The Data Open

Analysis of Government policies in response to Covid-19

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1 Problem Statement

Covid-19 virus showed how unprepared humanity was to fight pandemics. In many countries the governments were very slow to enact policies to stop the spread of the virus. Lack of concreteness in goals of different policies led to their defiance by many people. Being directly affected by the inefficient response to the Covid-19 pandemic, we pose the following topic for analysis of the dataset: *Which policies are the most effective and should be implemented during future pandemics to slow the spread of the virus?* We have answered three main questions in particular:

1. Which policies were the most and least efficient when tackling the pandemics?
2. Can we use clustering methods to classify countries/states by their effective actions?
3. In which countries/states the hospitals were worst prepared to tackle covid?

We believe that answering these questions will lead to smarter decisions in the future and thus to significantly lower losses.

2 Executive Summary

Covid-19 related data provided from Citadel and external sources (e.g., government website) are analyzed in this report. We notice that data from different continents has varying quality. For example, in countries with low testing volume the data is unrepresentative. Therefore, we focus on analyzing the posed questions in Europe and the United States (US). In order to avoid the bias of testing, we analyze the results based on three metrics: i) average number of total deaths per million, ii) number of days between 100 and 1000 cases per million, and iii) reproduction rate R_t (a measure of a disease's contagion). After analyzing Covid-19 datasets in EU and US, our key findings are:

1. In the US, face covering mandate, stay-at-home order, non-essential business closure, bar closure, and travel quarantine are the key factors that are statistically significant in reducing R_t. Ban of social gathering and limit of restaurant operation decrease R_t but not at statistical significance. Interestingly, in Europe, face covering policy and non-essential business closures were the only key restrictions. Nonetheless, the policy should differ from country to country based on human development index.
2. Clustering analysis separates countries in Europe by their total death time series into two clusters. The first cluster has been affected by Covid-19 more significantly. After considering the policy differences in these clusters we find: the more consistent the country was with imposing restrictions (longer days of policy) the lower were the number of total deaths. Longrun mandatory mask policy is the key difference between two clusters and it saves lives. Consistent closure of public spaces also partially reduces the number of deaths, while recommendations for teleworking do not play a key role.
3. We analysed the impact of effective testing and hospital utilization in reducing Covid-19 related deaths. Some states didn't utilize the inpatient beds available to admit Covid

related patients and experienced a high number of deaths. We identified states which conducted a large number of tests (per million population) and which conducted less number of tests. Impact of extensive testing was statistically significant in reducing Covid related deaths. Overall, states which experienced high numbers of deaths (per million of population) in the first wave (April-June 2020), were well prepared to deal with the second wave (Nov 2020-Feb 2021). States which were not impacted by the first wave were ill prepared to deal with the second wave. This shows the fragmented policy of the US government in guiding each state and transferring the learning of one state to another for preparedness related to Covid-19.

3 Technical Exposition

In the next sections we will present our key findings and assumptions that we have made. We will start with analysis of data related to all the countries of the world. Then we will analyse in detail the policies implemented in European countries and in the US.

3.1 Target Generation and Data Exploration

The main issue of the data related to Covid-19 is the target variable, as it is not homogenous between different countries. Reporting standards vary between Asia, US and Europe, therefore we will regard continents separately. If we take as a target number of cases, then it will heavily depend on the rate of testing in different countries. This is the main reason why we decided to use 3 different types of metrics in our analysis.

1. **Number of deaths per million:** Patients that die due to Covid have severe respiratory diseases and their symptoms are the same everywhere. Therefore it is possible in many countries to consistently count the number of severe cases with lack of testing. This assumption will not hold in countries that manipulate data, but we assume that US and European countries reported correct and consistent information.
2. **Number of days passed between 100 cases per million and 1000 cases per million:** This feature heavily depends on testing in the country. We assume that in most European countries the testing was consistent after the disease progressed and widely spread.
3. **Reproduction rate, R_t**, which measures the expected number of cases generated from one single case at a given time *t*. This metric directly represents the change in the spread of cases over time, allowing us to correlate its change with state restrictions. This metric also depends on the testing rate, but we use it for different states in the US and assume that testing was consistent after the first few months.

We believe that using numerous target variables will help us to avoid the inconsistency inherent to the dataset.

First we consider the data at world level. Figure 1 summarizes average total cases per million, average total deaths per million, GDP per capita and average stringency index during pandemics in each country.

