Simulating Effect of Vaccination on Disease Propagation Dynamics

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Executive Summary

Vaccination programs are very important to have. Such programs may require an initial investment, but in the long run, they are worth it. An outbreak impacts not just public health, but also impacts the economy, and these costs are much higher than the cost of the vaccination program and the cost of the vaccine combined.

To make such conclusions, we created a simulation that tested different vaccination coverage rates and provided data on which rate would be best in achieving the highest rate of prevention while still remaining achievable. We recommend that the city have a vaccination program that has a 71% coverage rate to reduce costs and maintain economic productivity.

We also recommend having a strong marketing campaign to support the program. This campaign will increase the total project cost by a small margin and will increase the overall reach of the program, making it much more effective.

Problem

Ineffectiveness of vaccination programs is not unique to this city. Most US cities fail to achieve a vaccination coverage rate greater than 40-60%. Nonetheless, every year, roughly $1-6 million per 100,000 individuals is spent to mitigate the impact of influenza. This is roughly $20-120 per person (considering 50,000 individuals are infected if the vaccine coverage is 40%), a cost which is much higher than the cost of influenza vaccines, which is either free for those with healthcare insurance (majority of the population), or ranges from $10-$40 for those without one.

Disease propagation does not only impact the public health department of the city, but also affects its economic productivity, in the form of work absenteeism and reduced efficiency at work. Hence, to understand the importance of increasing vaccine coverage, the total impact of an influenza outbreak needs to be considered, including its impact on the public health facilities of the city.

The main goal of increasing vaccination coverage is to create herd immunity, a phenomenon where sufficiently large number of people are immunized such that a disease is prevented from becoming an epidemic. To decide this ideal rate, also known as herd protection rate, two factors need to be considered: reproduction number and vaccination effectiveness.

Reproduction number is the number of secondary cases of infection per infected individual in a population. If this number is less than 1, then the disease propagates linearly, and a large vaccination coverage rate is not required. It has the following formula:

$$R_0 = (Probability\ of\ getting\ infected) * (Number\ of\ interactions/day) * (Days\ infected)$$
$$= (0.1) * (3) * (5) = 1.5$$

As can be seen from the above formula, R_0 is greater than 1, indicating that the disease propagates non-linearly. Hence, a vaccination coverage is required for the city. This problem is exacerbated by the fact that influenza vaccines have a low vaccine effectiveness (VE), that is, how well an immunized population is protected from an infection. For the year 2019, the effectiveness was a mere 47%, and this number has not exceeded 60% for the past few years. Combining the two factors, the herd protection rate was found to be about 71% using the following formula:

$$Herd\ protection\ rate = (1 - 1/Ro)\ /VE = 0.33/0.47 = 0.71$$

We decided to use this mathematically-predicted number in our model, to examine whether increasing coverage produces the desired result, that is, if it significantly reduced the number of infected individuals during an epidemic.

Assumptions

Before diving into our approach, we would like to discuss some of our base assumptions. We formulate our model by assuming that the city's total population equals 100,000, and will not change during the epidemic, that is, no one is born and no one dies during the epidemic, either due to the disease or from any other cause. Another assumption is that 0.1% of the city's population gets infected at the beginning of the epidemic. Additionally, we assume that infected people stay infected for 5 days before becoming immune. Our final assumption is that of 100% vaccination effectiveness, meaning people vaccinated prior to the epidemic become immune to the disease.

Approach

Conceptually, our approach involves using the expression for the probability that a susceptible person gets infected during the day, which is$1 - e^{-\lambda p \frac{N_I(d)}{N}}$. Here, λ is 3, the number of interactions per day, which we model as a Poisson variable, and which varies for each day; p is 10%, the probability of a susceptible person getting infected after interacting with an infected person; N is fixed at 100,000 and is the total size of the population of the city; and $N_I(d)$is the number of susceptible people at the beginning of day d. We note that the probability of a susceptible person getting infected during the day is equal to 0 for very small λvalues and 1 for very large λ values. That probability is also directly proportional to both p and $N_I(d)$. This all makes sense intuitively since higher λ means coming into contact with infected people with higher probability, higher p equals higher probability of getting infected upon meeting such people, and higher $N_I(d)$ means a higher number of susceptible individuals who can be infected. We also model the duration of the epidemic as a Poisson variable with lambda equal to 30 days/epidemic.

