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Analysis of the Impact of Vaccinations on Pandemic Metrics in the New York Metropolitan Area

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ABSTRACT

This study evaluates the relationship between pandemic cases and vaccination usage, ICU bed utilization, hospitalizations, and deaths in the New York City metropolitan area. The study includes variables for the lockdown period and confirmed infections. The evaluation addresses three periods: (1) before vaccinations, (2) after vaccinations, and (3) the lockdown period. In addition, the number of vaccines per day for the manufacturers (Pfizer, Moderna, and Johnson & Johnson) are included in the study. Comparisons with New Jersey and Connecticut are used to validate that New York statistics are consistent with other states. The results provide a general model of the effectiveness of the vaccines and other variables that can be used as the basis for estimating the impact of future pandemics on business operations. The research discusses the managerial implications of the findings, enabling businesses to proactively prepare for and mitigate the disruptions caused by future pandemics.

Keywords: Corona Virus; Pandemic; Statistical Models; Healthcare Management

INTRODUCTION

Early in the spread of the Corona Virus, New York City became the epicenter of the pandemic outbreak with its high-density population contracting the virus effecting more people than other areas of the country. This resulted in the initial shipments of the vaccine going to New York state. As the manufacturers produced the vaccine, 10,725 doses were initially distributed to New York on December 14, 2020, and through July 21, 2021, more than 24 million doses had been administered in New York to combat the pandemic. This study addresses the initial pandemic outbreak and the impact of the vaccines before the second wave, the Delta variant, in the summer of 2021. Cases of novel coronavirus (nCoV) were first detected in China in December 2019, with the virus spreading rapidly to other countries across the world (Shereen, 3030). This led WHO to declare a Public Health Emergency of International Concern (PHEIC) on 30 January 2020 and to characterize the outbreak as a pandemic on 11 March 2020. Since the disease is highly contagious, pandemic cases quickly increased around the world (Hu, 2020). This resulted in the declaration of an international public health emergency by the PHEIC (Public Health Emergency of International Concern) on January 30, 2020. The World Health Organization (WHO) declared the outbreak a public health emergency of international concern (PHEIC) on 30 January 2020 (WHO, 2020). On 5 May 2023, more than three years into the pandemic, the WHO Emergency Committee on COVID-19 recommended to the Director-General, who accepted the recommendation, that given the disease was by now well established and ongoing, it no longer fit the definition of a PHEIC. The importance of data in analyzing issues pertaining to the pandemic is reviewed by Barnes, et al (2020) when a "new normal" is described.

This research assesses the effectiveness of vaccines using data sourced from the Institute for Health, focusing on Pfizer, Moderna, and Johnson & Johnson vaccines. The study examines key variables such as the lockdown duration, ICU bed occupancy, and confirmed infections. The assessment spans three distinct periods: (1) pre-vaccination, (2) post-vaccination, and (3) the lockdown phase. A comparative analysis is conducted between New York and neighboring states, namely New Jersey and Connecticut, to ascertain if similar outcomes were observed.

The study analyzes the impact of vaccines on diminishing pandemic cases, hospitalizations, ICU bed occupancy, and fatalities. Several variables are examined to construct a comprehensive model. The analyses explore correlations: (1) between vaccination rates and pandemic cases in New York State, (2) between vaccination rates and the death rate in New York State, (3) between confirmed infections and

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the pandemic vaccination rate in New York State, (4) between the acquisition of new ICU beds and the mean death rate in New York State, (5) between the infection rate and pandemic death rate in New York State, and (6) between vaccination utilization and available ICU beds in New York State. Additional analyses include: (1) disparities in death rates between the unvaccinated and vaccinated populations in New York State, (2) variations in vaccination rates across three distinct age groups, and (3) differences in vaccination rates within the New York City Metropolitan Area. The outcomes from this set of analyses contribute to a comprehensive model assessing the efficacy of vaccines and other variables. This model can serve as a foundational framework for estimating the potential impact of future pandemics.

The paper is organized as follows: after the introduction, a literature review is presented. Following this, the study's results and analysis are detailed, and the paper concludes by summarizing key findings and exploring their managerial implications.

LITERATURE REVIEW

The impact of weather was the focus in much of the research on COVID-19. Early studies (Scaffetta et al., 2020) indicated that flu-like epidemics had less impact in the summer months. This applied to Italy where the pandemic spread in March and April 2020 and then decreased in the summer of 2020. In France, Aboura (2022) examined the relationship of weather and government regulations on Covid cases. If there is a rise in temperature, then the number of deaths decreases. If there are increases in relative humidity and less rain, then there is a reduction in deaths.

In other quantitative research, Anand et al (2021) evaluated the impact of the pandemic on the healthcare system, society, and the economy. The interdisciplinary research used the diffusion mechanism of health information and the acceptance of government restrictions. This resulted in a strategy to follow in a pandemic. In Austria, a retrospective analysis (Moshammer et al, 2022) examined correlations between a person’s political affiliation and smoking status, and COVID -19 infection or death.