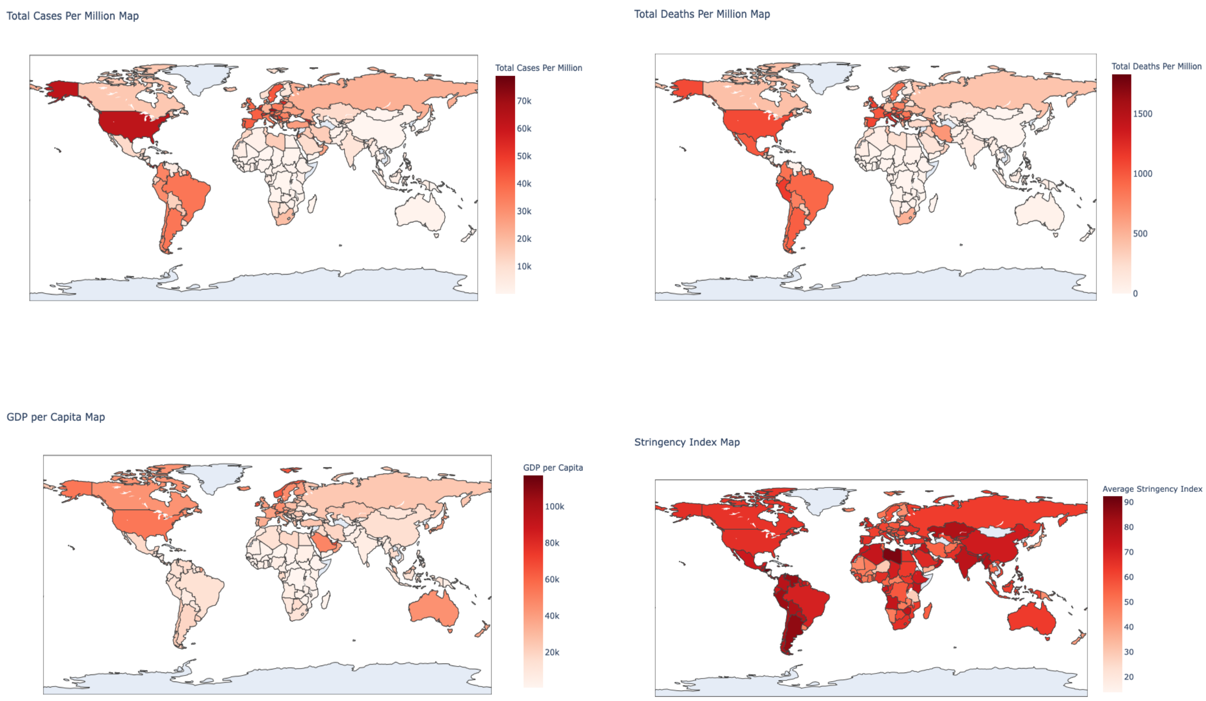

Figure 1: Covid statistics of the world

From the maps of cases and deaths, we can clearly see the biggest issue of the dataset - African and Asian countries had reported significantly lower deaths and cases than countries from other continents. The policy stringency in Africa was also on average lower than in the US or Europe. On data Africa was least affected due to low testing volume because of lack of resources. There also have been reports that many Asian countries manipulate the presented numbers. This is the main reason why in the next parts we will work with Europe and US data. In Europe the European Centre for Disease Prevention and Control regulates reporting and thus we believe that presented numbers are consistent. Similar function in the US has Centers for Disease Control and Prevention.

3.2 Regression Analysis of Covid-19 Spread and Demographics

We start the analysis by looking at how different demographic characteristics in European countries affected the spread of Covid. This will give insights into how the policy should differ among disparate countries. Figure 2 summarises regression results of spread speed (defined as days passed between 100 and 1000 cases per million) and stringency index (how strong were the limitations) when the country reached 100 cases per million.

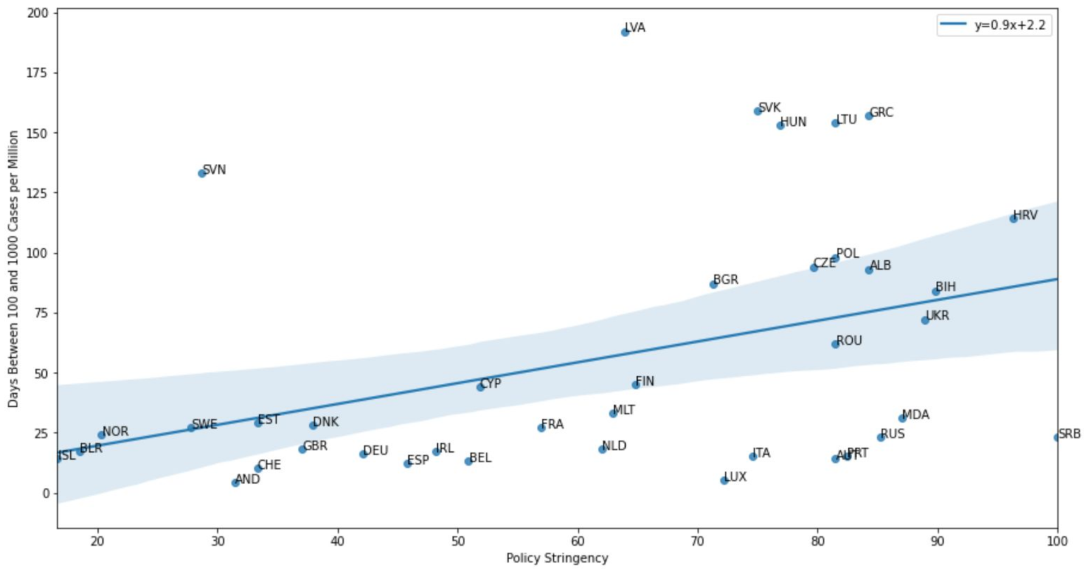

Figure 2: Days between and Policy stringency ($R^2 = 0.154, \ const \ = \ 2.18 \ (0.92), \ \beta_{policy} = 0.867 \ (0.013)$), coef.: (p-val)

On average, countries that enacted strong limitations took much longer to reach a high number of cases. This is extremely important as it shows that government intervention can buy some time to develop vaccines.

