the severity of potential loss since areas of higher population density are more susceptible to COVID-19 than areas of lower population density [24]. We used this data to determine the weight of each section of a zip code in the area enclosed by the vaccination distribution center. We also used this data to space out vaccine distribution sites in the Voronoi Model.

The second database used was the City of Chicago Data Portal on COVID-19 Cases per zip code. We used weekly updated data on cumulative COVID-19 cases per Chicago zip code from 3/1/2020 to 12/6/2020 [9]. We chose to use data up until December 6th to avoid mixing the data with Phase 1 vaccinations. This case data helps model historical and future trends in the cases of COVID-19 per zip code. This data also helps decide the operational order of vaccination sites based on the severity of the spread of infection.

The third database used was the U.S. Census Bureau, 2015-2019 American Community Survey 5-Year Estimates. We used the data of the total population of all of the individual zip codes to help model the risk each zip code faced. We used this data to help model the severity of each zip code's risk [7].

When developing the model, some of our desired data was unavailable. Data on vaccines allocated and distributed per zip code was not public due to the early stage of the vaccination process. Therefore, we had to make an assumption for the vaccination rate. We also could not find an exact percentage of Chicago residents unwilling to take the vaccine. We made the assumption that all Chicago re are willing to receive the vaccine.

Mathematics Methodology

Overview

Our goal in modeling is to predict the future number of cases and how long it would take to vaccinate the general population by considering many factors.

Our methodology can be summarized into the following 8 steps:

1. Calculation of Predicted Number of Cases without Vaccination (logistic regression)
2. Calculation of Susceptible Population
3. Calculation of the Number of Nodes
4. Gridded Vaccine Distribution Plan
5. Voronoi Vaccine Distribution Plan
6. Vaccine Distribution Priority
7. Calculations of Vaccination Rate
8. Simulation of Model

For each section, we will first list the assumptions made and then the modeling methodology. We will also introduce the variables used in the model.

Calculations of Predicted Number of Cases without Vaccination

Using Desmos, a graphing software, we fit a logistic regression curve to a graph of COVID-19 Chicago cases from March to December of 2020. We did this in order to model the number of cases in Chicago without a vaccination strategy.

Calculations of Susceptible Population

To model the prediction of the future number of cases, we first would need to know the number of people susceptible to the virus at the time our vaccination plan is in place. To do this, we used assumptions and data from the Center for Economic and Policy Research's analysis of the Census’s American Community Survey to calculate the susceptible population. The FDA approved the Pfizer vaccine for people 16 years or older and approved the Moderna vaccine for people 18 years or older [19]. We assumed that the vaccine in our distribution plan would be meant for people 18 years or older. We also excluded health care workers, essential workers, people over the age of 65, inmates, and people with underlying health conditions under 65 from the susceptible population. This is because our project aims to model vaccine distribution for people in Phase 2 of Chicago's population plan. All of the people excluded will have already been vaccinated in Phase 1.

$$S_i = total\ susceptible\ population\ in\ Chicago$$

We subtracted the number of people vaccinated in Phase 1 from the population of Chicago ages 18 and older to calculate the population susceptible to COVID-19 after the completion of Phase 1 [11, 21]. Since there are approximately 2,143,610 Chicagoans above the age of 18, we found that the total vaccinatable, susceptible population after Phase 1 was approximately 1.5 million people.

Calculation of the Number of Nodes

Each node in the Gridded and Voronoi Model represents a vaccination center in the city. According to the City of Chicago's Vaccine Location Map for Phase 1, we found 199 current distribution locations. We divided 199 by three and rounded down to 66 because 66 is close to the number of zip codes in Chicago, which is roughly 60 [10].

Gridded Vaccine Distribution Plan

When modeling COVID-19, we first thought of dividing the population into equally spaced regions where there would be a vaccination center at each region's center. In order to proceed with this model, we had to make the following assumptions.

The first assumption is that people are willing to get the vaccine for COVID-19. Since the vaccine promotes the health and well being of Chicago residents, we can assume that everyone would want to be vaccinated. The second assumption is that people will go to their appropriate vaccination site to receive the vaccine. The appropriate vaccination site people will go to will be the node in the region they are in. Since the node people are assigned to will be the node closest to them, we can assume that they would go to that node because it requires the least distance traveled.

We evenly spaced 66 nodes across the city. Each node bounded approximately 4.44 square miles of area, unless it was cut off by city limits, shown in figure 7. For the purpose of analysis in Geogebra, we used a scale factor of 1 square mile = 2.14 square units in Geogebra.

