How the Pandemic Affected Human Mobility and Government Spending in the US

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Introduction

Both datasets we decided to use for our analysis (using causal inference and hypothesis testing), are census data, and do not represent samples. The first dataset, a Region Mobility Report, which we refer to as '2020_US_Region_Mobility_Report', looks at different regions of a country and their mobility, in terms of percentage of change from a baseline of the previous year. The units for this dataset were presented as such: percentage of increase/decrease in mobility based on a baseline (the average of the increase/decrease across certain regions in a state based on the previous year). After grouping this data set by its state on average percentage change (mean), we took a look at the different changes in mobility using causal inference. The second dataset, 'Monthly_Transportation_Statistics', looks at government spending on transportation in different regions of the U.S. For this dataset, we also grouped by state and then selected the data for 2020-present date only, excluding the data prior to those dates. This transportation data was the one provided to us by the course.

We did not use our own data, but the Region Mobility Report was outside data that we found through Google datasets. This data was a CSV file download, for which we downloaded U.S. data only. It has reports on regions all around the world that were not necessary for our analysis. We simply downloaded the CSV file, and used the information for the year 2020-now. We also used cartographic boundary files ('.shp' files) for our heatmaps in our EDA visualizations, provided through the U.S. Census Bureau, which allowed us to use the U.S. maps by grouping our data on their region columns. This link provides shapefiles for numerous regions, large and small, around the world, but we used the file for the U.S. only, in order to visualize the mobility change rates per state. This visualization allowed us to determine what states to use our causal inference on during our analysis. The way we used these visualizations is elaborated in the causal inference section later on.

We wished that we had columns filtering the mobility and transportation dataset by state, so we could look at the effect of the pandemic on government spending by year for different states. This would have helped us with the hypothesis testing part. Overall, these datasets ultimately allowed us to use causal inference on our first dataset, and hypothesis testing on our second, to come up with conclusions to the questions we had in mind.

Research Questions

1) Does human mobility in grocery stores/pharmacies change in response to the pandemic in the United States (using causal inference through an observational study, observing the increase/decrease in mobility)?
2) For a specific area of interest, is there a significant association between government spending and the pandemic? We will be using multiple hypothesis testing and looking at the years 2019 and 2020 as pre-pandemic and post-pandemic respectively.

Causal Inference

Research Question: Does human mobility in grocery stores/pharmacies change in response to the pandemic in the United States (using causal inference through an observational study, observing the increase/decrease in mobility)?

Methods

The treatment we are looking at is the Covid-19 pandemic, and our outcome is the percentage change in mobility in different regions, with higher mobility rates. We are looking at the entirety of the year of 2020, thus including the pandemic from before it began, through lockdown, and during lockdown. The units are a percentage of increase/decrease in mobility based on a baseline (the average of the increase/decrease across certain regions in a state) from the previous year. We are looking at the lower-mobility states' probability of lower mobility than the higher-mobility states in response to the pandemic. In this case, for our study, we are going to look at Iowa as the state with the higher mobility rate, and California, Texas, and Hawaii for the states with the lower mobility. We determined to use these states by our visualization of the U.S. through a heatmap, which showed the change in mobility per state, with respect to one another (visualization 6, under EDA section). Taking a look at the percentage mobility change between the lower and higher states, we are going to specifically be looking at the change of mobility in grocery stores and pharmacies and how they changed in response to the pandemic. We are comparing the change between the states to see how they differ from one another, and the reason that might be so.

When we initially began our study, we anticipated that some confounding factors would be: rural vs. urban areas, location accuracy, and opting in to location history. Because we are looking at state-level data, these confounding factors may be present, but not at a significant level. We can consider the population of a state as a confounding factor at a larger level, applicable to our study. The drastic changes in mobility for many states is due to lockdown measures. We can consider reasons for why the states with lower mobility rates from the baseline of the previous year were lower. California and Texas are extremely populous states, so the lockdown measure probably drastically affected their statistics. Hawaii is a state with high rates of tourism, so once lockdown measures were implemented, it caused the largest decrease in mobility for all the states. Iowa had a higher mobility rate than the baseline, and as stated earlier in the visualizations, we could speculate that the high mobility in the midwest may have been due to the lack of preventative measures during the pandemic.

Another confounding variable we could consider is the amount of grocery stores per square area. There may be a lot more grocery stores in more populous states, whereas in less populous states, there may be fewer grocery stores, making them farther spread apart. But, this would be an unobserved confounding variable, as we do not have any measure that would allow us to find an association with our results. We could also consider political affiliation. The pandemic became a political game in the early stages of its spread, making many individuals not take preventative measures seriously. Based on the political affiliations of the majority individuals of a state, it may have an apparent influence on the results of change in mobility. But, this is merely an assumption, so we cannot use it as a confounding variable.

Using a causal inference, we can only observe states' mobility if they increased or decreased. If we want to adjust on a certain variable, let's say the decrease of mobility in Hawaii with the increase of mobility in Idaho due to the following/lack of following of lockdown measures, we can use the quantity, $E[Y|T=1]-E[Y|T=0]$ to provide a measure of association (rather than causation) for our study and assume an unbiased estimate of causal effect. A collider influences two or more variables, and in this case, there are colliders. Covid-19 affected the mobility of states with a change that was lower than the baseline of the previous year, and states with a change that was higher.