Next we considered how the human development index - a proxy for life quality, affected the spread of Covid, which was defined again the same as above. Figure 3 summarises the results. Interestingly, on average we find that the higher the quality of life - the higher the speed of spread (at 93% confidence level). There are few explanations to this phenomenon. First of all, people from developed countries are used to their everyday life and freedom and they respond to restrictions more negatively. Secondly, the medical research has shown that the higher the quality of life - the more vulnerable the people are to developing allergies or catching a virus. Although this is something that has to be investigated in much more detail, we think it is a reasonable explanation, but is outside the scope of this work.

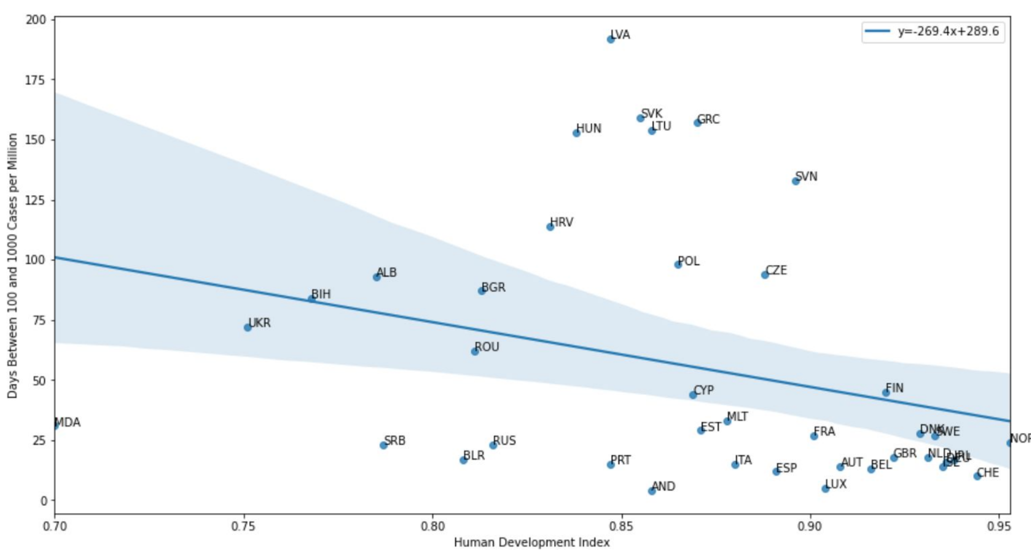

Figure 3: Days between and Human Development Index ($R^2 = 0.091,\ const\ =\ 289.5\ \ (0.023),\ \beta_{HDI} =\ -263.5\ (0.063)$), coef.: (p-val)

Overall, it shows that in developed countries, government policy should be more organized and stringent.

3.3 Efficiency of government restrictions - Europe

In April of 2020 it was extremely concerning to observe how countries such as Italy were struggling with containment of Covid with drastic measures while countries like Sweden were not adding any restrictions. That is one of the reasons why we decided to use the time series of death rates and cluster countries based on it. The dendrogram from hierarchical clustering of time-series data is presented in figure 4.

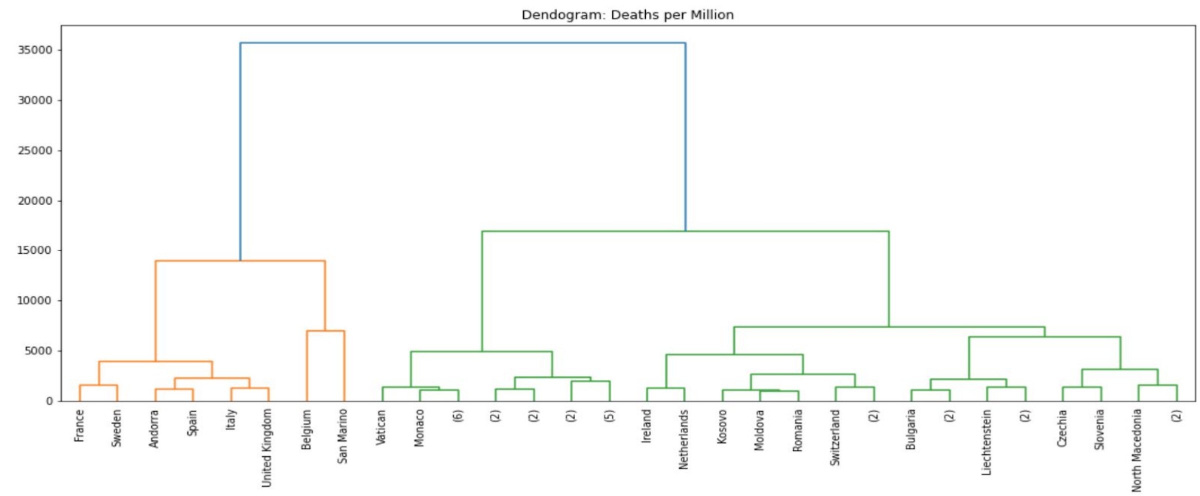

Figure 4: Hierarchical clusterization of deaths per million series for European countries

The dendrogram clearly implies that there are two clusters of countries in Europe based on the trajectory of Covid deaths. Figure 5 visualizes the clusters and the time series associated with them.