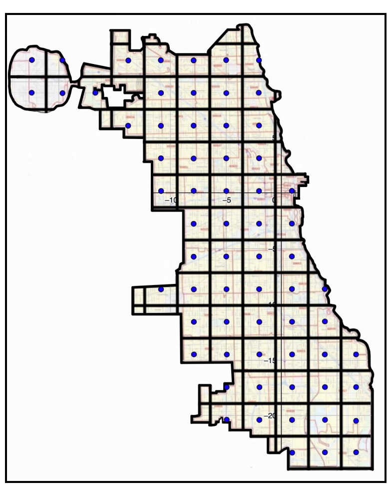

Figure 7. Gridded Model of Chicago.

Voronoi Vaccine Distribution Plan

In the Geogebra application, we used the Voronoi method to assign vaccine distribution locations, or nodes (p_i), and corresponding residential area regions, or Voronoi polygons (V(p_i)). First, we plotted generator points (p_i), or nodes, on a map of the city of Chicago.

We first placed nodes at the largest population clusters, or regions where the population density was greater than 15,000 people per square mile. Then, to ensure that different residential area regions surrounding distribution locations were relatively even in population, we plotted additional nodes near the city's areas with the highest population density. We then added nodes in regions with population densities of between 9,000-15,000 people per square mile. Lastly, we plotted the remainder of the nodes in areas where population density was below 9,000 people per square mile.

In developing the Voronoi diagram, each generator point (p_i) was bounded by a Voronoi polygon V(p_i) with the property shown below in equation 1,

$$\mathrm{V}(p_i) = \{\mathrm{q} \mid \mathrm{d}\,(p_i\,,q) \leq \mathrm{d}\,(p_j\,,q), \qquad i \neq j, \tag{1}$$

where d (x,y) was the distance from point x to point y, i.e. the set of all such q is the set of points closer to p_i than to any other p_j [23]. A diagram was produced by V = {$V(p_i)$,...,$V(p_n)$}, shown below in figure 8.

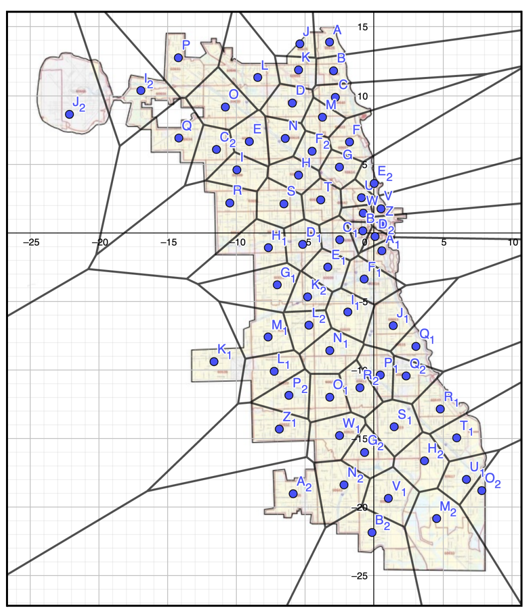

Figure 8. Voronoi Model of Chicago.

Vaccine Distribution Priority

To account for scenarios in which Chicago's resources are limited, we developed an algorithm to help identify high priority distribution regions. In these scenarios, not all of the nodes would be operational, so we ranked the nodes by case rate to determine which regions would be open and which would be closed. To calculate each region's case rate, we used data on cumulative cases per zip code from the City of Chicago Data Portal.

Calculations of Case Rates per Zip Code

Due to COVID-19's unpredictable nature, case rates are constantly changing. However, to continue modeling the rest of the steps, we need case rates to be a constant value. In order to do this, we used a linear regression model to calculate the case rate. We chose to use linear regression to model case rate instead of a model more traditionally used for a pandemic, such as a SIR model, because COVID-19 is not in a controlled environment and is influenced by many factors that are unmodelable, such as government decisions or human behavior. Even though a linear regression does not fit the curve exactly, it accurately models the general trend of cumulative cases associated with the pandemic.

Let

$$C_i = Case\ rates\ per\ zip\ code\ (cases\ /\ week).$$

To find the case rates per zip code in Chicago, we graphed each zipcode's cumulative cases from March 1st, 2020 to December 6th, 2020. Before March 1st, 2020, COVID-19 did not substantially spread to Chicago yet, which is why we did not account for the cumulative cases before March 1st, 2020. We did not account for cumulative cases after December 6th, 2020 because Chicago began vaccinations, which would influence the number of cases per zip code.