While the findings provide insight into these variables, a more comprehensive model is required. In a micro analysis, a study (Briz-Redon, 2022) addressed the transmission of COVID-19 between neighborhoods in Valencia, Spain. They used sociodemographic characteristics, mobility flows and distance between the

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different areas. This study evaluates the impact of vaccines and is limited to the data available from the Institute for Health Metrics & Evaluation (IHME). One of IHME's main goals is to provide researchers with tools to better monitor population health and identify ways to improve it. COVID-19 vaccines of several types have been developed, evaluated, and partially deployed with remarkable speed. Vaccines are now the primary control measure for returning to normalcy. However, hesitancy concerning these vaccines, along with resistance to masking and other control measures, remains a substantial obstacle.

RESEARCH MODELS AND FINDINGS

The study evaluates the impact of vaccines and is limited to the data available from the Institute for Health. Pharmaceutical vaccine manufacturers in this study are Pfizer, Moderna, and Johnson and Johnson. Variables evaluated include the lockdown period, ICU bed utilization, and confirmed infections. The evaluation addresses three periods: (1) before vaccinations (2) after vaccinations, and (3) the lockdown period. The study also compares New York to New Jersey and Connecticut to determine if comparable results applied to these states.

In addition, the study also addresses the impact of the vaccines on reducing the number of pandemic infections/cases, hospitalizations, ICU bed utilization, and deaths, by evaluating several variables to be used in a general model. The analyses evaluate the correlations (1) between vaccination usage and Pandemic Cases in New York State, (2) between vaccination usage and death rate in New York State, (3) between confirmed infections and pandemic vaccination rate in New York State, (4) between obtaining New ICU beds and mean death rate in New York State, (5) between Infection Rate and Pandemic death rate in New York State, and (6) between vaccination utilization and available ICU beds in New York State. Also included were analyses for the (1) difference in the death rate between the unvaccinated and vaccinated in New York State, (2) difference in the vaccination rates among the three age groups, and (3) difference in the vaccination rate in the New York City Metropolitan Area.

Initial Findings

An initial evaluation of the preliminary data indicated that there is a declining trend in the incidence of infection due to the pandemic as shown in the Figure 1. This trend coincides with the introduction of the first vaccine by Pfizer in December 2020, followed by Moderna and Janssen. Prior to December 2020, the infection

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trend was still increasing. However, soon after the introduction of vaccines, usually within two weeks, the death rate began decreasing.

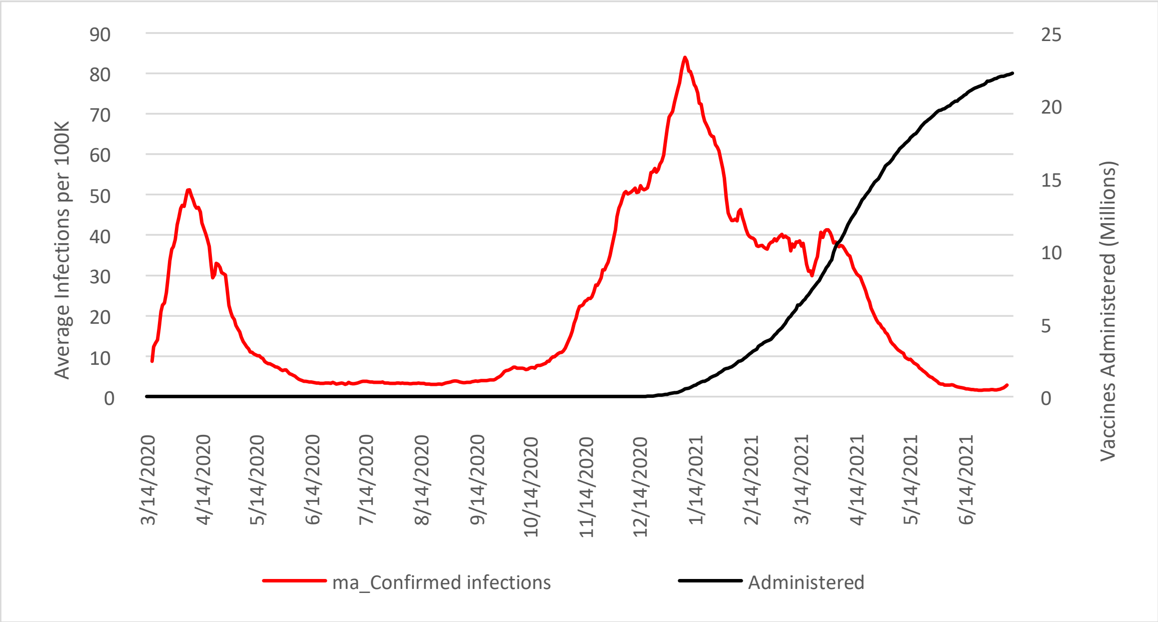

Figure 1: Average Infection Rate Vs All Vaccines Administered in New York State

Analysis of Vaccine Usage and Cases

The correlation between vaccine usage and the pandemic cases in New York state was examined with the results presented in Table 1. The observations for infections per 100,000 (i.e., confirmed_infections_p100k_rate) had an average of 22.07 (SD = 21.83, SEM = 0.99, Min = 1.10, Max = 98.85, Skewness = 1.04, Kurtosis = 0.27). The observations for the use of vaccines (Administered) had an average of 4.74 × 106 (SD = 7.65 × 106, SEM = 343,773.09, Min = 0.00, Max = 2.26 × 107, Skewness = 1.33, Kurtosis = 0.11).