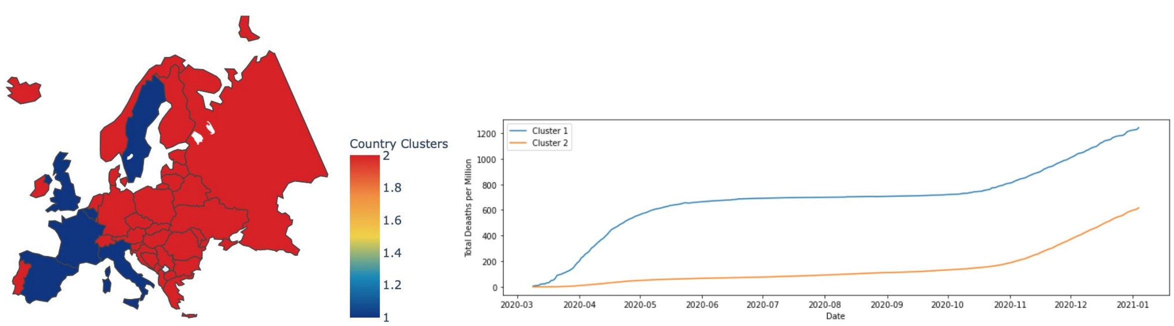

Figure 5: Results of clusterization: country map (left) total death per million (y-axis) vs date (x-axis)

The second graph in figure 5 shows that on average countries from cluster 1 had much higher death rates. It also shows the struggle that these countries had at the start of the pandemic. The hierarchical clustering clearly divides European countries and suggests to compare their policies. Before doing that, for each policy across European countries we will look at its impact on the decrease in death rates. For each policy and each country we save the time series of percent change in total death rates per million from 21 days before the policy was enacted to 21 days after. This data helps us to understand how much the policy helped to decrease the death rate. In figure 6 for different enacted laws we plot median rate across EU countries.

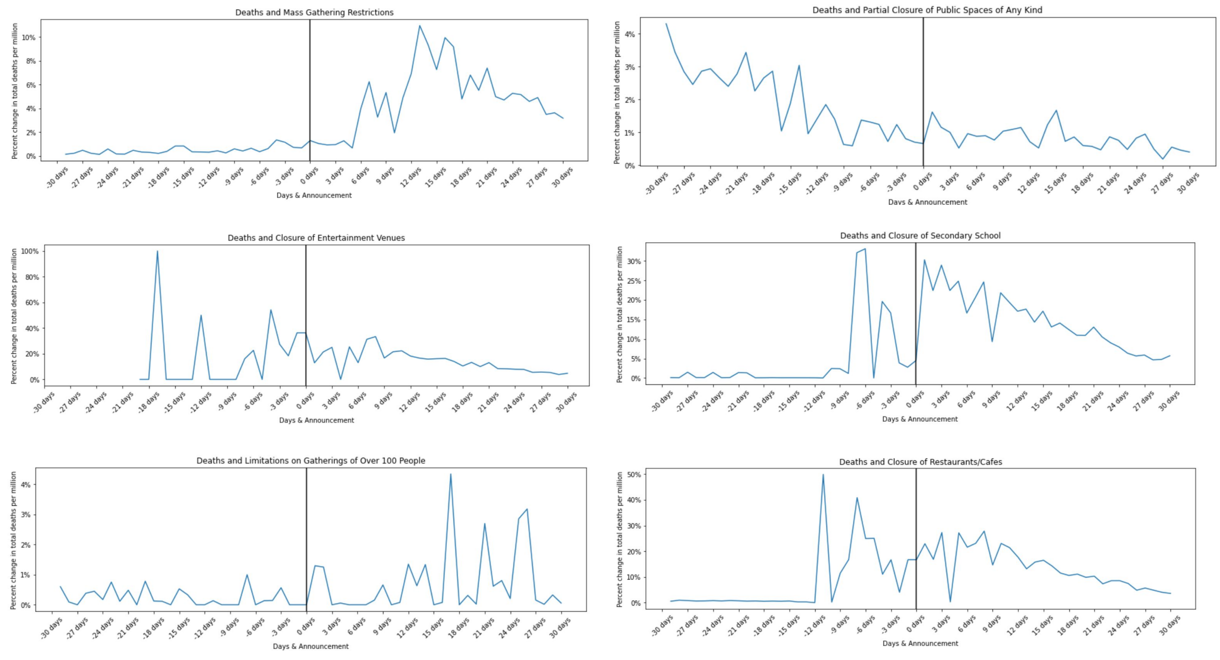

Figure 6: Percent change in total deaths per million (y-axis) before and after different policies.