After graphing the cumulative cases of each zip code, we modeled the data with linear regression. The slope of the line can be thought of as the case rate because the line's slope shows the speed of growth in cases throughout the COVID-19 pandemic. For example, Figure 9 shows the slope of the linear regression as 110 for the zip code 60609, with an R^2 value of 0.915.

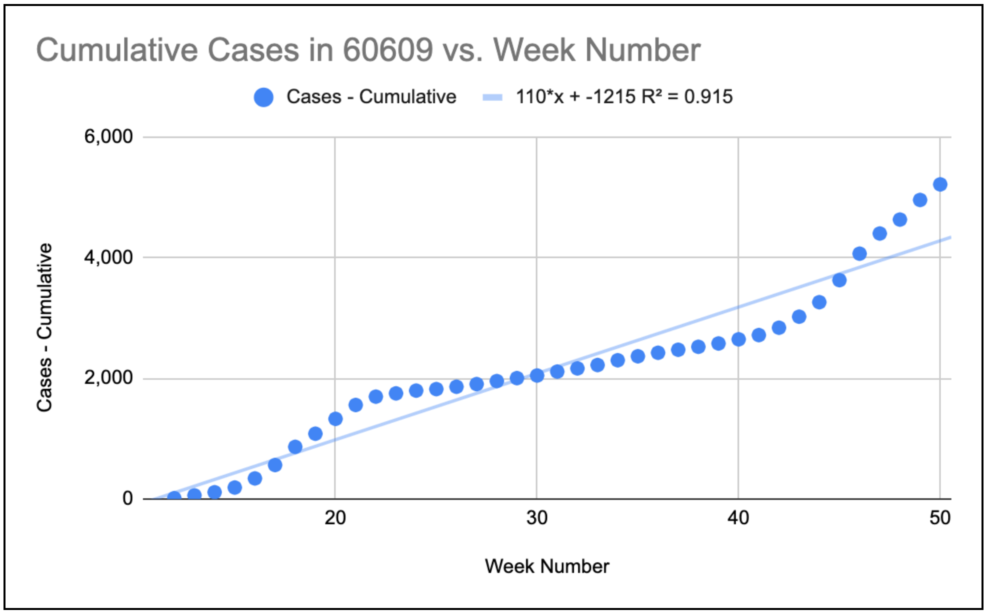

Figure 9. Graph of cumulative cases for 60609 vs. number of weeks after March 1, 2020 [9].

Calculations of Case Rates per Vaccine Distribution Region

Once we determined a case rate for every zip code, we used a weighted average method to find the case rates per distribution region. To use the regions in the Gridded and Voronoi Models, we had to convert zip code case data to node case data. Since each region bounded fractions of zip codes, we found the weighted averages of their case rates [6].

Calculations of Vaccination Rate

Due to the unavailability of information on vaccination rates at the time of our model development, we were unable to find Chicago's vaccination rates, which is why we had to approximate. In order to calculate the vaccination rates, we needed to make some assumptions.

The first assumption is that each vaccine administrator at a site takes 10 minutes to vaccinate a person. However, due to the vaccine requiring two doses to maximize effectiveness, one person will spend a total of 20 minutes (10 minutes per dose) at a vaccination site. The second assumption is that each node is open for 10 hours, 7 days a week, with shifts for vaccine administrators. This means that one vaccinator can vaccinate 30 people per day, or 210 people per week. Finally, the third assumption is that the chance of developing infection with COVID-19 following immunization is 0.05%. This assumption is based on data collected from clinical trials of the Pfizer-BioNTech COVID-19 Vaccine [17]. To account for this percent efficacy, we multiplied the vaccination rate by 0.9995, shown in Equation 2.

$$V_i = \text{vaccination rate per administrator per node (vaccinations / week)}$$

V_a = *number of vaccine administrators per node*

$$V_i = 0.9995(210 \cdot V_a) \tag{2}$$

Vaccination Rate for Gridded Model

For the Gridded Model, we assigned V_a to be 5. This is because this model took an equal approach for each distribution site, so each node had the same vaccination rate. Therefore the vaccination rate for each node was 998 vaccinations per week.

Vaccination Rate for Voronoi Model

Since each vaccination node included different numbers of populations, the number of vaccination administrators varied. Below is a table showing the number of administrators and the vaccination rates per node.