We used this individual-level information, the probability that each susceptible people gets infected, to infer population-level information, the number of newly infected people for day $d > 0$. We associate the probability distribution of a susceptible individual becoming infected as a binomial distribution, with n, the number of draws being equal to the number of susceptible people for $d - 1$, and the probability of success as the probability of getting infected.

Subsequently, we first simulate the epidemic's propagation in a baseline case where no individual is immunized. For each day d of the epidemic, we draw the number of interactions/day from the Poisson distribution and compute the probability of a person being infected, as per the expression mentioned earlier. Then we compute the number of newly infected people, as deterministically equal to 100 for $d = 0$, and draw from the Binomial distribution as previously discussed for $d > 0$. We also compute the number of newly immune people as 0 if day $d< 5$, and as the number of newly infected people from $d - 5$ for $d > 5$, to take into account infected people who have become immune after 5 days. Finally, we compute the running total number of infected, immune, and susceptible people at day d. The number of susceptible people, for $d = 0$, equals 99,900, since 0.1% of 100,000 people are initially infected, and for $d>0$, equals the number of susceptible people from d-1 minus the number of newly infected people for d. The number of infected people equals the number of infected individuals from $d - 1$plus the number of newly infected people for d minus the number of newly immune people for d. The number of immune people equals the number of immune people for $d - 1$plus the number of newly immune people for d.

Each simulation run represents a different epidemic. For each run, we find the day d^* that equals the last day of the epidemic by sampling from the Poisson distribution of rate 30 days/epidemic. Then, we compute the total number of infected people at the end of the epidemic by taking the corresponding total number of infected people for day d from that particular day d^*. To incorporate vaccination coverage, we only need to adjust the number of susceptible people for $d = 0$, by multiplying the total population by 1-% initially infected - % vaccinated instead of just 1-% initially infected, as in the baseline model. We also add the number of vaccinated people to the number of immune people for d=0.

Variables

We had some deterministic inputs that could be varied. A key one was vaccination percentage, for which we tested values of 0%, 20%, 40%, 60%, and 71%. Some other variables were the number of interactions/day, probability of a susceptible person getting infected upon interaction, initial % infected, and the number of days it takes for an infected person to become immune. We decided to run sensitivity analysis on the first two variables.

Analysis

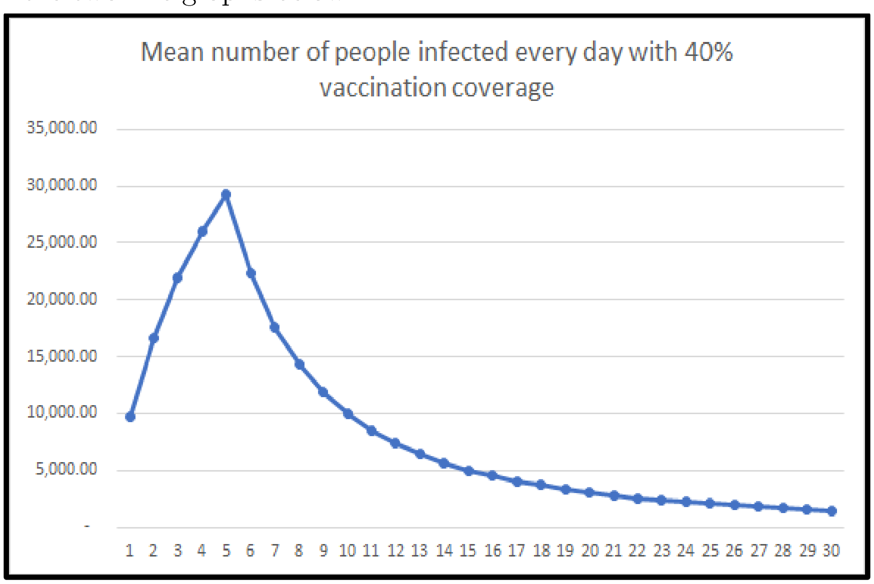
Given the variables mentioned above, we decided to choose the output as the total number of people infected during a typical epidemic. This would help us evaluate the total impact of the epidemic on the city's hospitals, and on the economy, and would help us understand how widely the disease propagated for different vaccination coverage rates. We created 5 simulations for the following 5 vaccination coverage rates: 0%, 20%, 40%, 60% and 71% (the ideal rate). The table below illustrates some important metrics used for three of the five simulations that clearly showed the drastic difference in the mean number of people infected for the different vaccination coverage rates.