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Table 1: Summary Statistics Table for Interval and Ratio variables

Variable	Mean	SD	n	SE_M	Min	Max	Skewness	Kurtosis
confirmed_infections_p100k_rate	22.07	21.8	485	0.99	1.1	98.9	1.04	0.27
Administered	4.74×10^6	7.65×10^6	495	343,773.09	0	2.26×10^7	1.33	0.11

The results of the correlation were examined based on an alpha value of .05. A significant positive correlation was observed between confirmed_infections_p100k_rate and Vaccines Administered, with a correlation of .09, indicating a small effect ($p = .037$, 95.00% CI = [.01, .18]). This suggests that as confirmed_infections_p100k_rate increases, administered also increases. Table 2 presents the results of the correlation.

Table 2: Spearman Correlation Results between Confirmed_infections_p100k_rate and Administered

Combination	*r*	95.00% CI	*n*	*p*
confirmed_infections_p100k_rate-Administered	0.1	[.01, .18]	485	0.037

The IHME data from March 2020 to June 2021 was matched with the New York State vaccination records between December 2020 and June 2021. The reason for this apparent time discrepancy is that vaccinations did not exist anywhere in the United States prior to December 2020. Therefore, prior to December 2020, there was extensive ongoing research on the creation of a vaccine; and the first vaccine created in the United States was by Pfizer in December 2020. Figure 2 shows the characteristics of the pandemic virus, superimposed on the characteristics of the vaccine. As shown in the graph, New York experienced two waves of the virus. The first occurred in March 2020 prior to the development of the first Pfizer vaccine. The second wave occurred right around the time the Pfizer vaccine was approved for general use in December 2020. The death trend has been declining since the introduction of vaccines. This is reflected in Table 3 which shows that there is a strong negative correlation between vaccine usage and the pandemic cases

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(r = -0.912). This is to be expected; as the vaccine usage increased, the number of the pandemic cases continued to decline.

Table 3: Correlation between Confirmed Infections with Vaccines Administered

		infections	Administered
infections	Pearson Correlation	1	-.912**
	Sig. (2-tailed)		<.001
	N	209	209
Administered	Pearson Correlation	-.912**	1
	Sig. (2-tailed)	<.001	
	N	209	209

*** Correlation is significant at the 0.01 level (2-tailed)*

Analysis of Vaccine Usage and Deaths

The Pearson correlation between vaccination usage and the pandemic deaths in New York state examined the relationship between the Pfizer vaccine (Administered_Pfizer) and its effect on mortality (deaths mean). Cohen's standard was used to evaluate the strength of the relationship: (1) coefficients between .10 and .29 represent a small effect size, (2) coefficients between .30 and .49 represent a moderate effect size, and (3) coefficients above .50 indicate a large effect size (Cohen, 1988).

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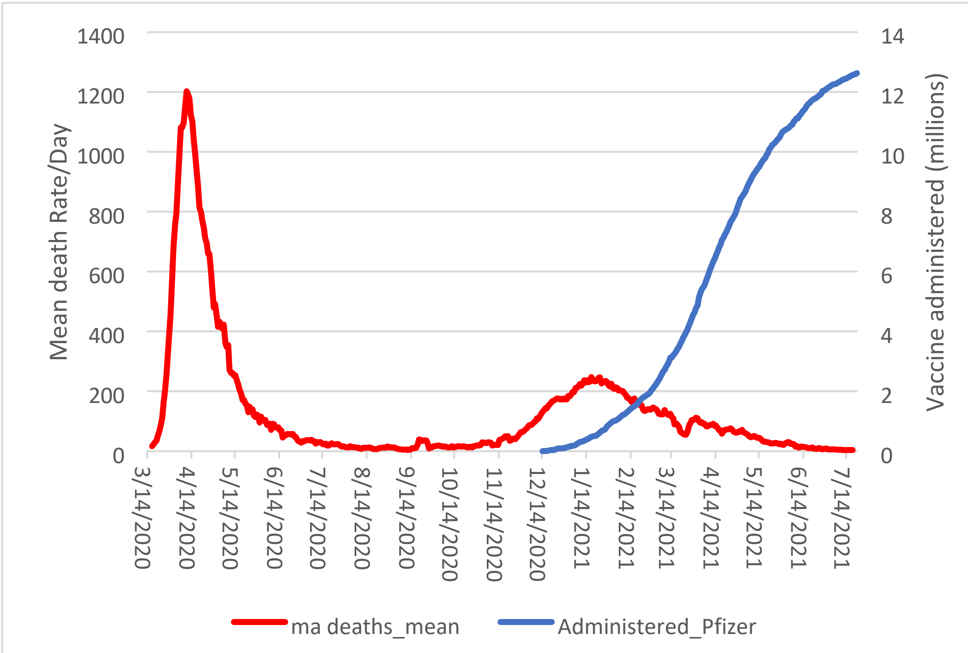

Figure 2: Average Death Rate Vs All Vaccines administered in New York State

The result of the correlation was evaluated based on an alpha value of .05. A significant negative correlation was observed between Administered_Pfizer and deaths_mean, with a correlation of -.90, indicating a large effect size ($p < .001$, 95.00% CI = [-.92, -.87]). This suggests that as Administered_Pfizer increases, deaths_mean tends to decrease. Table 4 presents the results of the correlation. Figure 2 shows the relationship between the Average death rate and the vaccines administered in New York State.