Vaccine Administrators (V_a)	Population Per Node	Node Vaccination Rate
0	0	0
5	1,000 to 9,999	1,050
6	10,000 to 14,999	1,259
7	15,000 to 19,999	1,469
8	20,000 to 24,999	1,679
9	25,000 to 29,999	1,889
10	30,000 to 34,999	2,099
11	35,000 to 39,999	2,309
12	more than 40,000	2,519

Table 1. Vaccine Administrators for Nodes.

Simulation of Model

Variables

Variable	Definition	Units
P_n	The Susceptible Population of a Node	Number of People
C_n	The Number of New Cases per Week in a Node	Cases / Week
V_n	The Number of Vaccinations per Week in a Node	Vaccinations / Week
R_n	The Ratio of the Number of New Cases to the Total Susceptible Population	New Cases per Week / Total Population
S	Total Susceptible Population in Chicago	Number of People
Q	New Cumulative Cases in Chicago	Cases

Table 2. Variables Used in Simulation.

To simulate long and short-term effects of our two vaccination plans on Chicago residents, we coded a program using Python and the Pandas library. We input four parameters for each node: P_n, C_n, V_n, and R_n, where n is an integer from 1 to 66 representing node n. We created two variations of the simulation with the first outputting the cumulative cases after 20 weeks, and the second outputting the total number of weeks for the susceptible population to reach zero. In both variations, the code sorted the data by descending case rate to determine which nodes should be vaccinated first; the nodes with the highest case rates were vaccinated first.

We used Python's compound assignment operators to update the values of the inputs. Assignment operators assign the value on the left side of the equal sign to the right side of the equal sign. One example is x += 1 which is equivalent to x = x + 1 [20]. This operator updates the value of x by adding one to the previous value of x. If we assume x originally equals 1, then after we use the assignment operator, x will equal 2. There is also a subtraction compound assignment operator. It is the same as the above example but subtracts from the variable rather than add.

We then chose the *n* active nodes with the highest case rates and updated the inputs for these nodes every iteration, where one iteration represents one week, as these values changed once people were vaccinated or infected.

Each iteration, we made the following updates to the inputs:

$$P_n \mathrel{-}= V_n + C_n \tag{3}$$
$$S \mathrel{-}= V_n + C_n \tag{4}$$
$$C_n = R_n * (P_n + V_n + C_n) \tag{5}$$
$$Q \mathrel{+}= C_n \tag{6}$$

The susceptible population of an active node and the total susceptible population of Chicago decreases by the quantity of the vaccination rate plus the case rate as those who have been vaccinated and those who have been infected are no longer susceptible. The case rate of each node decreases because the susceptible population decreases. The $(P_n + V_n + C_n)$ in Equation 5 is the susceptible population before it is updated to account for vaccinated and infected people. Multiplying this quantity by R_n yields the updated case rate of that node. Equation 6 adds the number of new cases in a node to the cumulative cases.

We also updated the values of the inputs for the remaining inactive nodes every iteration. Since these nodes are not vaccinating their susceptible populations, the following updates do not use V_n.

$$P_n \mathrel{-}= C_n \tag{7}$$
$$S \mathrel{-}= C_n \tag{8}$$
$$C_n = R_n * (P_n + C_n) \tag{9}$$
$$Q \mathrel{+}= C_n \tag{10}$$

In the first variation, we ran this process 20 times to determine the cumulative cases after week 20 and re-ranked the nodes each time. By re-ranking the nodes every iteration, both the Gridded and Voronoi models are able to vaccinate the nodes that have the highest case rates at that week number, allowing them to adapt to the current situation. In the second variation, we ran this process until the number of susceptible people in Chicago reached zero, at which point, the model outputted the number of weeks to reach a susceptible population of zero.

Model's Responsiveness to Trends

Both models are able to respond and adapt to current COVID-19 case trends due to the re-ranking process in the code. This process finds the nodes with the highest instantaneous case rates and provides vaccines to those nodes every week. Due to the adaptiveness of both models, a node can be prioritized if an outbreak occurs in that node.

The Voronoi Model is highly responsive to trends and changes in population density because vaccination distribution center nodes can easily be relocated to new clusters of high population density. This is important for being able to model future epidemics in Chicago or other metropolitan areas.