Results

For this question we worked with the covid mobility dataset which only looks at the year 2020 (when the pandemic began). This dataset measures the change in mobility from the previous year. We conducted observational studies as a method of causal inference for different pairs of states at a particular location. We observed the causal effect of two states (state as the treatment variable) on grocery store mobility during the pandemic. Looking at the states of California and Iowa, we observed that there was about 14.09 percent less mobility in California than in Iowa in the year 2020. From the histogram we can see that the distribution of grocery store mobility is different for California than it is for Iowa. The distribution for California is shifted to the left in comparison with Iowa, since California's percent change from baseline of the previous year is on average lower than Iowa's. Therefore, the pandemic had a causal effect on human mobility to grocery stores for California and Iowa, but the causal effect was different among these two states. This is as expected since California and Iowa had different approaches to handling the pandemic and lockdowns. These findings point strongly to Covid-19's strong impact on states declining in mobility.

Uncertainty may arise when looking at why the mobility is lower for each state. For example, Hawaii and Iowa have a lot lower mobility (~-34.202%) in comparison to one another, while California and Iowa (~-14.086%) also have lower mobility with respect to one another--but a lot higher than with respect to Hawaii and Iowa. This goes against our hypothesis that there is an increase or decrease, by us only getting decreasing results. If we adjust for our confounding variables, it may give us different results. There were also states with similar mobility changes, such as Alabama and Georgia, which had only a ~1.163% change with respect to one another. The purpose of us using causal inference on these states, was to show the small change in mobility between two states, in contrast to the larger states. It was to show that there were states other than Iowa that had low changes in mobility. These small changes in mobility lean away from our hypothesis (that Covid-19 had an impact on mobility).

Discussion

We are looking at the data at a state level, which doesn't translate to causal effects at the individual level. Our trial is also not randomized, so there is no independence assumption. Because we are not looking at the data at an individual level, we can only make state-level assumptions. We cannot determine a measure for the average treatment effect (ATE). But, we can determine the ATE for the general states to measure the mean in outcomes between units by whether or not they increased from the baseline or decreased. We could not identify any instrumental variables, which is why we did our best addressing any potential confounders. There would also be confounders that we cannot account for, such as if a state is considered such as the amount of grocery stores per person, which additional data would be helpful for. There could also be selection bias, when excluding samples from the data, if there are places where the data is not available (NaN values).

Based on our results there seems to be a causal relationship between the higher states and lower states, so we are confident that Covid-19 has an impact on mobility for different states in the U.S., whether mobility increased or decreased. Data on the confounding variables we have thought about would be helpful for us to answer our causal question because it would give us insight and allow us to determine an association between our treatment and outcome.

We are confident that there is a causal relationship between Covid-19 and mobility changes in different states in the U.S. Our causal inference shows the change in mobility by comparing states with higher changes from the baseline values of the previous year, with states that have lower changes from the baseline, with respect to one another. These comparisons allow us to understand that the changes in mobility have an effect on the entire nation, rather than just an individual state, comparing with itself from a previous year. It allows us to see a bigger picture by comparing states with one another rather than only looking at the change for an individual state. We can understand from our causal relationship that the impacts of Covid-19 were beyond a state level to a national one. Our analysis may allow us to compare findings with other nations in the future, moving our understanding beyond a nation level to an international one.

Multiple Hypothesis Testing/Decision Making

For a specific area of interest, is there a significant association between government spending and the pandemic? We will be using multiple hypothesis testing and looking at the years 2019 and 2020 as pre-pandemic and post-pandemic respectively.

Methods

We classified 2019 as pre-pandemic and 2020 as the start of the pandemic/ post-pandemic. The hypothesis that we will be testing is that there is no underlying difference in the distribution of government spending at a series of locations/areas of interest pre-pandemic and post-pandemic; that the distribution of the data is different just due to chance. In other words, we are trying to see how the pandemic is associated with government spending? We are setting our alpha value to be 0.2 in the hypothesis tests.

For a specific location/area of interest:

> **Null hypothesis:** In the population, the distribution of state and local government construction spending is the same in 2019 and 2020. The difference in the data is due to chance.
>
> **Alternative hypothesis:** In the population, state and local government construction spending is less in 2020 on average than state and local government construction spending in 2019.

It makes sense to test many hypotheses because government spending could have increased in certain sectors pre and post pandemic, but decreased in other sectors. So for example in the healthcare/public health sector government spending increased from 2019 to 2020 in response to the pandemic. But as we saw in the EDA, government spending on sports and recreation had a spike in 2019, but decreased for most of 2020, so on average spending was less in 2020 than in 2019. By looking at a different area of interest for each of the six hypothesis tests, we can look at how the pandemic affected government spending in different sectors. Trying to look at the distribution of government spending for just one area of interest would not make much sense since the distribution differs per area of interest.

We will be doing A/B testing to test each of the hypotheses. We will be testing whether the two numerical samples (government spending in 2019/2020) come from the same underlying distribution of government spending in that area of interest, which is why we decided to do A/B testing. The year refers to the labels of the two samples, A and B.

We corrected for multiple hypothesis tests using the Bonferroni Correction and the Benjamini Hochberg correction. The Bonferroni correction controls the family wise error rate, which is the probability of coming to a false positive in a series of hypothesis tests (the probability of making at least one Type I error). Benjamini Hocherb controls the false discovery rate, which is the number of false positives divided by the total number of discoveries. Bonferroni punishes all input p values equally, while Benjamini Hochberg punishes p values according to their ranking. The number of discoveries we make is dependent on the correction method we use. Bonferroni is more likely to produce false negatives and is more likely to discard significant observations, while Benjamini Hochberg is not, as it’s more likely to reject the null when there is a significant difference.

Results

Rejecting the null hypothesis in this case would mean that the difference in distribution of government spending from 2019 to 2020 for an area of interest is not just due to chance, and that the result is statistically significant if it is less than the threshold. This would mean that there is a relationship between government spending and the pandemic, and that government spending decreased in the pandemic from 2019. Failing to reject the null would mean that our tests did not identify a consequential relationship between government spending and the pandemic.