The first graph shows that banning mass gatherings has a real effect on decreasing the number of deaths. The peak in the deaths comes approximately 2 weeks after the ban is enacted (in line with the lag that we expect). Afterwards there is a clear decreasing trend. The results do not hold for partial closures, although the graph has decreasing trend even before the policy is enacted. This shows that partial closure policy is less efficient. For restaurant closures policy we see that it is not decreasing too much the rate after 2 weeks, this also indicates that it is not that effective. Finally we consider the policies that were enacted by the clusters and compare the main differences. Table 1 summarises findings:

Policy	Cluster-1 (%) enacted	Cluster-1 average duration of policy (days)	Cluster-2 (%) enacted	Cluster-2 average duration of policy (days)
Mandatory Masks	62%	24 days	42%	119 days
Ban on Mass Gatherings	38%	66 days	58%	81 days
Primary School Closure	62%	98 days	89%	82 days
Ban on Indoor events over 50 people	25%	74 days	53%	54 days
Closure of Public Transport	12%	28 days	16%	78 days
Teleworking recommendation	100%	70 days	44%	72 days
Private Gathering Restrictions	87%	98 days	97%	56 days

Table 1: Differences between enacted policies

Results clearly indicate that long term mask policy implemented by cluster 2 countries was very efficient. The ban of mass gatherings was also a key difference between two clusters, and thus a very important measure. Closure of indoor events and ban of public transport was another effective policy implemented. The least efficient policy was the teleworking recommendation as it didn't stop the spread of virus in cluster 1. Finally private gathering restrictions were also not that efficient as they were enacted longer in cluster 1. Overall we can clearly see that policy makers in cluster 2 were much more consistent and this also played a role in the lower number of deaths.

3.4 Efficiency of government restrictions - United States of America

We analyze the effectiveness of the "lockdown" policy in the United States in each state. The policy data have been collected from several sources (see appendix A). We group the policy into eight categories: 1) mask/ face covering mandate, 2) school closure, 3) ban of social gathering, 4) restaurant limit operation, 5) stay-at-home order, 6) nonessential business closure, 7) travel quarantine order, and 8) bar closure. Figure 7 illustrates the reproduction rate (R_t) with time. According to the policy data in the United States, the first round of "lockdown" happened in March, 2020. Then, around late April to May, some restrictions were lifted or eased. Nonetheless, the number of reported cases increased, and, some states went into the second "lockdown".

Several pieces of literature have already suggested the success of the mask requirement in reducing the spreading of Covid-19 (e.g., Lyu and Wehby 2020; Worby and Chang 2020). And, therefore, we would not analyze such a policy here and would focus on the other policies. In the United States, we analyze the effectiveness in two aspects:

1. how effective each policy is in reducing the reproduction number (R_t) one month before and after the policy is in place, and,
2. how effective is the second lockdown in the United States?

States are split into two categories for A/B testing. Since we do not know the distribution nature of the data, we employ two types of statistical tests: T-test (parametric) and U-test (non-parametric). Note that there is a statistical interference between each policy. In other words, it is impossible to measure the effectiveness of an individual treatment because the other treatments are still being in place. Hence, this violates the assumption of statistical testing.

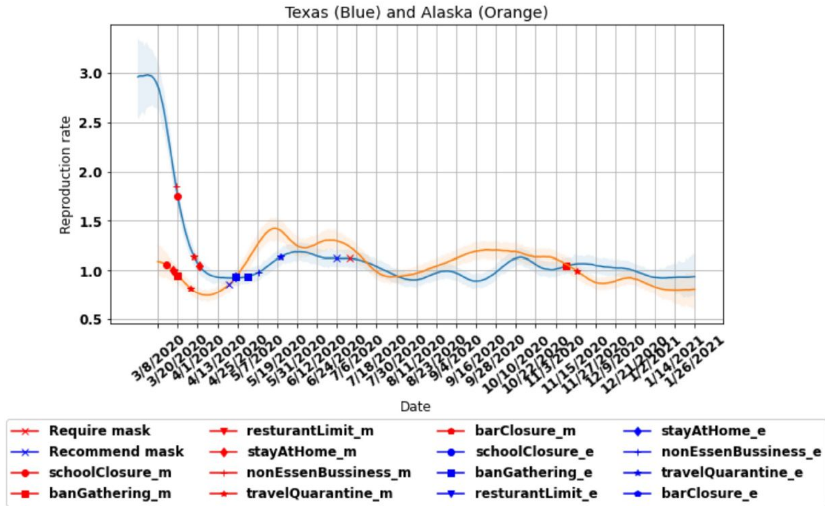

Figure 7: The reproduction rate curve for Texas (blue) and Alaska (Orange) plotted with 80% confidence interval. The mandate orders are plotted with red symbols and the easing orders are plotted with blue symbols.

3.4.1 Effectiveness of policy

The policies do reduce the spreading rate of Covid-19, R_t. On average, the reduction in R_t with a specific restriction in place is -42%, whereas the reduction in R_t without a specific policy in place is -31%. According to the statistical test, stay-at-home order, nonessential business closure, bar closure, and travel quarantine show a statistical significance in reducing R_t. According to the analysis, the ban of social gathering policy surprisingly does not significantly reduce R_t. We hypothesize that the face-covering mandate might have already been in place; and, therefore, reduces the infections. Table 2 summarizes the results of R_t reduction with statistical tests. Note that we do not include the school closure policy as most states implemented it.

