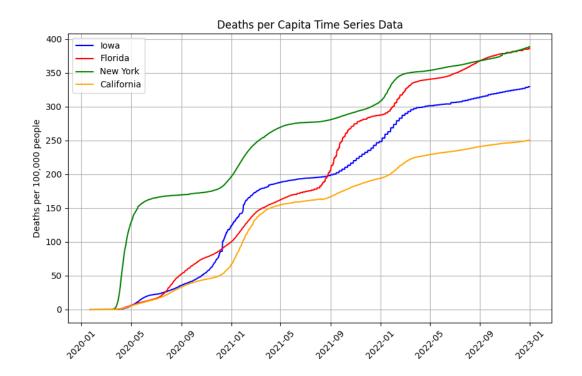
A Comparison of the States California, Iowa, Florida, and New York's Health Policies and How Affective They Were During the Years 2020, 2021, and 2022

Abstract

This paper will go over comparisons of Health Policies that the states of California, Iowa, Florida, and New York used starting from January 2020 until December 2023. Using data from The Oxford COVID-19 Government Response Tracker (OxCGRT) that assigned the policy a number 0 meaning that the policy was not in use up to level 3 which is the most extreme level of policy implication.

Our hypothesis was New York was going to struggle the most with deaths due to its highly condensed population. However, Iowa was going to struggle the most because of the lack of health policies the state implemented to protect citizens from COVID-19.

We first began by creating a time series of deaths per capita for each state we were interested in comparing. In the graph, we noticed a shockingly high spike in New York state deaths compared to the other selected states.



New York

A lot that factors into the high number of deaths in New York City is such a congested city that holds a lot of New York's state population. Whereas states like Florida and California might have dense populations in certain cities, their populations also spread out a lot more than the state of New York. During the time of this high death rate due to the COVID-19 pandemic, the state government released Health Policies to try to protect their citizens.

The first statement that was made was from Dr. Oxiris Barbot, New York City's health commissioner after the 1st case of Covid-19 was found in the United States was that if you had traveled to Wuhan, China, in the last 14 days and are feeling ill to visit a doctor. Furthermore, she recommended practicing everyday precautions like washing your hands frequently with soap and water and covering your mouth and nose when you sneeze. After this statement was released, the data started to label the Public Information Campaigns a 1 as more statements followed. When covid-19 reached New York, they were wildly unprepared for the pandemic. With little information coming out about how to protect citizens from the disease.

On April 17th, 2020, the Governor issued an executive order mandating that all people in New York wear a mask or a form of face covering when in public and in situations where social distancing cannot be maintained, such as on public transportation.

However, before this mandate, there were little to 0 guidelines around facial coverings except for a statement that was given a couple of weeks prior recommending people wear masks after a study showed that Singapore was finding success in mitigating cases with this policy. The Governor issued an executive order requiring all people in New York to wear a mask or a face covering when in public and in situations where social distancing cannot be maintained, such as on public transportation. About a week later, the Governor also announced that the state expanded its testing criteria to first responders, healthcare workers, and essential employees to be tested even if they aren't feeling any symptoms. Cuomo also issued an executive order that allowed pharmacists to conduct COVID testing, opening effectively 5000 more sites across the state of New York. This would ramp the policy to increase from a 1 to a 2 within the dataset. Another crucial health policy that was released during this timeframe was a new nation-leading COVID-19 contact tracing. After these policies were released, we started to see the number of deaths from COVID-19 per capita drop. Furthermore, showing how effective having the right health policies in place can lower the amount of people dying from the disease. If the state of New York had more information on the disease and put these policies into action quicker, it could have led to a safer environment for the citizens of New York state.

Furthermore, this was not the only issue that led to a high death rate in the state of New York. The state is known as a global economic and travel hub which increased the amount of people who walk the streets than their typical residents. This was a big issue at the beginning of the Covid Pandemic which correlates with the time series above. Additionally, New York State's healthcare systems struggled with the overwhelming number of patients which led to a shortage in medical equipment and workers. These factors along with the late response in health policies contributed to the high death rate in New York State.

California

California, home to the cities of Los Angeles and San Francisco was able to do a lot better job keeping the death rate per capita low compared to Florida, New York, and Iowa in 2020. However, there were little differences in the timing of health policies that were implemented between the states of New York which had the highest death rate.

So why was California able to limit the number of deaths?

California for one, is not as population dense as the State of New York. New York City has over 8 million residents almost half of New York State's population. California's biggest city, Los Angeles holds 3.8 million people which is a small number compared to California's 40 million residents. The residents of California were able to adapt easier to social distancing guidelines in most areas due to how much more spaced out their cities are located. Along with this, the cities' suburbs tend to have a lot of houses compared to New York's suburbs consisting of mostly apartments.