For the Bonferroni method:

We fail to reject the null for all 6 hypothesis tests. This means that for all the 6 areas of interest, government spending did not change from 2019 to 2020.

For the Benjamini-Hochberg method:

We reject the null for all hypothesis tests except for healthcare. This makes sense as in the health care sector, government spending actually increased as a response to the pandemic in 2020, so we fail to reject the null since our alternative hypothesis is that government spending decreased in the pandemic. Since Bonferroni is more conservative than the Benjamini Hochberg, we would expect to see less discoveries with it than with the Benajmini Hochberg method. Bonferroni made 0 discoveries while B-H made 5.

The Bonferroni correction controls the family wise error rate, which is the probability of coming to a false positive in a series of hypothesis tests (the probability of making at least one Type I error). Benjamini-Hochberg controls the false discovery rate, which is the number of false positives divided by the total number of discoveries. Controlling the FWER controls the probability of making a Type 1 error at all, while the FDR allows Type 1 errors but controls how many of them you make in proportion to the number of true positives. The FDR has a higher power than the FWER since its Type 1 error rate is higher, so there is a trade off between these two error rates.

Discussion

After applying the Bonferroni correction procedure we see we accepted the null in all 6 hypothesis tests. After applying the Benajimini Hochberg correction procedure we see that we accepted the null in just one out of the six hypothesis tests. We did not make any discoveries with the Bonferroni correction since Bonferroni is more likely to produce false negatives, and is a more conservative threshold than the B-H. Hence, the B-H correction is more likely to make discoveries than the Bonferroni correction. The Bonferroni threshold is generally lower than the B-H threshold for FWER <= alpha and FDR <= alpha. This is why after applying our correction procedures we got the results we did.

We cannot make any decisions from the results in aggregate since we know that government spending changes are different for separate areas of interest. Since Bonferroni is a little too conservative we want to look at the B-H correction. From the individual tests if we use the B-H method, we can make the decision that government spending decreased from 2019 to 2020 in the following areas of interest: government spending in sports/recreation, park/camps, amusement/recreation, high school, higher education, and did not decrease from 2019 to 2020 in the healthcare sector. This is as we would expect since major fiscal cuts were made to state and local government budgets in those 5 sectors as a response to the pandemic, while the healthcare sector required a government budget increase in order to manage hospital and medical care. For example, in areas like sports/recreation and amusement we would expect to see a decline in government spending from 2019 to 2020.

Limitations in our analysis include the missing nan values in our columns, and the fact that we defined pre-pandemic to be 2019 and post-pandemic to be 2020. This is a slightly loose assumption/definition since the pandemic began a few months into 2020, (WHO declared Covid-19 to be a pandemic in March 2020), so by looking at the average government spending in 2020 we are also considering those few months before the pandemic was announced. Looking at just the months after 2020 and defining pre pandemic to be 2019 and the months before March could have affected our hypothesis tests. However we just made the assumption of associating 2020 with the pandemic, and associating 2019 with pre-pandemic.

If we had more data about the government spending in specific states for all the months in a particular year, we could have filtered by year and state and conducted hypothesis tests for the distribution of government spending at a specific area in 2019 and 2020 in just California for example. We could also have looked at two states simultaneously, for example if government spending increased or decreased in Iowa versus California for one particular year. If we had more data about the states we could have looked more closely into the effect of the pandemic on government spending over different states in the same year or the same state in two different years.

Conclusion

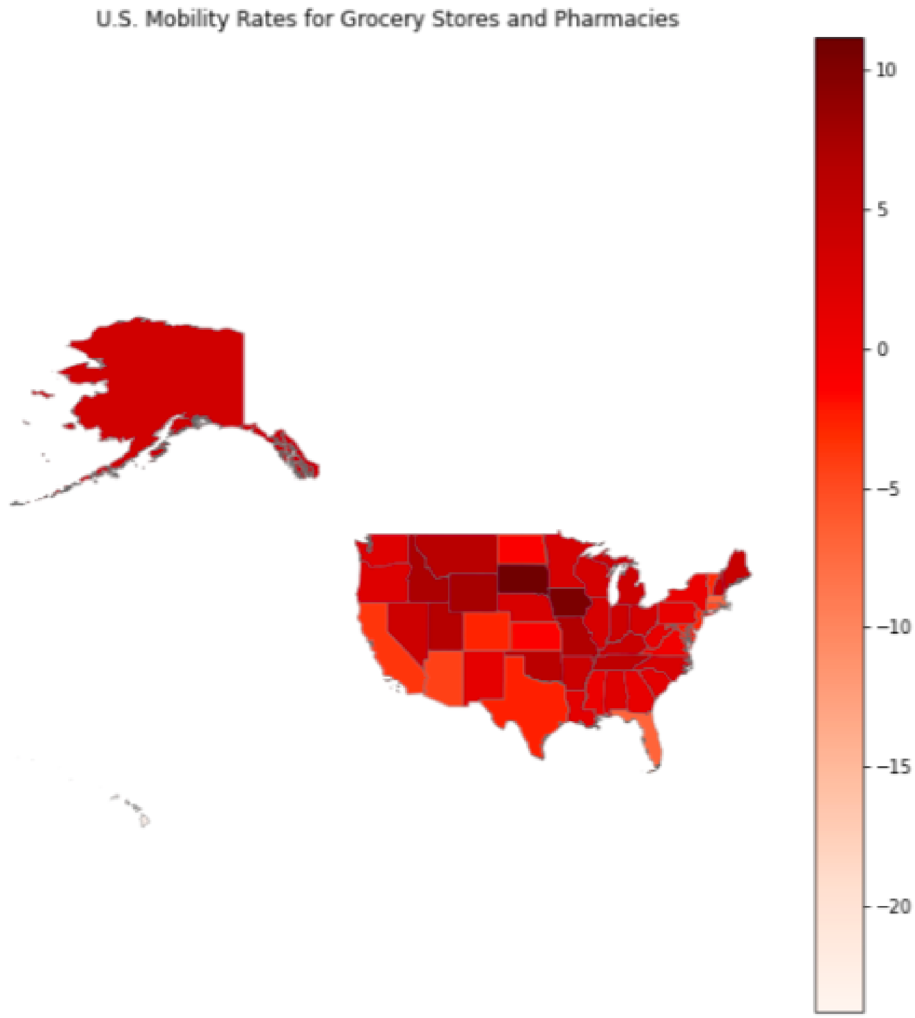
There was a causal effect on human mobility to grocery stores in different states, depending on how each state approached COVID-19 restrictions. However since we are looking at the data from a state level, we are unsure of causal effects at the individual level. There are also confounding variables we could not take into account, and if we had extra data on confounding variables, that would be useful in answering the causal question. Overall, we are pretty confident that there is a causal relationship between COVID-19 and mobility changes in different U.S. states.