Table 4: Pearson Correlation between Administered_Pfizer and Deaths_mean

Combination	*r*	95.00% CI	*n*	*p*
Administered_Pfizer-deaths_mean	-0.9	[-.92, -.87]	220	< .001

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Analysis of the Vaccination Rate Compared to Infections

A Pearson correlation analysis examines the relationship between Administered and Metropolitan Area Confirmed Infections (ma_Confirmed_infections_100K). The result of the correlation was based on an alpha value of .05. A significant negative correlation was observed between Administered and ma_Confirmed_infections_100K, with a correlation of -.21 as shown in Table 5, indicating a small effect size ($p < .001$, 95.00% CI = [-.29, -.12]) as defined by Cohen's standard. This suggests that as Administered increases, ma_Confirmed_infections_100K tends to decrease.

Table 5: Pearson Correlation between Administered and ma_Confirmed_infections_p100k

Combination	*r*	95.00% CI	*n*	*p*
Administered-ma_Confirmed_infections_100K	-0.21	[-.29, -.12]	482	< .001

Analysis of New ICU Beds and Deaths

Another Pearson correlation analysis was conducted between New_ICU and ma_deaths_mean and evaluate by Cohen's standard to estimate the strength of the relationship.

Using an alpha value of .05, a significant positive correlation was observed between New_ICU and ma_deaths_mean, with a correlation coefficient of .42, indicating a moderate effect size ($p < .001$, 95.00% CI = [.34, .49]) as defined by Cohen's standard. This suggests that as the demand for New_ICU increases, ma_deaths_mean tends to increase. Table 6 presents the results of the correlation.

Table 6: Pearson Correlation Results between New ICU Beds and Ma_deaths_mean

Combination	*r*	95.00% CI	*n*	*p*
New_ICU-ma_deaths_mean	0.42	[.34, .49]	489	< .001

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Analysis of the Infection Rate and the Death Rate

The relationship between Confirmed_Infections_Scale and Average_Dailly_Deaths_Scale was conducted using Pearson Correlation. Figure 3 presents the scatterplot of the correlation. A regression line has been added to assist the interpretation.

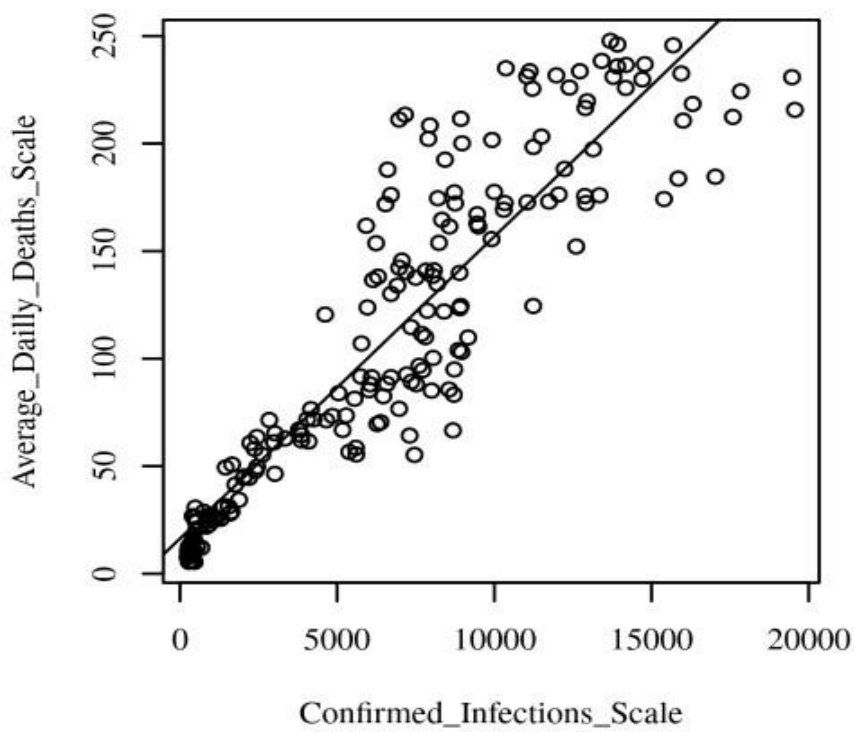

Figure 3: Scatterplots for Confirmed Infections scale & Average Daily Deaths Scale

The result of the correlation was examined based on an alpha value of .05. A significant positive correlation was observed between Confirmed_Infections_Scale and Average_Dailly_Deaths_Scale, with a correlation of .91, indicating by the Cohen standard, a large effect size ($p < .001$, 95.00% CI = [.88, .93]). This suggests that as Confirmed_Infections_Scale increases, Average_Dailly_Deaths_Scale tends to increase. Table 7 shows the results of the correlation.

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Table 7: Pearson Correlation Results between Confirmed_Infections and Average_Daily_Deaths

Combination	*r*	95.00% CI	*n*	*p*
Confirmed_Infections_Scale-Average_Daily_Deaths_Scale	0.91	[.88, .93]	199	< .001

Analysis of the Death Rate Compared to Vaccinated and Unvaccinated Populations

A significant difference in the death rate between the unvaccinated and vaccinated people was assessed. Table 8 shows a much higher spread among the unvaccinated, than there is among the vaccinated. A t-test was performed between the death rate pre-vaccine usage, against the death rate since the introduction of vaccines. The results of the t-test are shown in the Table 9. The Test for Equality of Variances shows a highly significant difference (Table 9); in the variance of the two groups; (p <.001). This is an indication that there are much less deaths after vaccination, than there is prior to vaccination. Irrespective of whether homoscedasticity is assumed or not, the result of the test for equality of means (Table 10), shows a highly significant difference in the mean deaths between pre- and post-vaccination periods.