Another important aspect of how spaced out the state of California is healthcare facilities not being overwhelmed with the number of hospitalized cases they were getting which was also a key reason deaths were limited during the early stages of COVID-19.

In the next part of the project, we decided to run OLS regression models to see how effective policies were in each different state.

Iowa

Iowa had a relatively high number of deaths per capita relative to their population density and we think this can be attributed to a couple of factors. I would say the main contributing factor is the state's predominant culture. Being very conservative, combined with a low national health rating, it would not be surprising if a lot of the state's population were ignoring certain health policies such as vaccines, social distancing, and facial covering policies. This was explicitly shown when the governor of Iowa announced her intent to lift all COVID health mandates on February 8th and lifted the mask mandate on February 14th, 2021. This was following an extreme public backlash against COVID-19 health mandates, and the effect on public health can be seen in the time series as a spike in deaths around March of the same year. Also, because Iowa has a relatively high rate of diabetes and obesity relative to both New York and California, it is not surprising to see comparative death rates despite the much lower population density. We also saw a spike in deaths around August of 2021 which is most likely a direct result of Iowa's governor passing a law prohibiting anyone from enforcing mask mandates. Since it takes a while for the effects of these policies to show in statistics it would make sense why there is not a spike in deaths until 2-3 months later. We also see a leveling in deaths which comes around the same time a government mandate required the enforcing of mask policies in Iowa again. I think certain health policies do have a direct impact on COVID-19 deaths, but they take a while to show an effect and vice versa. So, when a policy is disbanded when looking at

deaths, you will not see an increase until 1-2 months later. And when a policy is enacted, you will not see a decrease in deaths for a similar period. This lines up with the timeline of the COVID-19 virus, and if we had instead analyzed COVID-19 infections, we would see a much less delayed impact.

Florida

Unsurprisingly, Florida initially saw a much slower rise in COVID-19 deaths than New York, most likely due to their much lower population density. After the initial outbreak, they saw a steady increase, much higher than New York, or California, which can likely be attributed to a culture like that of Iowa. As a state with relaxed COVID health policies and a population that took the pandemic much less seriously, it is not surprising that Florida's deaths per capita increased at a much higher rate than California or New York. We can see an increase in COVID-19 deaths around the middle of 2020. Around the same time, Florida mandated a reopening of Miami Beach despite other federal mandates. Also, shortly after this trend in deaths happened, we can see a series of health policies being implemented, including a restriction on the size of public gatherings and a strong warning toward elderly individuals going into public. This likely reflected in the public taking COVID more seriously and saw a slight decrease in the trend of deaths. We then see an increase in the slope of deaths which coincides with Florida not enacting any vaccine policies, while most of the country did. Although face coverings and social distancing were highly encouraged at this time it was not mandated. Also, contact tracing is being enacted which could potentially explain the small decrease in deaths around the middle of 2021. In May of 2021, Governor Desantis issues a statement disbanding all covid 19 health restrictions and we subsequently see the highest increase in covid deaths of the pandemic in the following months. As schools return, mask mandates are re-implemented on a county level. In October, Desantis signed an order superseding all federal mandates, but vaccines are also starting to be offered for free. This could be considered a contributing factor to the decrease in COVID-19 deaths, although the rate is still high. It is easy to see that Florida has a general disregard for COVID-19 health policies which is reflected in its government's handling of the pandemic. This is a culture like Iowa but is exacerbated in deaths per capita due to its higher number of highdensity cities and higher population per square mile across the state.

Machine Learning Models: OLS

Key to Helping Understand the Independent Variables In the Regression:

Contact tracing = H3E Testing policy = H2E Public information campaigns = H1E Facial Coverings = H6M Vaccination policy = H7E

Protection of elderly people = H8

New York

0LS	Regression	Results
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Dep. Varia	ble:	ConfirmedDe	aths F	R-squared	:		0.956
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H1E	4546.2289	839.872	5.4	13	0.000	2898.242	6194.216
H6M	1976.9624		10.1		0.000	1596.124	2357.801
H7E	5472.3304		55.8		0.000	5280.125	5664.536
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Kurtosis:		8	.501 (Cond. No.			62.9

<u>Iowa</u>

OLS Regression Results

Dep. Variable: ConfirmedDeaths OLS R-squared: 0.950 Model: Method: Least Squares F-statistic: 3368. Date: Thu, 04 Apr 2024 Prob (F-statistic): 0.00 Time: 02:24:00 Log-Likelihood: -8726.4 No. Observations: 1075 AIC: 1.747e+04 Df Residuals: 1068 BIC: 1.750e+04 Df Model: 6 6 6 Covariance Type: nonrobust	=======	=======							
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<u>Florida</u>