Our results are pretty generalizable and broad. Since COVID-19 happened everywhere across the globe, these results could be applied to almost anywhere. If we focused our results primarily on one location, then the results could be less generalizable and more specific. Having generalizable and broader results is not necessarily a bad thing though; it just means that it can also apply to different locations and people.

Of the 6 areas of interest that the government spends on, we have evidence, using Benjamini-Hochberg method, that government spending in the healthcare sector varied from 2019 to 2020. This finding is not surprising due to the COVID-19 pandemic. However, what is surprising is even though government spending in this sector increased, we did not find evidence that this had an effect on other sectors. In light of our findings, we suggest the government continue its spending on healthcare until there is evidence that other sectors are being negatively impacted. If increasing spending on healthcare is not affecting other areas, we don't see a problem in prioritizing healthcare and putting an end to COVID-19. However, there were confounding variables that we could not take into account such as the exact date when the pandemic started.

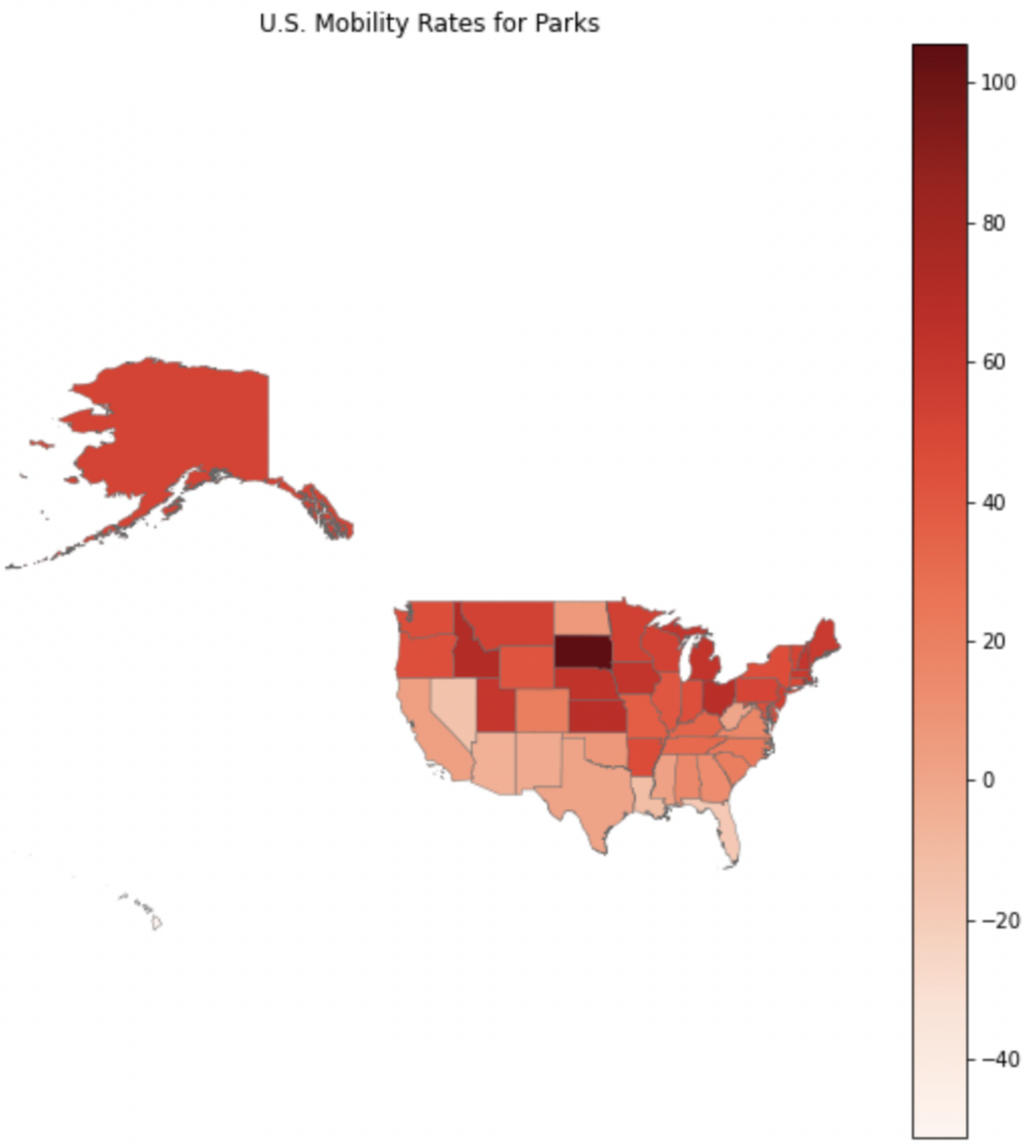
In the future, economists and historians who are studying how the government played a role in ending COVID-19 could build on our work. When this pandemic ends, our work could be used by those who specialize in this field e.g. economists as they could use this to help them determine how much the government contributed in ending this pandemic. Government researchers and congress could also use our work to help them decide whether or not they could use more of their spendings on healthcare without impacting other areas given that we found no evidence of other areas being significantly affected thus far.