Table 8: Group Statistics between the Vaccinated and the Unvaccinated

Vaccination Status	N	Mean	Std. Deviation	Std. Error Mean
Unvaccinated	272	157.67	278.289	16.874
Vaccinated	217	101.54	76.623	5.202

Table 9: Levine's Test for Equality of Variances

	Levene's Test for Equality of Variances		t-test for Equality of Means	
	F	Sig.	t	df
Equal variances assumed	74.392	<.001	2.884	487
Equal variances not assumed			3.178	321.31

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Table 10: t-test for Equality of Means

	One-Sided p	Two-Sided p	t-value
Equal variances assumed	0.002	0.004	56.123
Equal variances not assumed	<.001	0.002	56.123

Analysis of Vaccine Usage and ICU Beds

The next issue to address is the relationship between vaccination utilization and availability of ICU beds. Historically, the availability of ICU beds is not guaranteed. Therefore, a measurement of vaccination rates with the utilization of ICU beds should be managed very carefully. In this research, comparison is predicated on the assumption that ICU beds are available to be used when required. At the beginning of the pandemic however, there was an acute shortage of ICU beds because the hospitals required ventilators that were not readily available (Figure 4). Major manufacturing plants in the country had to modify their production process and focus primarily on the production of ventilators. The United States was therefore able to accelerate the manufacture of ventilators, to the extent that ventilators were exported to other countries. The initial lack of availability of ICU beds created a “bottleneck” for the hospitals, and strategies were developed to distribute the scarce resource of ventilators among the states. This was done because the incidence of the pandemic was not occurring simultaneously across the United States; so, strategies had to be developed to distribute ventilators to different states, depending on the level and intensity of demand. Ventilators contributed significantly to the drastic reduction in death rates later in the life cycle of the pandemic virus.

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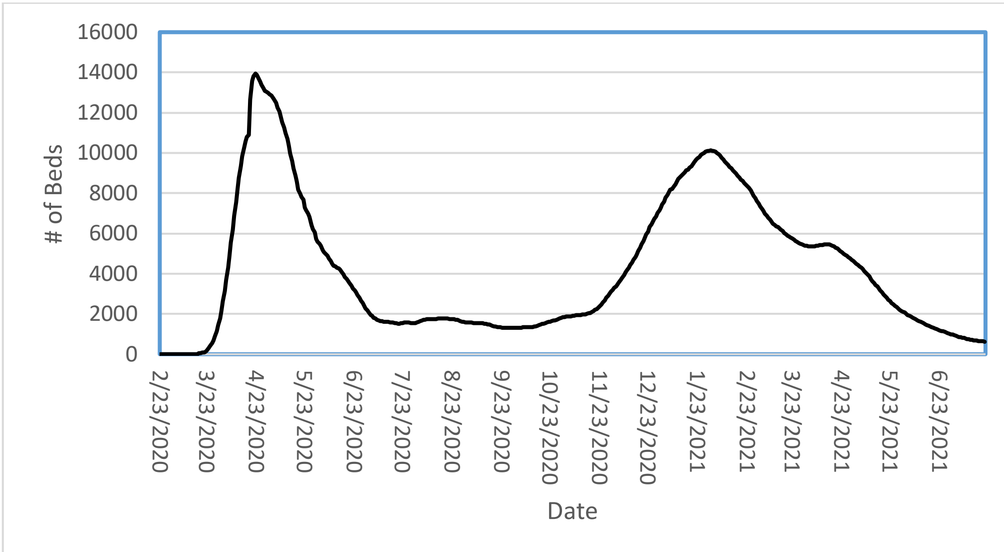

Figure 4: Availability of Beds in New York State

Based on the accelerated production of ICU beds, the utilization of ICU beds stabilized as more vaccines were administered (Figure 5). At the beginning of the pandemic, the issue of using ICU beds was irrelevant because they did not exist. However, as the virus spread, patients would need ventilators which were in short supply. However, because of the accelerated production of ICU beds, supply caught up with demand. As a matter of fact, there was surplus availability of ventilators, and the overflow were distributed to other states in need of ICU beds. This explains why the graph is turbulent in the beginning, and eventually reached a steady state as the availability of ventilators increased.