3.4.2 Second "lockdown"

Some states, such as Florida, did not impose a second lockdown. Comparing the average R_t between 9/11/2020 to 1/1/2021 shows that the states with the "lockdown" policy have a lower average R_t ($p = 0.04$). As such, we conclude that the second lockdown does decrease the spread of Covid-19.

	Rt reduction- policy	Rt reduction without policy	T-test	U-test
School closure	-	-	-	-
Ban social gathering	-46%	-34%	0.41	0.14
Restaurant limit operation	-45%	-43%	0.7	0.36
Stay at home	-46%	-37%	0.09	0.03
Nonessential business closure	-48%	-38%	0.04	0.02
Travel quarantine	-33%	-24%	0.14	0.02

Bar closure	-33%	-8%	0.02	0.008

Table 2: R_t measure for each policy in the United States one month before and after the policy implement date.

3.5 Inpatient beds utilization efficiency for US

For this analysis, we compare the hospital admission policy for each state in the US. We have gathered external data from the National health safety network provided in the following link: https://www.cdc.gov/nhsn/covid19/report-overview.html

Please note that this data is only available through July and the daily estimates of inpatient bed capacity varies. We have determined the total capacity for each state by averaging this daily estimate and assuming that no new hospitals are built after July.

Since the hospitals also admit patients who don't have Covid but require hospitalization. We assumed that the percentage of such patients remains constant for each state over the entire length of analysis.

Since the positive number of Covid cases depends a lot on policies and number of tests performed, we decided to keep deaths per million people for each state as our key parameter.

For each state in the US, we averaged the hospital occupancy rate for each month and looked into the total deaths happening in the corresponding month.

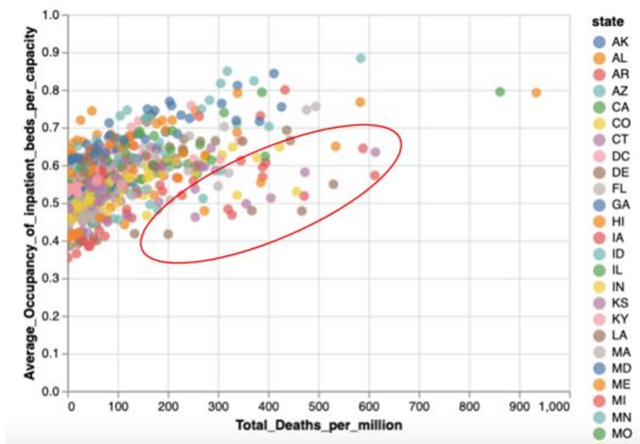

Figure 8: Scatter plot for each state and month on the average hospital utilisation and total deaths per million

In Figure 8, we are interested in the states which fall under the encircled region. These states have high deaths per million population while their average hospital occupancy is low. We found out these states by looking into points having higher distance from the regression line.

State	Month
IA- Iowa	2020-12 , 2021-01
IN-Indiana	2021-02
KS- Kansas	2020-12, 2021-01, 2021-02
ND- North Dakota	All months
OH- Ohio	2021-02

SD- South Dakota	All months
WY- Wyoming	2021-01, 2021-02

Table 3: Key states identified having low hospital utilization and high Covid deaths.

There are few trends which can be identified from the above graph, the key states captured in our analysis, only experienced their first peak of Covid cases in november and december. We know that states like New York (NY) were first to experience the Covid wave in the US. We have included the state of NY to study this trend. Identified key states like North Dakota (ND), Indiana and South Dakota (SD) reduced the average occupancy rate in hospitals while Covid related deaths remained the same.
New York, saw a sudden surge in Covid cases in April 2020 and utilized 80% of the available capacity and still witnessed a high number of deaths. In the second wave, NY responded swiftly, increasing the number of hospitalized patients and saw lesser deaths as compared to states like ND and SD. This trend also suggests that these states who experienced a wave quite late didn't learn from the experience of states like NY and handled the pandemic poorly in the winter. These states could improve the hospitalization occupancy by admitting more people into hospitals, effectively reducing the number of Covid-related deaths.

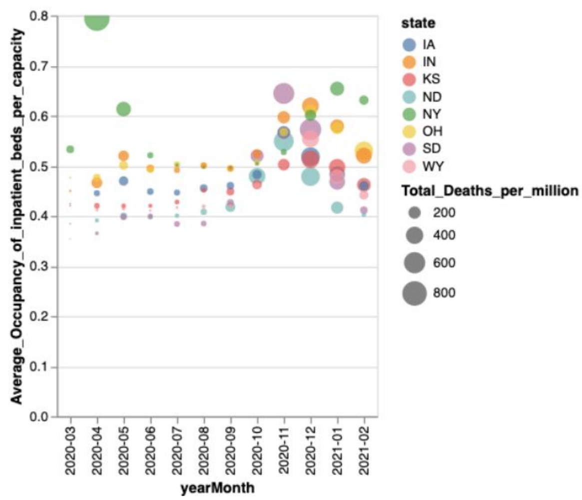

Figure 9: Analysis of key states with their average occupancy and monthly deaths per million.