Exploratory Data Analysis (EDA)



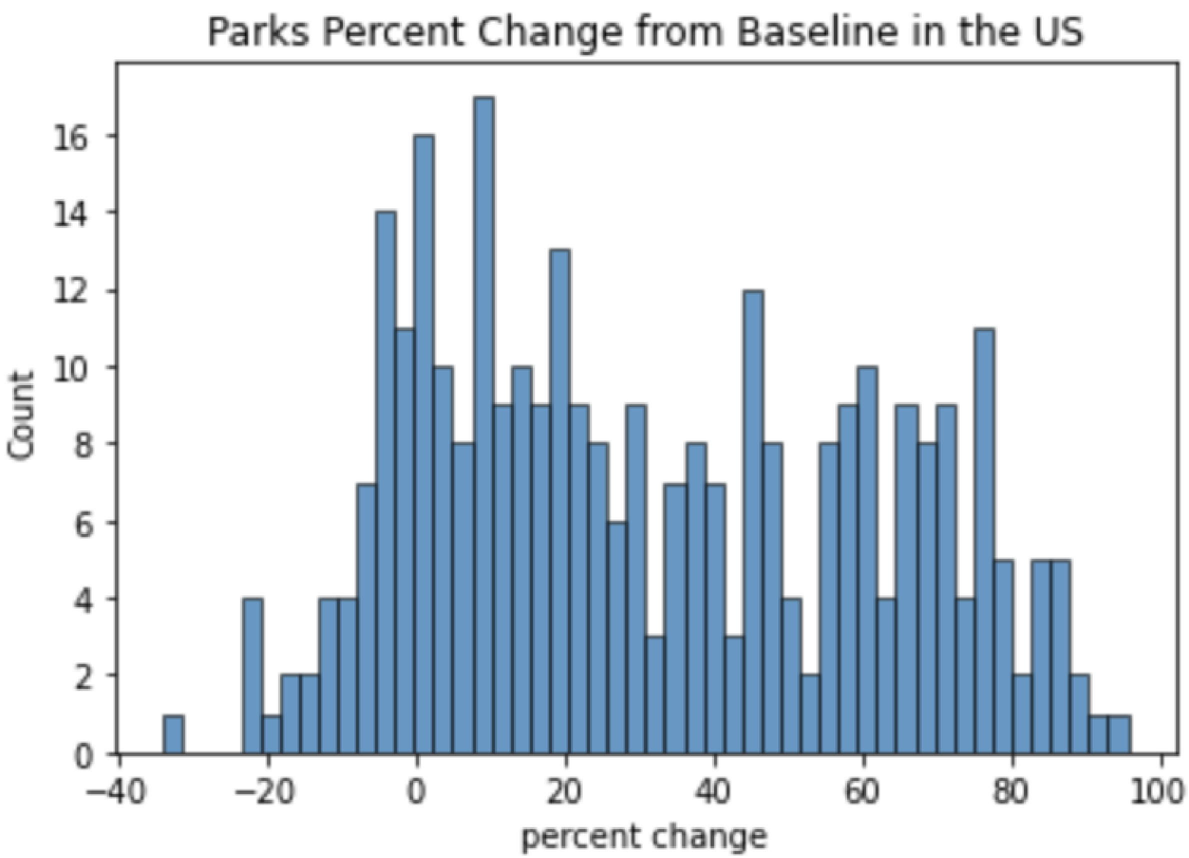
(1) This visualization represents the percentage change of mobility of people (walking in and out) of grocery stores and pharmacies in 2020, from the baseline value, or the median of the percentage changes in mobility. Looking at our map, it's evident that South Dakota, and Iowa increased the most in their mobility percentages, while states such as Massachusetts, California, Texas, and Florida decreased their mobility percentages. Most notably, Hawaii had a significant decrease in mobility to grocery stores and pharmacies. We first took our covid mobility dataset and renamed the column 'sub_region_1' to 'NAME', to match the data set that held the information for our .shp file that was our U.S. map with all the states. We then grouped our covid mobility dataset by state, taking the average mobility percentages of each state. We then merged the two datasets (covid mobility + .shp file's dataset) by state to have one dataset (titled 'heatmap_mobility'). We then plotted heatmap_mobility as a scalar mappable to get a heatmap of the U.S.

representing the average mobility of individuals at grocery stores and pharmacies in 2020. This visualization makes sense, as California, Texas, and Florida were states with higher Covid-19 cases, so the lower mobility may have been preventative measures, such as lockdown, that prevented people from frequenting grocery stores and pharmacies in person. Hawaii's significant decrease may have been due to the stop in tourism at the start of the pandemic. We could speculate that the high mobility in the midwest may have been due to the lack of preventative measures during the pandemic. These questions ultimately make us wonder what caused these trends and why they may have occurred.