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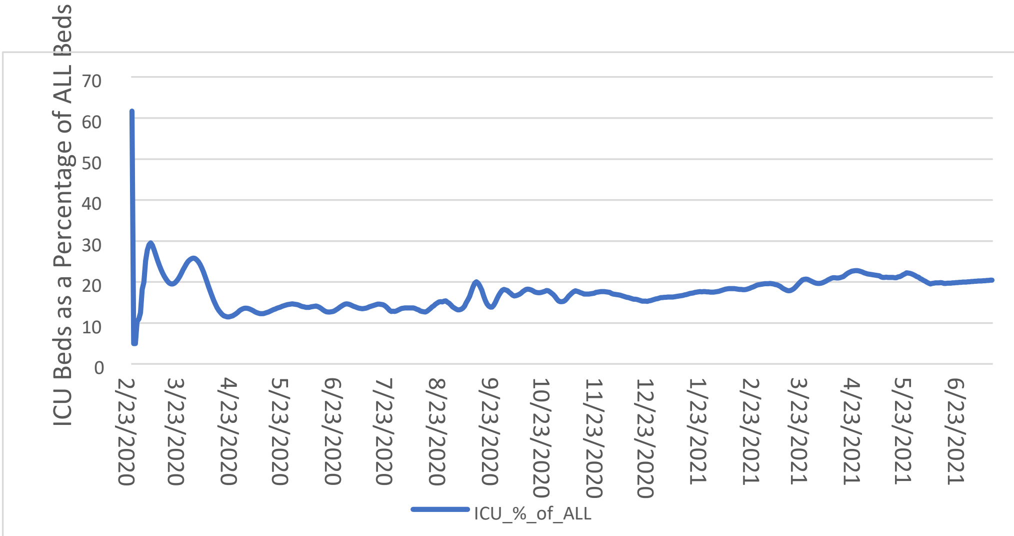

Figure 5: Number of ICU Beds as % of All Beds

Analysis of Vaccinations Among Different Age Groups

When the Pfizer vaccination became available in the tri-state area (New York, New Jersey, and Connecticut), New York, with the most pandemic cases, received the major share of the vaccines. Since the vaccination were administrated in phases, with people 65 and over being the first in line to receive the vaccine, the study focused on that population. The assumption is that the relationship is similar for other age categories. To make a comparison therefore, it is useful to compare the vaccination usage as a percentage of the population in each age group. An analysis of variance (ANOVA) was conducted to determine whether there were significant differences in vaccination rate by type (manufacturer).

The assumption of normality was assessed by plotting the quantiles of the model residuals against the quantiles of a Chi-square distribution, also called a Q-Q scatterplot (DeCarlo, 1997). For the assumption of normality to be met, the quantiles of the residuals must not strongly deviate from the theoretical quantiles. Strong deviations could indicate that the parameter estimates are unreliable. Figure 6 presents a Q-Q scatterplot of model residuals.

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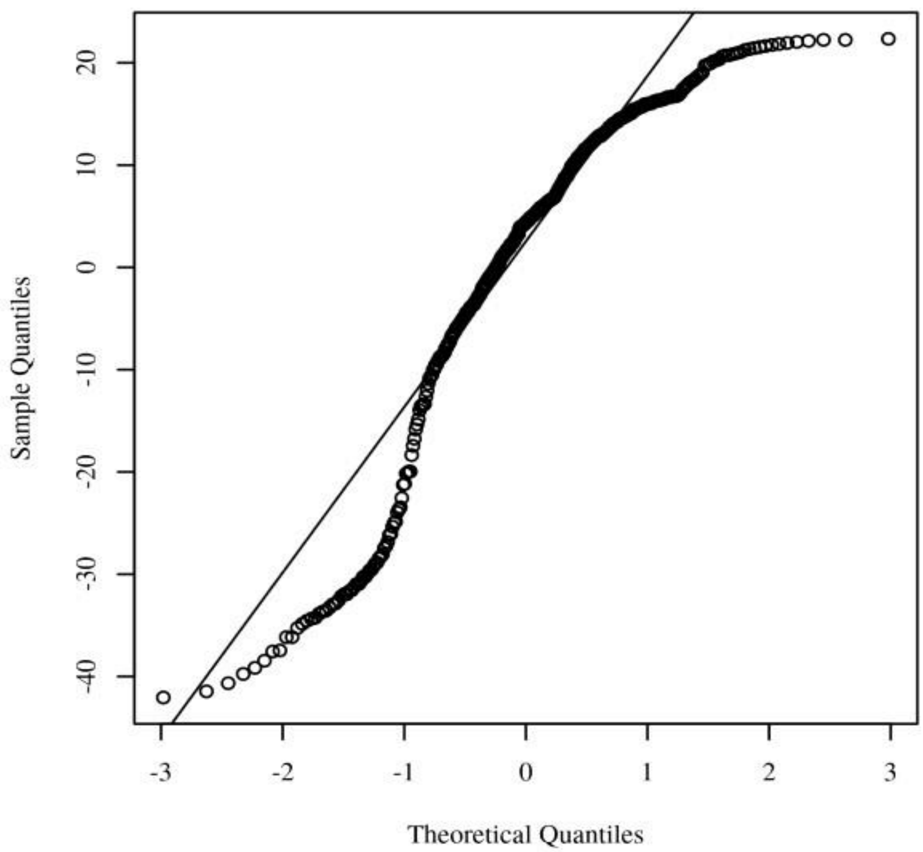

Figure 6: Q-Q Scatterplot of Model Residuals

Homoscedasticity was evaluated by plotting the residuals against the predicted values (Bates et al., 2014; Field, 2017; Osborne & Walters, 2002). The assumption of homoscedasticity is met if the points appear randomly distributed with a mean of zero and no apparent curvature. Figure 7 presents a scatterplot of predicted values and model residuals.