Model Results and Analysis

Outputs of Models

Without a vaccination plan, the number of cumulative cases is projected to grow by an additional 297,755 cases in 20 weeks following December of 2020 based on existing trends, as shown in figure 10. In 143 weeks, Chicago is projected to approach 1.5 million cumulative cases of COVID-19.

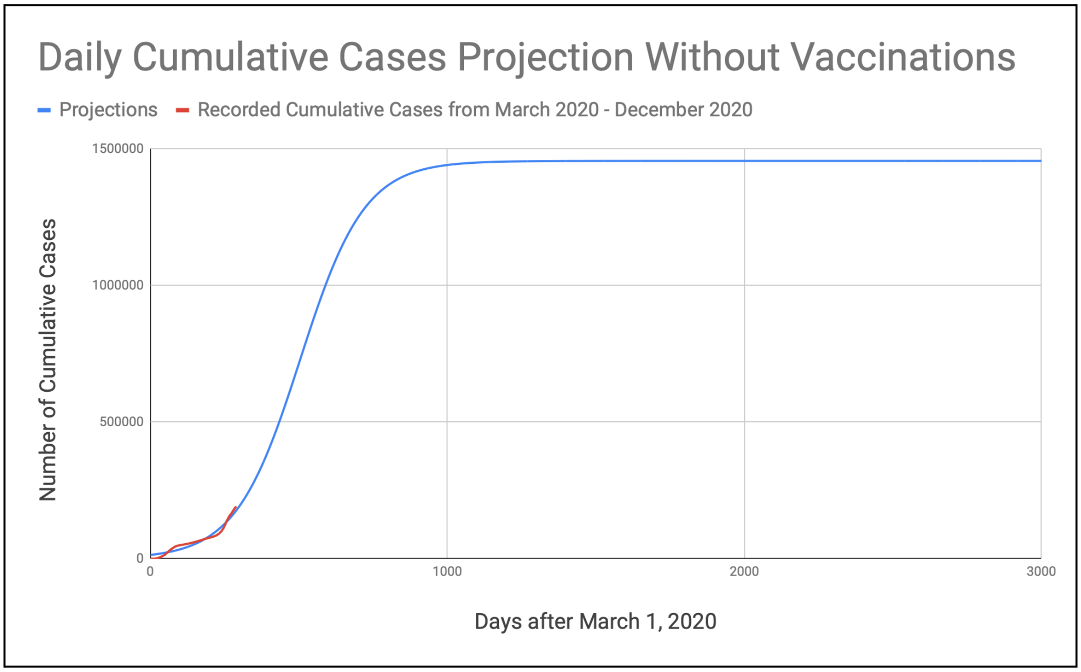

Figure 10. Daily Cumulative Cases Projection without Vaccinations based on cumulative cases from March 2020 to December of 2020. Source of Recorded Cases: Chicago Data Portal.

We compared the efficacy of the Voronoi and Gridded Model based on the time it takes to vaccinate the entire susceptible population after the end of Chicago's Phase 1 distribution. Below, figure 11 shows a projection for vaccination time, depending on the number of operational nodes every week. Based on the simulation results for all 66 operational nodes, the Voronoi Model will finish vaccinating everyone in 14 weeks, while the Gridded Model will finish in 22 weeks.

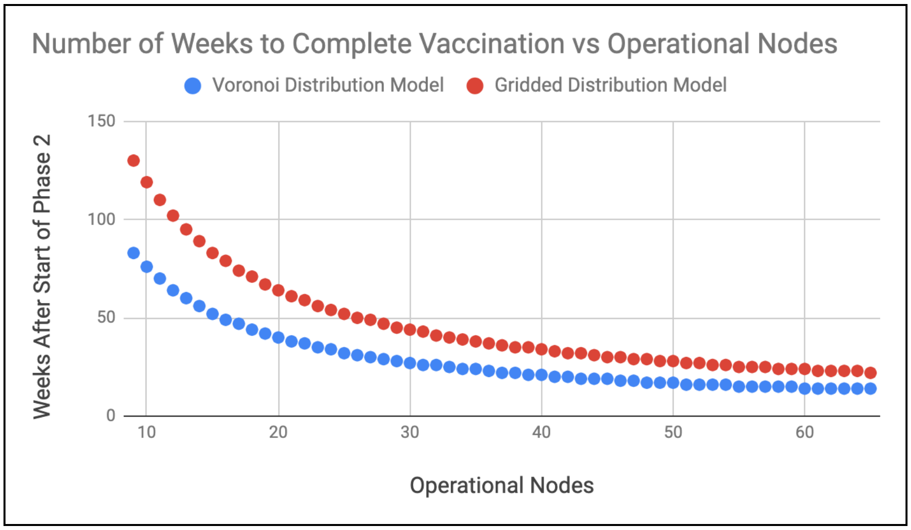

Figure 11. Time it will take to complete vaccination, depending on the number of operational nodes (vaccination distribution centers).