3.6 Evaluation of Covid-Testing policy for US

We did similar analysis for testing policy of each state in the US as we did for inpatient bed utilization efficiency for each state. Here too we are interested in states having low testing numbers and high number of deaths. Based on the regression analysis of points having higher than 100 deaths per million population in a month, we found out the low performing states.

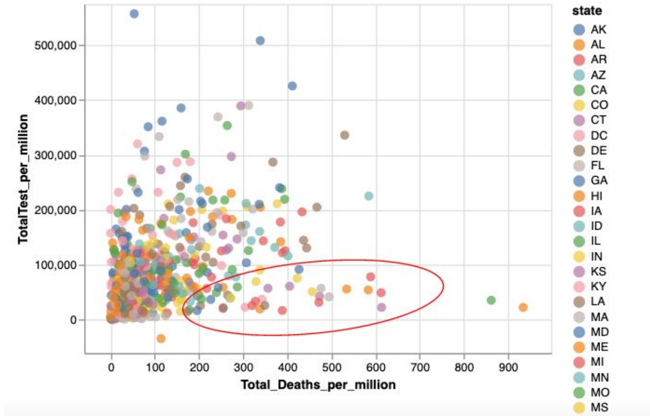

Figure 10: Scatter plot of total deaths per million for each state and month compared to total tests performed

State	Month
AL	[2021-01, 2021-02]
CT	[2020-04, 2020-05]
IA	[2020-12]
LA	[2020-04]
MA	[2020-04]
MI	[2020-04]
NJ	[2020-04, 2020-05]
NY	[2020-04]
OH	[2021-02]
SD	[2020-12, 2020-11]
WY	[2021-02]

Table 3 : States and months picked up from regression analysis

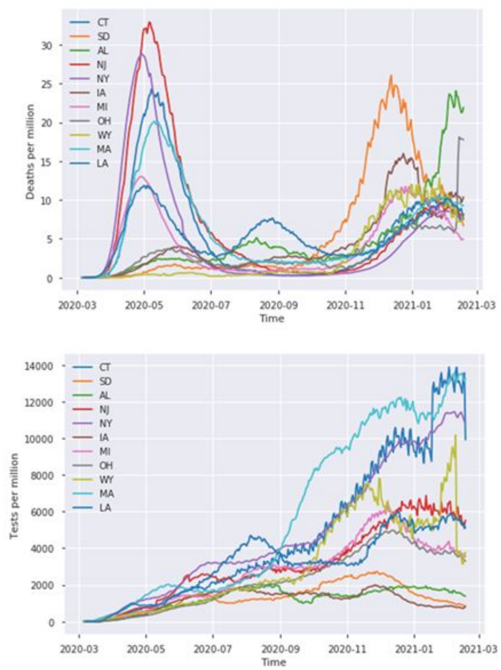

Figure 11: Total deaths per million and total tests per million for selected states.

Figure 11 and Table 3 indicate that some states had very bad testing policies even in the months of october and november 2020. States like LA, MA, MI, CT, NJ and NY experienced very strong first waves in the month of april and may 2020. There was no rampant testing in the US in these early months. While some states like SD,WY, AL and IA had a huge impact of Covid-19 in winter 2020-2021. These states didn't ramp up testing and this resulted in significant deaths.

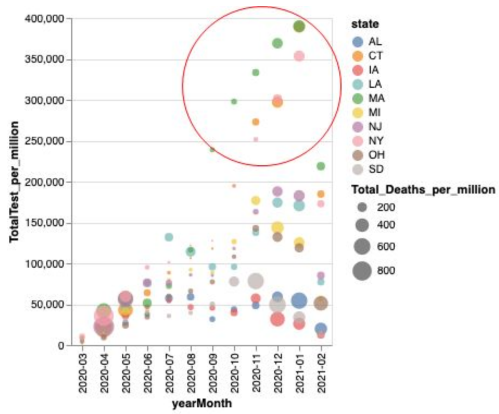

Figure 12: Analysis of key states overtime.

A strange result is obtained for states CT and MA as shown in Figure 12. These states did extensive testing but still have a significant number of deaths. The overall trend indicates that states like SD, OH, AL and IA had high numbers of deaths probably due to less testing.

Since testing in the US became rampant after June, we looked into daily tests done by states after June and found the top 6 states and bottom 6 states when compared on the basis of average tests per million. This is shown in Table.4

States with low testing	Avg tests per million(daily)	States with high testing	Avg tests per million(daily)
PR	284.631519	ND	6835.078047
ID	1295.609092	NY	7021.308346
IA	1349.497024	CT	7135.857773
KS	1554.477016	MA	8807.352177
AL	1611.169367	AK	8862.054066
SD	1634.136633	RI	10433.37033

Table 3 : States with low and high tests performed daily

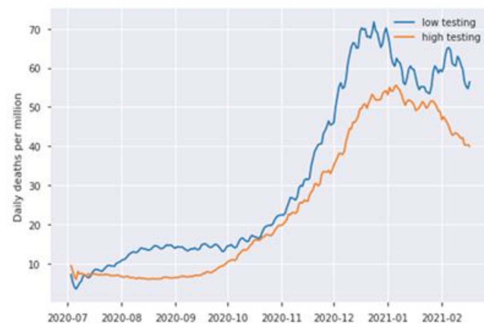

Figure 13: Daily deaths per million in the two identified cluster of low and high testing