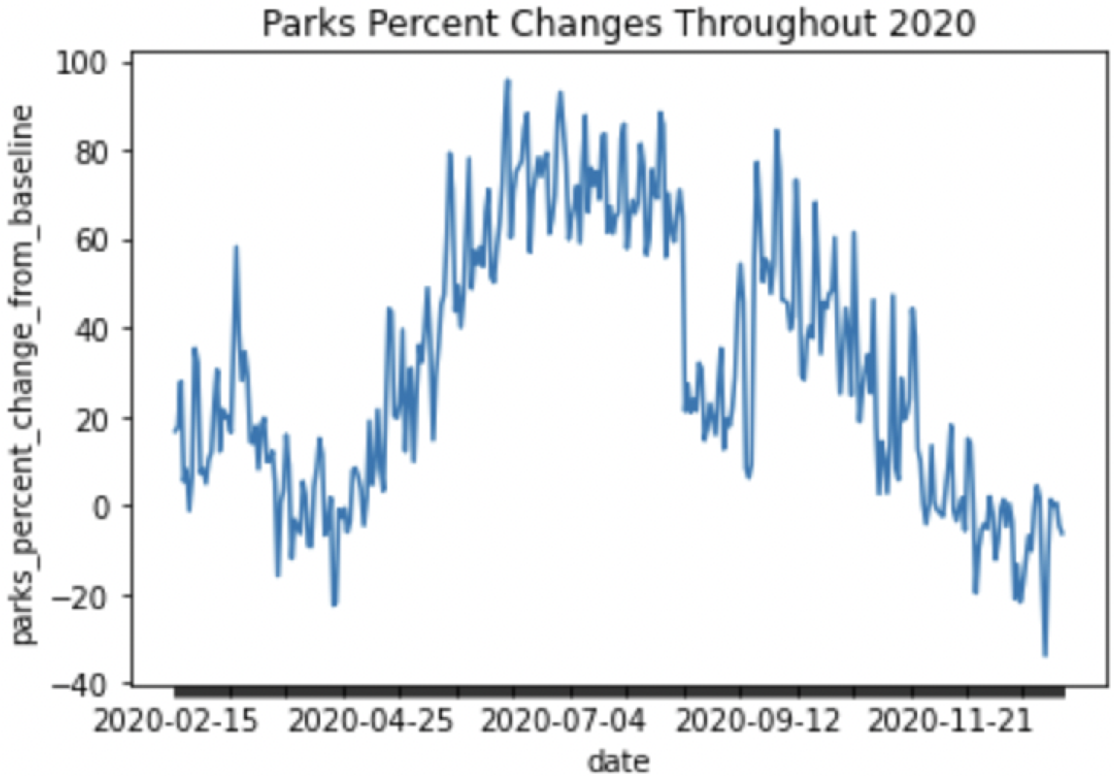


(2) This visualization shows the percentage change of mobility of people (walking in and out) of parks in 2020, from the baseline value. Looking at the heat map, it is clear that many southern states had less park mobility than before than the states on the northern

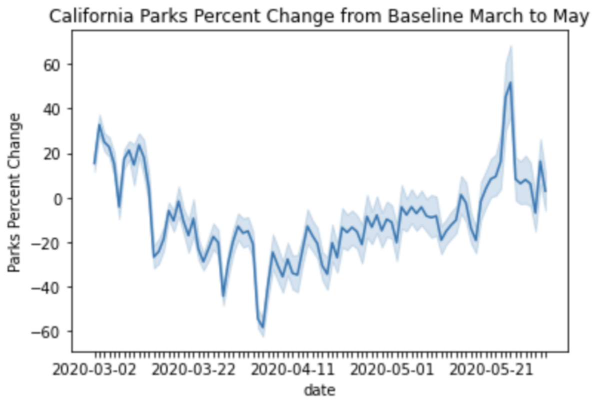
side. The state with the most mobility increase is South Dakota. The data cleaning steps are the same as the previous visualization. This visualization is relevant to my research question because it shows one way mobility increased or decreased for every state since the start of the pandemic. Parks are interesting to observe because even though there was a shelter in place at the time, parks are primarily outdoor. They are not essential to everyday living, so not many people may be visiting during the pandemic. However, parks are "safer" alternative activities during the pandemic. Because of this, park mobility may not have as much change as the other features we are looking at for mobility.

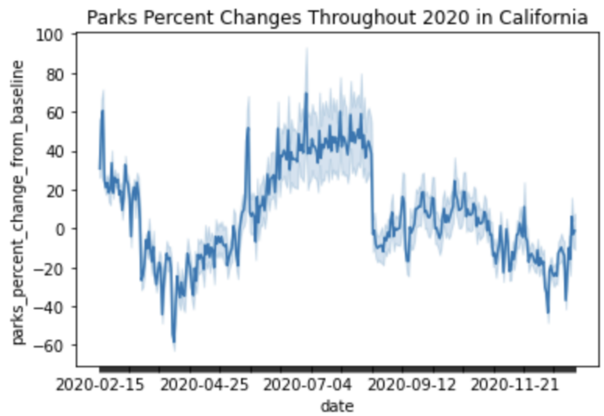


(3) This visualization is the percent change of park visits from the baseline in the United States throughout the year of 2020. To better understand this, let’s graph the percent changes with respect to the dates. We know that at some point in March of 2020, stay-at-home orders were enforced so we should expect a decline or change in the percentage of park visits.