To further compare the two vaccination models, we projected the number of new cumulative cases after the start of Phase 2 in a certain week and graphed it against the number of operational distribution sites. Figure 12 compares the new cumulative cases 20 weeks after the start of vaccinations. As the number of operational vaccination sites (nodes) increases, the new cumulative cases will decrease. With 0 active nodes, the number of cases will follow a logistic regression, resulting in nearly 300,000 cases after 20 weeks. Even one active node can decrease the number of cases by a significant amount. This graph also shows that the Voronoi Model is more effective in lowering the number of COVID-19 cases in Chicago. If all 66 sites are operational every week, the Voronoi Model yields 22,599 new cumulative cases while the Gridded Model yields 42,349 new cumulative cases after week 20.

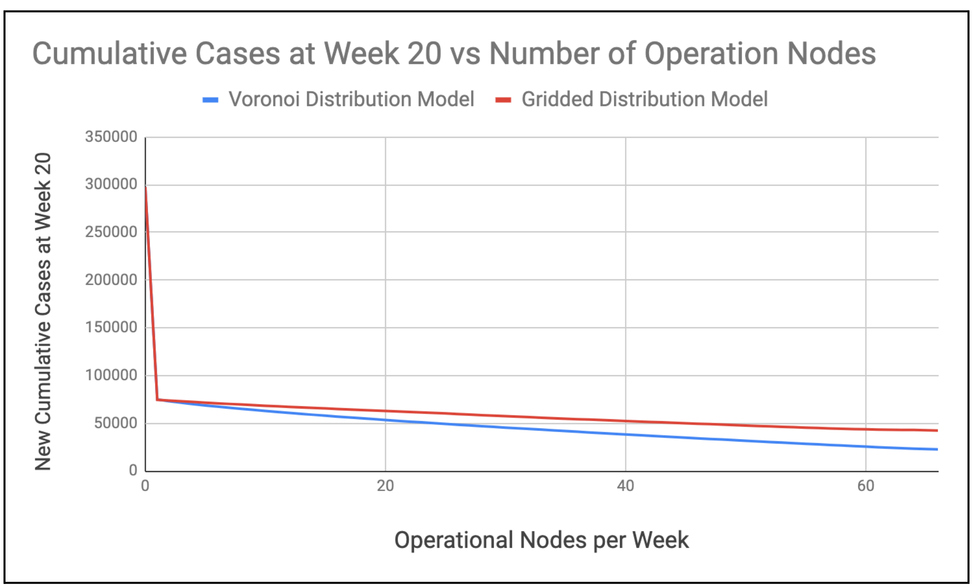

Figure 12. Graph of new cumulative cases against operational nodes after 20 weeks.

Finally, we compared the number of new cases per week with all 66 nodes operational in figure 13. Even though both models result in similar numbers of cases after the first week, the Voronoi Model significantly reduces the number of new cases per week.