Measure	0%	40%	71% (Ideal rate)
Mean	90,155	50,688	21,689
5th Percentile	86,945	47,845	19,427
95th Percentile	92,760	53,043	23,478
Standard Deviation	1,869	1,788	1,245

As can be seen from the table above, more than 90% of the population is infected during the epidemic if there is no vaccination coverage. This number, more than anything, indicates that some form of vaccination coverage is essential for the city. Furthermore, given that the 5th percentile of this metric is almost 87000 individuals, this means that under most scenarios, a very large majority of the population will be infected, and will not be able to function effectively for about 5 days.

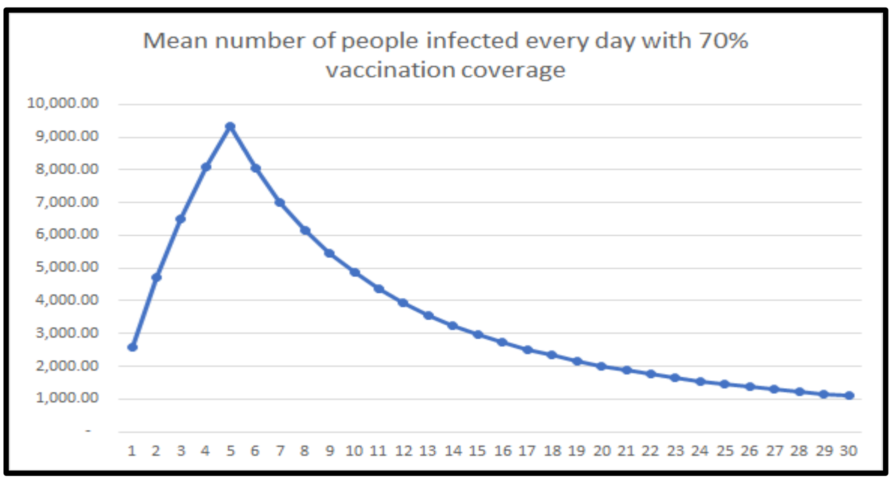
On the other hand, continuing the existing vaccination programs, which would achieve a coverage rate of 40%, will reduce the total number of infected people to about 50% of the population. While this number is significantly lower, it is still not low enough to not have a detrimental impact on the city's resources. In comparison to this, a 70% coverage rate results in only 20% of the population being infected during a typical epidemic. If we can achieve this vaccination coverage rate, especially by immunizing children and adults over the age of 65, we can significantly reduce the impact of an influenza epidemic on the city's public health department.

We also found the mean total number of people infected in the city every day, to track the number of infected people each day that may visit a hospital or may be unable to function at their full capacity. This would help us analyze how many days the city's hospitals may face operational issues due to the epidemic. We found these numbers for the status quo (vaccination coverage of 40%), and compared it with those for a vaccination coverage rate of 71%. The results of our model are displayed in the two line graphs below.