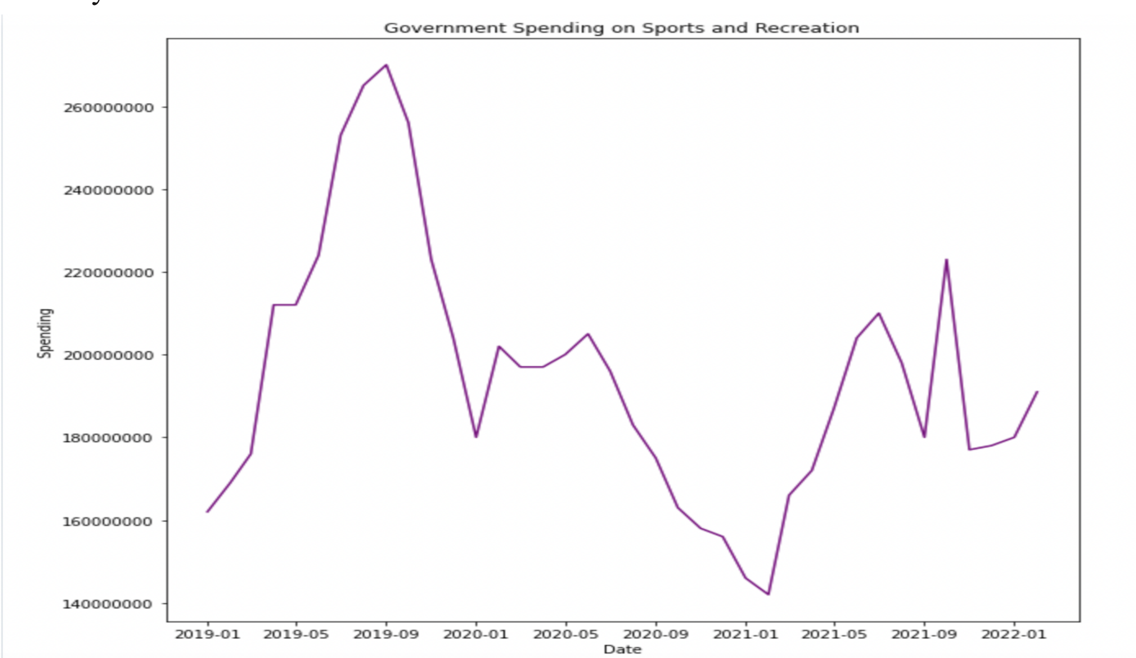


(4) Here we see that around late March and early April, the percent change was negative, and around late summer in August, the change normalized back to zero and continued to decline after. First, let's understand why there was a negative percent change in late March and early April. Referring to the Covid-19 timeline released by Yale Medicine, we see that California went into lockdown on March 19, 2020. In April, the country already went into lockdown, businesses shut down, and social distancing was enforced. Hence, we see this decline in park visits especially when national parks are closed as well. The economy tried to pick up and reopen businesses in June, so we would expect more headcounts going out, which we could assume that some parks reopened but under limited capacity. In November, cases rose again as more people hung around indoors due to the cold, and we saw a spike in Covid cases, and record breaking daily cases/deaths. This of course halted reopenings, and hence why parks percent change decreased significantly during this period.



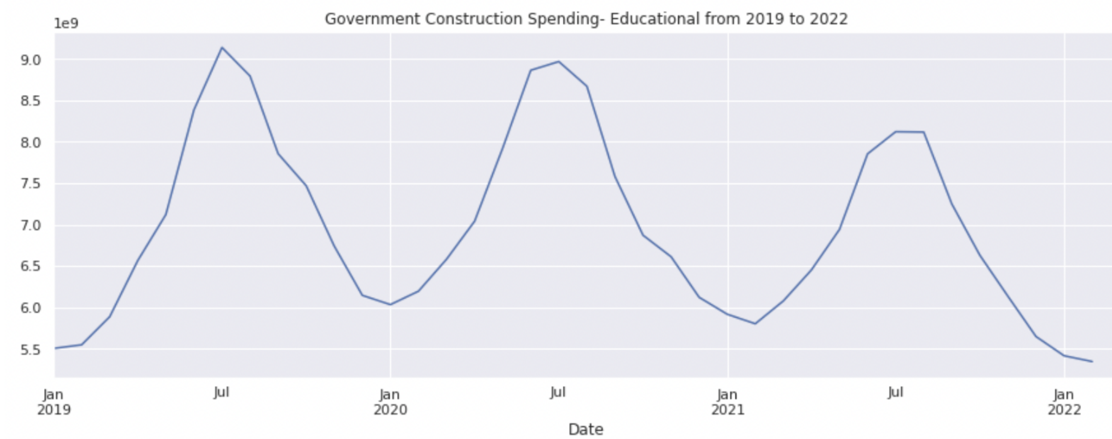


(5) We could take a look at California and how policies affected the park percent change as we have more information from ABC7's COVID timeline. Here, we are looking at the dates between March 1 and June 1 of 2020. Looking at the ABC7 Covid timeline, California went into lockdown on March 19, and all California state parks were closed on March 29, 2020. However, throughout April and May, some public parks were open only for people to walk, but the restrooms still remained closed. As a result, we see an increase in the park percent change. However, in the figure below, we see that the drop continued starting July as we see from the timeline that cases continued to rise and break records daily.