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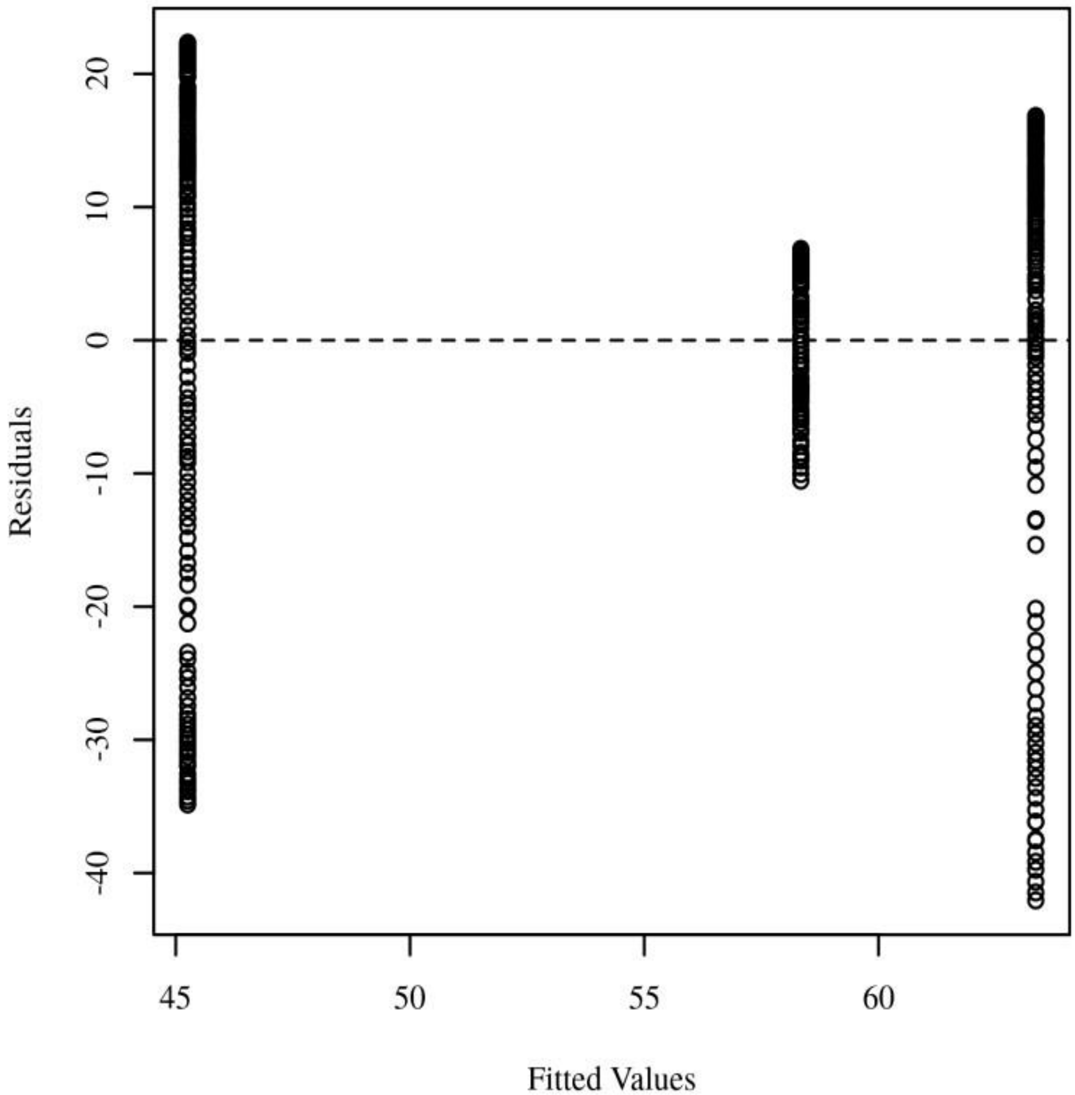

Figure 7: Residuals Scatterplot Testing Homoscedasticity

To identify influential points, Studentized residuals were calculated, and the absolute values were plotted against the observation numbers (Field, 2017; Pituch & Stevens, 2015). Studentized residuals are calculated by dividing the model residuals by the estimated residual standard deviation. An observation with a Studentized residual greater than 3.11 in absolute value, the 0.999 quantile of a t

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distribution with 347 degrees of freedom, was considered to have significant influence on the results of the model. Observation numbers are specified next to each point with a Studentized residual greater than 3.11.

The ANOVA was examined based on an alpha value of .05. The results of the ANOVA were significant, $F(2, 345) = 41.97$, $p < .001$, indicating there were significant differences in Vaccination_Rate among the levels of Type. The eta squared was 0.20 indicating Type explains approximately 20% of the variance in Vaccination_Rate.

Paired t-tests were calculated between each pair of measurements to further examine the differences among the variables based on an alpha of .05. The Tukey HSD p-value adjustment was used to correct for the effect of multiple comparisons on the family-wise error rate. For the main effect of Type, the mean of Vaccination_Rate for 1 ($M = 58.34$, $SD = 5.23$) was significantly larger than for 2 ($M = 45.25$, $SD = 19.10$), $p < .001$. For the main effect of Type, the mean of Vaccination_Rate for 2 ($M = 45.25$, $SD = 19.10$) was significantly smaller than for 3 ($M = 63.36$, $SD = 18.09$), $p < .001$. No other significant effects were found.