From Figure.13 we can clearly distinguish that daily deaths are more prominent in states having low testing. We performed the two sided t-test on daily deaths per million on the two clusters and got the results t-statistic=5.48, p-value= 10^{-7}

This clearly shows that extensive testing is very important criteria for reducing the number of deaths and reducing impact of Covid-19. The low testing states identified in Table.4 failed to implement extensive testing even after witnessing the first wave. Meanwhile, the states which had high deaths in the first wave of Covid-19 were prepared to tackle the second wave and did extensive testing to control the impact of Covid-19.

3.7 Conclusion

We hope that the analysis presented in this work will help to have more refined policy during the pandemics and save lives.

References

Lyu, Wei, and George L. Wehby. 2020. “Community Use Of Face Masks And COVID-19: Evidence From A Natural Experiment Of State Mandates In The US.” Health Affairs (Project Hope) 39 (8): 1419–25. https://doi.org/10.1377/hlthaff.2020.00818.

Worby, Colin J., and Hsiao-Han Chang. 2020. “Face Mask Use in the General Population and Optimal Resource Allocation during the COVID-19 Pandemic.” Nature Communications 11 (1): 4049. https://doi.org/10.1038/s41467-020-17922-x.

Appendix - A

The US Policy (USP) were collected from multiple sources. The three main sources include:

1) https://www.kff.org/report-section/state-covid-19-data-and-policy-actions-sources/
2) https://www.aarp.org/health/healthy-living/info-2020/states-mask-mandates-coronavirus.html, and
3) official website of the state.

We found several conflicts in the start date of USP among the sources. To be consistent, we prioritize the integrity of the data as follow:

1) mandated orders/ state emergency orders/ executive orders from state official website
2) www.kff.org
3) https://www.aarp.org (mask/ face covering order)
4) local news (e.g., CNN, CNBC, KXAN, etc.)

Table schema

Data size: 11 KB

Field	Type	Description
stateSymbol	STRING	State’s acronym.
maskDate1	DATE	Date (m/d/y) of the first mask mandate policy .

isMaskRequired1	BOOL	True means mask or face covering is required. False means mask or face covering is optional and/or only needed for essential business people.
maskDate2	DATE	Date (m/d/y) of the second mask mandate policy, if existing.
isMaskRequired2	BOOL	Same as isMaskRequired1.
maskDate3	DATE	Date (m/d/y) of the third mask mandate policy, if existing.
isMaskRequired3	BOOL	Same as isMaskRequired1.
schoolClosure_m1	DATE	The first date (m/d/y) which school, university, educational institute, and/or post-secondary school are being asked to close.
banGathering_m1	DATE	The first date (m/d/y) that mass gathering defined as more than 3 people on a confined space is prohibited.
resturantLimit_m1	DATE	The first date (m/d/y) which restaurants have to either 1) suspend their business, 2) take-out only, or 3) outside dine-in only. Note that some states include bars (serving alcoholic drinks) in this category.
stayAtHome_m1	DATE	The first date (m/d/y) when the people are asked to stay in their shelter. Note that citizens can still leave their shelter for food, perform essential business, exercise (e.g., running) etc.
nonEssenBussiness_m1	DATE	The first date (m/d/y) when non-essential business needs to be closed.
travelQuarantine_m1	DATE	The first date (m/d/y) when international and/or interstates travelers are asked to quarantine themselves for a certain period.
barClosure_m1	DATE	The first date (m/d/y) which bars have to be closed.

schoolClosure_e1	DATE	Easing date (m/d/y) for school, university, educational institute, and/or post-secondary school to resume their business with social distancing limitation (e.g., online class). **Note that most states do not explicitly "ease" the school closure.** Some states include this policy as easing social gathering and/or stay at home order.
banGathering_e1	DATE	Easing date for the social gathering.
resturantLimit_e1	DATE	Easing date for restaurant closure.
stayAtHome_e1	DATE	Easing date for stay at home order.
nonEssenBussiness_e1	DATE	Easing date for non essential business closure order.
travelQuarantine_e1	DATE	Easing date for travel quarantine order.
barClosure_e1	DATE	Easing date for bar closure order.
schoolClosure_m2 banGathering_m2 resturantLimit_m2 stayAtHome_m2 nonEssenBussiness_m2 travelQuarantine_m2	DATE	The second date that the policies have been reimplemented. Follow the same format as before.

schoolClosure_e2 banGathering_e2 resturantLimit_e2 stayAtHome_e2 nonEssenBussiness_e2 travelQuarantine_e2	DATE	The second date that the policies have been lifted. Follow the same format as before.

For those who would like to use this data, we have addressed our concerns about the USP dataset as follow:

1) even the policies are in place; some people do not adequately follow the regulations, especially the mask mandate order,

2) some states may have local orders such as the local mask mandate in Iowa City,

3) due to the limitation of time, we recommend double-checking the policy date.