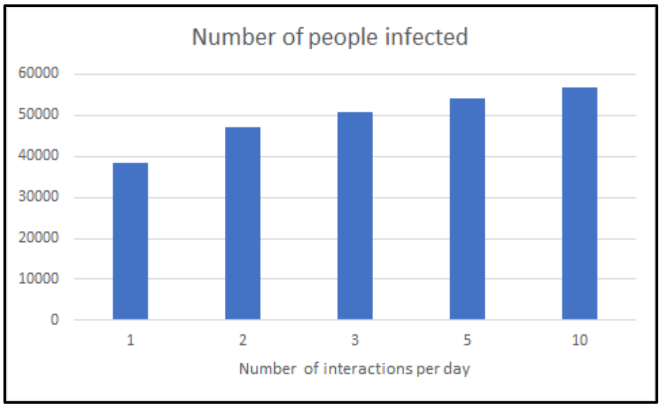


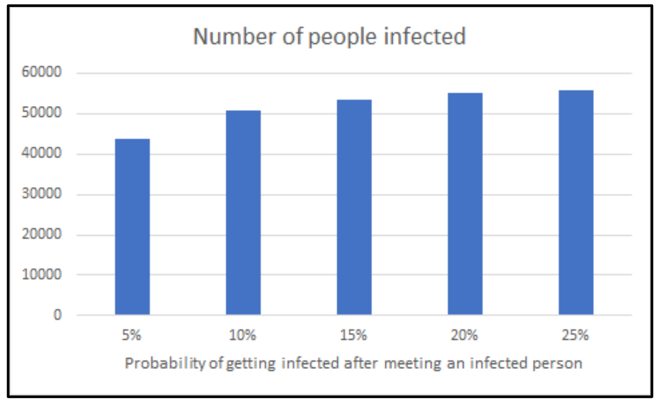
With 40% coverage rate, the results reveal that there are at least 10 days when more than 10,000 people are infected with the influenza virus. Additionally, this number quickly peaks to 30,000 infected individuals within 5 days. Reports from Centers of Disease Control and Prevention (CDC) in the US suggest that at least 50% of the population that is infected during an epidemic visit the hospital. This indicates that there will be days when anywhere from 5000-15000 individuals will use the city's hospital facilities. Depending on the city's current hospital capacity, this may put a huge strain on the operations of the city's public health department.

On the other hand, with a 71% coverage rate, the number of infected individuals on any given day never exceeds 10,000, and is above 5,000 for about 10 days. This indicates that about 2500-5000 individuals may visit the hospital on any given day, a number that is much more manageable for a city of this size. Additionally, by adjusting operations during first several days of the epidemic, to accommodate the sudden rise in infected individuals visiting the hospital, the public health department can strategically deal with the epidemic without facing significant operational inefficiencies.



A final part of our model involved performing a sensitivity analysis with certain variables in our model that we assumed to be deterministic. Specifically, we adjusted the number of interactions per day (lamda), which was fixed at 3 per day in our model, and the probability of a susceptible person getting infected, which was fixed at 10% in our model. The results from our model are displayed in the graphs below. These values have been calculated by fixing the vaccination coverage rate to 40%.





As expected, both measures have a direct relationship with the total number of infected individuals. However, these two variables do not have a drastic impact on the total number of people infected in the city. Nonetheless, an influenza outbreak can be dealt with more effectively if a more holistic is taken by the health department. This involves improving preventive measures available to the general public, such as making sanitizers or face masks more readily available in public spaces, in order to reduce the probability of a susceptible individual becoming infected. These measures may help prevent a few thousand individuals from getting the virus.

Recommendation

Marketing

New York City has a high success rate with its vaccination program's marketing campaign. It has a 71.5% vaccination rate of children aged six months to 17 years, 44% vaccination rate of adults aged 18 to 64 years, and 66% vaccination rate of adults aged 65+. While 44% is similar to the vaccination rate of the city, NYC has a high vaccination rate of people in the most susceptible age groups. Because of this, we recommend utilizing a marketing campaign similar to New York City's. The marketing campaign is low cost and will assist in increasing vaccination coverage.

We recommend that the city makes the vaccines widely available. By having vaccines easily accessible, people will be more willing to get the vaccination. Vaccines should be marketed in the form of posters on public transportation and advertisements on social media to reach the most people. The posters and ads should not only persuade people to get the vaccine, but also present statistics on deaths caused by the influenza and information on how to prevent getting sick in general. Schools should send out letters to parents encouraging them to vaccinate their children.

The city should also make it mandatory for students aged six months to five years to be vaccinated each year.