Analysis Comparing New York to Other States

An analysis of variance (ANOVA) was conducted to determine whether there was significant difference in vaccination by state with the results in Table 11. To make the analysis comparable among the three states, the data was based on the percentage of population vaccinated. Also, due to the sequencing of the administration of the vaccine, the analysis was done for people over 65 years, because that is the population that had the most data during the vaccination period of interest.

Table 11: Analysis of Variance (ANOVA) Summary Table (NY-NJ-CT)

	Sum of Squares	df	Mean Squares	F	Sig.
Between Groups	127361.45	2	63680.725	92.723	0
Within Groups	339956.635	495	686.781		
Total	467318.085	497			

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To identify influential points, Studentized residuals were calculated, and the absolute values were plotted against the observation numbers (Field, 2017; Pituch & Stevens, 2015). Studentized residuals are calculated by dividing the model residuals by the estimated residual standard deviation. An observation with a Studentized residual greater than 3.10 in absolute value, the 0.999 quantile of a t distribution with 659 degrees of freedom, was considered to have significant influence on the results of the model. Observation numbers are specified next to each point with a Studentized residual greater than 3.10. The ANOVA was examined based on an alpha value of .05. The results of the ANOVA were significant, $F(2, 657) = 146.17$, $p < .001$, indicating there were significant differences in Vaccination among the levels of State. The eta squared was 0.31 indicating State explains approximately 31% of the variance in vaccination.

Paired t-tests were calculated between each pair of measurements to further examine the differences among the variables based on an alpha of .05. The Tukey HSD p-value adjustment was used to correct for the effect of multiple comparisons on the family-wise error rate. For the main effect of state, the mean of vaccination for NY (M = 1.03 × 107, SD = 7.88 × 106) was significantly larger than for NJ (M = 4.77 × 106, SD = 3.64 × 106), $p < .001$. For the main effect of state, the mean of vaccination for NY (M = 1.03 × 107, SD = 7.88 × 106) was significantly larger than for CT (M = 2.13 × 106, SD = 1.59 × 106), $p < .001$. For the main effect of State, the mean of Vaccination for NJ (M = 4.77 × 106, SD = 3.64 × 106) was significantly larger than for CT (M = 2.13 × 106, SD = 1.59 × 106), $p < .001$. (Intellectus Statistics, 2022).

Managerial Implications

The high density of population in New York City created an epicenter for the spread of the virus and a model for other major metropolitan areas. As it spread to the less populated areas of upstate New York, Connecticut, and New Jersey, the effect on smaller cities and rural areas are evaluated. This provides pharmaceutical companies with a strategy for future distribution of vaccines as a pandemic develops.

From experience with this pandemic, businesses have developed contingency plans for working from home and conducting meetings with attendees in distant locations. Also, future strategies could include closing offices in different regions when the pandemic starts based on the number of employees infected and before any government regulations are imposed. Travel restrictions could be imposed depending on the destination. A future pandemic could be an additional factor to be

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considered when the company evaluates moving their headquarters and regional offices to new locations outside the metropolitan areas. These models and findings can assist with future management decision-making.

Ensuring effective hospital preparedness is important for managing pandemics. Key strategies to enhance hospital readiness for pandemics include (1) consistently monitoring ICU bed availability for informed managerial decisions, (2) developing surge capacity plans to expand critical care capabilities during crises, (3) fostering regional collaboration to optimize resource utilization, (4) creating business continuity plans to mitigate potential bottlenecks, and (5) coordinating cross-regionally to distribute resources effectively. These approaches collectively enhance hospitals' responsiveness to demand surges while optimizing resource allocation, thereby enhancing their capacity to mitigate the impact of future pandemic.

CONCLUSION

Prior to December 2020, when vaccines were first introduced, the number of pandemic cases were on the rise. Shortly after the first set of vaccines were introduced by Pfizer, and later Moderna, the rate of increase of Covid19 cases began to decrease. The incidence of cases peaked around the middle of January 2021 – indicating that there is a lag between when the vaccine is administered and when it begins to take effect. That explains why the cases began to decline after one month. The death rate is a function of the number of covid-19 cases and is particularly lethal for people over the age of sixty-five. That is why persons over the age of 65 were given high priority in the administration of the vaccine. The resultant effect is that it contributed significantly to the drop in the death rate for the rest of 2021.

At the early stages of the pandemic virus, reliable testing needed to be developed to identify who had contracted the virus, and who did not. The combination of testing, hospitalization, and the availability of ICU beds, all contributed to the decline of positive pandemic cases, and ultimately, the death rate.

A comparative analysis was also conducted between New York, New Jersey, and Connecticut. The characteristics of the evolution of the virus in the three states were somewhat different. The population of New York State is much larger than that of New Jersey and Connecticut; and that explains a significant difference between the vaccination rate in New York, compared with New Jersey and Connecticut.

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One year after the introduction of vaccines, the efficacy of the drug decreases. This resulted in the introduction of a booster vaccine later in the year. The effect of the booster shot on the overall efficacy of the vaccines, is material for future study, because it falls outside the timeline for this research.

It will be illuminating to break down the research further to assess the efficacy of each of the major vaccines - (Pfizer, Moderna, and Johnson & Johnson). Also, over the life of the pandemic virus, it has morphed into a Delta variant, an Omicron variant, and some other variants that have not yet been identified. It is expected that this research will continue to follow the evolution of the virus and all the treatments that are being developed to combat it.

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