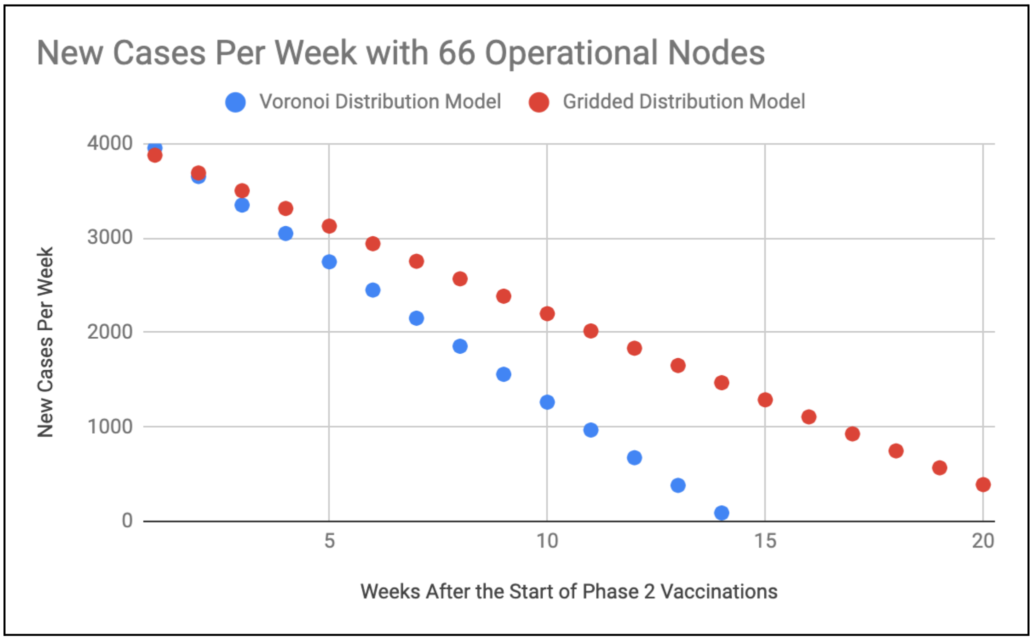

Figure 13. Projections of New Cases per Week using the Voronoi Model and the Gridded Model.

Analysis and Conclusions

Risk Characterizations

Model Risks

The largest risk to our models is that if the vaccine distribution plan is inefficient or ineffective, the frequency of COVID-19 cases will increase. This can result in a domino effect with public health and economic implications. As the timespan of the pandemic increases, the severity of these implications will increase.

Strengths and Limitations of the Model

The population of zip codes and case data in our model come from reliable and credible organizations. This helps eliminate unintentional bias from our model. In addition to strong data reliability, our model is also highly flexible and adaptable to changes in inputs such as number of vaccinators per site and amount of nodes giving out vaccinations per week. As a result, multiple potential distribution cases can be developed and examined for their efficiency.

However, our model is limited in its dependency on assumptions and its scope of analysis. Furthermore, it is difficult to precisely model COVID-19 cases because of random, unpredictable contact patterns. This being said, our model is workable, plausible and replicable. It can be applied to other cities, towns and states if relevant data is available.

Health Risks

In just over one year since the world's first reported human infection with SARS-CoV-2, there have been more than 110 million reported cases of COVID-19 and more than 2 million reported deaths worldwide. The overall severity of the pandemic will be defined by the number of global cumulative cases and deaths, which will only increase as the length of the pandemic increases.

Racial Disparities

In Chicago and other metropolitan areas, COVID-19 causes severe infections in every demographic, while disproportionately affecting people of color. According to Dr. Allison Arwady, the Commissioner of the Chicago Department of Public Health (CDPH), a higher rate of chronic disease among African Americans, in comparison to white people, increases their risk of dying of COVID-19. Additionally, chronic disease among African Americans can be linked to decades of inequitable access to important resources, such as healthcare and economic opportunities [12].