			OLS R	egress	ion Res	ults		
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California

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H2E	1.533e+04			.371	0.000	1.39e+04	1.67e+04
H1E	2.51e+04			.399	0.000	2.26e+04	2.76e+04
Н6М	-1598.7930		_	.943	0.003	-2664.593	-532.993
H7E	8454.2376			.692	0.000	8056.344	8852.131
H8E	-1.081e+04	489.877	-22	.059	0.000	-1.18e+04	-9844.801
Omnibus:		 27.	 444	Durbir	 n-Watson:		 0.081
<pre>Prob(Omnibus):</pre>		0.000		Jarque-Bera (JB):			16.752
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Regression Data Analysis

Many policies seemed to have a high positive correlation with deaths in each state. So, do these health policies increase deaths? The answer is no. The positive correlation is due to the time these policies were released. A common theme during the pandemic was the strictness of health policies when death rates started to increase. The issue is that these policies cannot stop death in a matter of seconds so people there will still be a high number of deaths no matter when policies are implemented. While the data uses random sampling that helps take away bias from the research, it doesn't necessarily show how affect each policy is. states when deaths from COVID started to ramp up.

Another interesting aspect I noticed in the data was out of the policies, H7E (Vaccination Policy) had the highest positive correlation in most states. When vaccinations were starting to be released to the public states started to loosen up more on social distancing guidelines. For many people, the vaccine was a power that made them feel like they had immunity to death. Well, they were not immune as all states spiked once the vaccines were released in December 2020.

Looking back at the time series graph, you can see that each state's curve starts to flatten out showing that the policies that were put into place managed to slow down deaths through a long period. We can speculate that health policies played a big factor in reducing the death rates of COVID-19 throughout the pandemic. If we wanted to see which policy was the most effective, we would need to create a more controlled environment with the same use of random sampling.

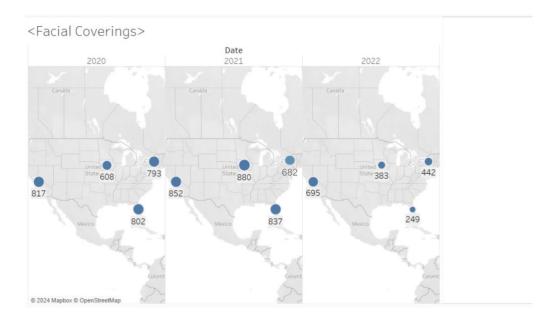
Geospatial Mapping: Comparing Health Policies of the 4 States in the Years 2020, 2021 and 2022



It was hard for most states to get people to listen to public information campaigns because of state culture and people wanting to maintain their normal lifestyles. We noticed this in every state that we researched even though each state's culture played a different role in how they were affected by the pandemic.



Looking at the sum of how serious contact tracing policies were in each state we can see the low switches between Florida and New York in 2022. The high remained in California throughout this time. In our regressions, contact tracing was seen to be one of the most effective policies in each state. However, this could be due to when states decided to release this policy compared to others.



Facial coverings were seen to be one of the most scientifically proven methods to stop the spread of COVID-19. Florida had few masking policies during 2022, which raised the amounts of deaths per capita while other states flattened out a bit more. Ultimately, causing Florida to be neck in neck with the state with the most deaths per capita.



California and New York were the leaders for the most part in testing policies. For these states with denser populated areas unlike lowa, it was easier to make testing more accessible to the public. Iowa and Florida could have been affected greatly by not implementing more policies as COVID-19 could not be detected as easily. Another effect of low testing policies is the increase in undetected cases. The more cases are the more spreading of the disease which can lead to more deaths.



When vaccines came out in December 2020, from Pfizer (BioNTech) it brought a lot of hope around lowering deaths from the COVID-19 pandemic. However, the effects of the vaccines reducing deaths would not show up in the data until the vaccine was more available and accepted by people in the individual states.



The last category we researched was about the protection of elderly people in each state. Florida had high protection policies implemented in the years 2020 and 2021 which makes sense as they have one of the oldest populations amongst all states. Iowa had the least amount of guidelines around the protection of elderly people which can relate to the number of deaths per capita.

Conclusion

After analyzing the data, we have concluded that even though New York was one of the leaders in implementing health policies. However, they still had a high death rate per capita due to the condensed New York City and the city's culture. While Iowa had the least amount of health policies, they have still had a lower death count per capita compared to Florida. This was not due to the strictness around health policies or when they were put into action. But Florida's large population and the high percentage of elderly people. We still believe if Iowa increased the strictness around policies like the other states, we analyzed there would be fewer deaths.