Risks

Our recommendation has several risks. The first risk is that vaccination effectiveness might not be 100% because existing influenza vaccines made to counter previous strains may not deal as well with new strains that will be circulating in the future. Thus, to compensate, vaccination coverage needs to be higher to achieve the same benefits as those under the assumption, which in turn increases operating costs. A second risk results out of the seasonal nature of the virus. Every year a new strain of the virus affects individuals, meaning another possible epidemic. Thus, the population needs to be vaccinated every single year if there are new strains, which also increases cost. A third and final risk is the difficulty of achieving a high vaccination coverage rate due to limited outreach. It is logistically difficult to increase awareness. It would require ad campaigns, which introduces more costs. However, even a person who knows about the vaccine might not necessarily be willing to get vaccinated, whether due to religious or moral beliefs or confidence in their belief that vaccines are harmful to their health.

Opportunities

Our recommendation offers several opportunities. The first is immunity to a particular strain if it emerges in the future. The second is the protection of non-vaccinated, susceptible people through the herd effect. With a high enough population of vaccinated people, it will act as a buffer, breaking the chain of infection by ensuring each case only produces one new case, preventing epidemics. The final opportunity is the benefit from reducing influenza costs on the heath care, individual, and societal levels. On the health care level, this involves fewer visits to the doctor and fewer hospitalizations due to complications from influenza and reduces medical cost. On the individual level, avoiding work absenteeism prevents lost wages. Additionally, it creates savings of up to $13 per person, as can be displayed from the table below. Finally, on the societal level, preventing sickness-caused work absenteeism will allow companies to work efficiently. In turn, this increase in economic productivity will lead to growth in the city.

Cost Category	Mean Costs per Person Vaccinated, $
Costs of Vaccination	
Direct costs	
Of vaccination	10
Of potential side effects	0.64
Indirect costs	
Of vaccination	4.58
Of potential side effects	1.47
Total Costs of Vaccination	**16.69**
Direct medical care costs averted	
Physician visit	2.50
Hospitalizations	1.49
Indirect costs averted	
Work absenteeism	18.06
Reduced work effectiveness	2.81
Present value of future earnings forgone due to premature mortality	5.49
Total Costs Averted	**30.35**
Net Costs (Savings) Due to Vaccination	
Mean costs (savings)	(13.66)

Appendix

The following screenshots present the model we created on Microsoft Excel.

Output					
Total number of people infected	21,831.00				
Sensitivity Analysis					
Number of people infected each day					
Day	1	2	3	4	5
Mean number of people infected	2,595.49	4,710.39	6,513.49	8,057.62	9,319.48

Simulation

Day	Interactions per day	Susceptible individuals count	Probability of one person getting infected	Newly infected individuals	Total number of infected people	Newly immune people	Total number of immune people	Total number of people (Sanity Check)
-	3	29,687	-	100	100	-	-	29,787
1	3	27,157	0.085	2,530	2,630	-	-	29,687
2	3	25,032	0.078	2,125	4,755	-	-	27,157
3	3	23,221	0.072	1,811	6,566	-	-	25,032
4	3	21,658	0.067	1,563	8,129	-	-	23,221
5	3	20,296	0.063	1,362	9,391	100	100	21,758
6	3	19,097	0.059	1,199	8,060	2,530	2,630	22,926
7	3	18,034	0.056	1,063	6,998	2,125	4,755	23,852
8	3	17,084	0.053	950	6,137	1,811	6,566	24,600
9	3	16,230	0.050	854	5,428	1,563	8,129	25,213
10	3	15,459	0.048	771	4,837	1,362	9,491	25,721

Inputs					
Given					
Total Population	100,000				
Percentage vaccinated	0%				
Simulations	0%	20%	40%	60%	70%
Number of immune individuals	0				
Percentage infected initially	0.10%				
Number of infected individuals	100				
Percentage susceptible initially	99.9000%				
Number of susceptible people	99,900				
Number of days infected	5				
Number of daily interactions					
Distribution	Poisson				
Lambda (#/day)	3				
Probabiliy of getting infected	10%				
Number of days an epidemic lasts					
Distribution	Poisson				
Estimate	30				

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