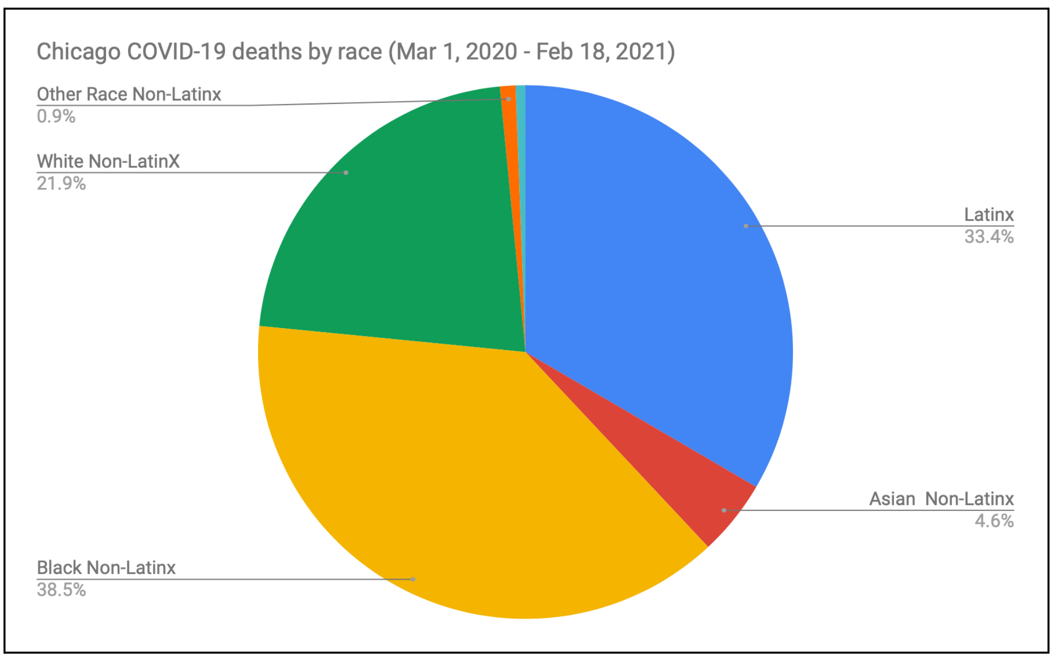

Figure 14. Total Chicago COVID-19 related deaths by race from March 2020 to February 2020. Source: Chicago Data Portal.

Shown in figure 14, although white people make up nearly 50% of Chicago's population, over 50% of Chicago COVID-19 deaths have been among Black Non-Latinx and LatinX populations, further highlighting resource disparities [26, 28].

Long-Term Health Conditions

Furthermore, COVID-19 can increase the risks of long-term health conditions [29]. According to Mayo Clinic, COVID-19 symptoms can persist for months after the initial infection. Sustained damage to organs such as the brain, lungs and heart can exacerbate existing medical conditions and increase the risk of developing other long-term conditions. Much is still unknown regarding long-lasting and lingering effects of a COVID-19 infection on the human body [8].

COVID-19 Vaccine Efficacy

As of February 2021, two vaccines were administered in Chicago- the mRNA based Moderna and Pfizer Vaccines. Each was shown in clinical trials to have about a 95% efficacy in preventing symptomatic cases of COVID-19 [17]. Specifically, a 95% reduction in the number of new cases was observed in the vaccinated group of people in comparison to the placebo group. For example, if a population of 1000 people were vaccinated, we would expect approximately 1% or 50 people would eventually be infected with the virus. Although the efficacy of both vaccines are high, people vaccinated are still at some risk of being infected. As more of the population is vaccinated, this risk will decline.

Recommendations

<u>Government Recommendations</u>

When deciding how to vaccinate the city of Chicago in phase 2 of the Illinois plan, we recommend that the Chicago Public Health officials should focus on an equitable distribution of vaccines, rather than an equal distribution of vaccines to areas across the city. The Gridded Distribution Model initially seemed like the optimal distribution and risk mitigation strategy due to it distributing the vaccine evenly by area. However, due to differing population densities and differing case rates, this vaccination plan would not prioritize the communities that have been affected more by COVID-19. The Voronoi Distribution Model proves to be the more optimal distribution method and risk mitigation strategy as it considers population density and case rate, which are key factors when trying to mitigate a pandemic.

These claims can be supported in the output of the two distribution models. Vaccinating with the Voronoi Distribution Model is completed about 1.6 times faster than vaccinating with the Gridded Distribution Model. A calculated projection of the Voronoi Distribution Model also predicts lower cumulative cases of COVID-19 than the Gridded Distribution Model.

Therefore, we recommend that the government implements the Voronoi Distribution Model immediately after the Phase 1 vaccinations, or a plan as close to that model as possible. We recommend that each of our 66 distribution sites will be mapped onto Chicago, in a 5 block radius, allowing the Chicago government to find an optimal, large, and accessible location for vaccination distribution. An example of that would be an empty parking lot.

Further Recommendations

Risks associated with the COVID-19 pandemic can also be mitigated in a number of ways. The U.S. Center for Disease Control and Prevention (CDC) recommends that members of the general public wear cloth masks to slow down the transmission of COVID-19. We also recommend for everyone to practice social distancing, as that is a cautionary measure that can help prevent further transmission of the disease [5].

Conclusion

In short, our mathematical modeling and analysis of the data concludes that when implementing a vaccination plan, focusing only on dividing the city into equal areas may prove to be dangerous for the city’s population and costly for businesses that rely on in person interaction. To address these risks, we developed a vaccination model that implements factors such as population density and case rates to reduce the time it takes to vaccinate the general public of Chicago and to lower the number of COVID-19 cases.

Appendix

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Technical Computing

The simulation of the model was performed using Python 3.x in a standard Python environment. All code and data can be found in this link: https://github.com/theAvman/COVID-19_Vaccine_Distribution_Plan.git. The calculations were performed using the base Python packages, but the Pandas library was used for data manipulation.

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