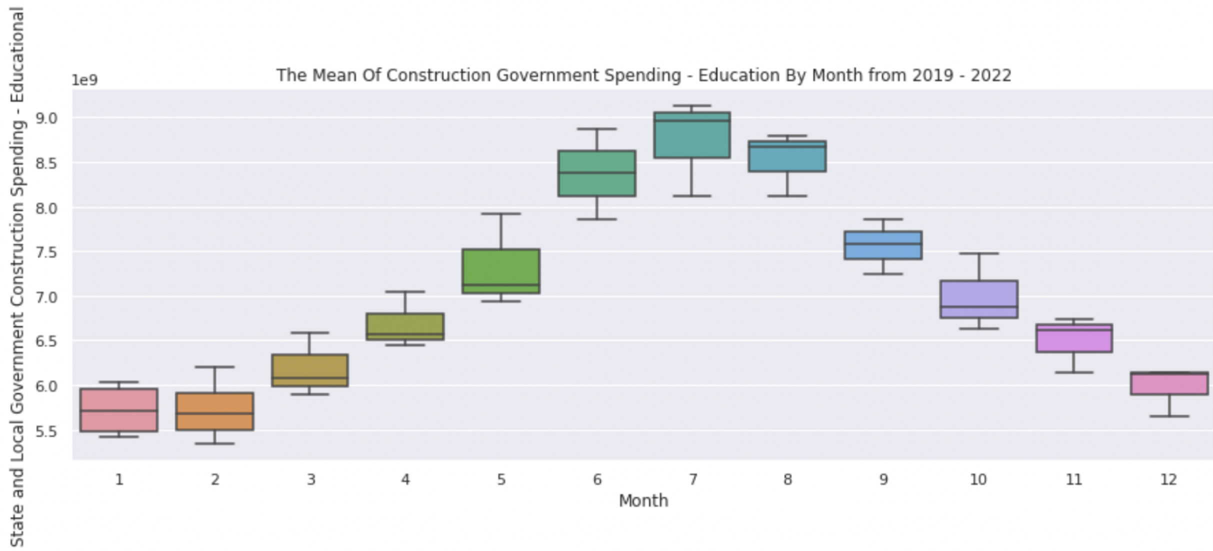


(6) In the visualization of government and local spending on sports and recreation in the United States, there is an increase in overall spending in the year 2019 (pre-pandemic). In the year 2020 there is an initial increase and then a decline in spending between January and May of 2020, due to the pandemic restrictions and the first government

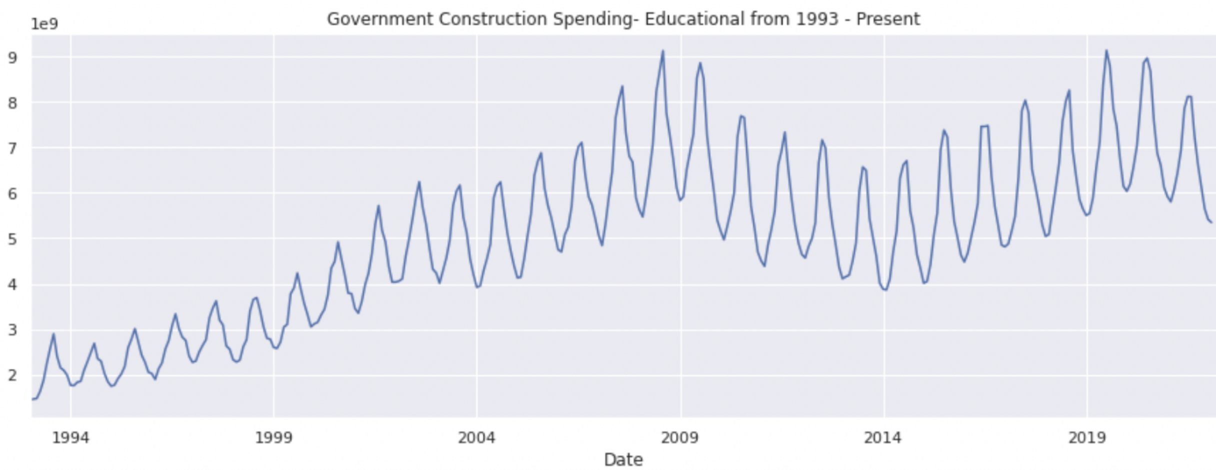
lockdown/stay at home order being announced in March of 2020. Then with the U.S. on lockdown there is a major decline in government spending on sports and recreation for the second half of 2020, and it doesn't increase again until around January 2021. We would like to use these trends as an explanation of how recreation and sports agencies were forced to make cuts to their fiscal year budgets beginning less than six weeks into the shutdown. The data cleaning steps we took included only looking at the years 2019-2022 (filtering the date column), so we could visualize carefully the difference in government spending pre-pandemic and post-pandemic. This visualization will be relevant to the research question of whether human mobility was affected by the changes in government spending on sports and recreation during the spending decrease in 2020 and spending increase in 2021. We can answer this question by looking at the covid mobility dataset for this time frame and observing how the number of trips to recreational areas and gyms shifted.



(7) Let's analyze the government spending on construction for education from 2019 to 2022. We would like to see if there is a difference in spending between the times before and after COVID. From looking at the time series graph above, it appears that there is a difference in the average of government spending, especially the average cost is less than before since Jan 2021. We will perform hypothesis tests for this to see if we have enough evidence to support this. Just from this figure, we see that government spending depends on the season as we see that the spending increases during the summer and drops during other seasons. Let's take a look at another visualization to get a better understanding of what is going on during the months.



(8) From this time span, we see that government spending is highest during the summer.



(9) To better understand our data and see its accuracy, let's take a look at the government spending from 1993. It appears that government spending does spike drop seasonally. Let's take a look at if, since 1993, the spikes are highest during the month of July and drops during other months.

(10) We see that on average, the summer does indeed have the highest spending. After doing some research, it appears that usually schools spend the summer going under construction and fixing up facilities (Rosenberg, M.). This as a result contributes to government spending more so during the summer than during the school year.

References

1. "COVID-19 Community Mobility Report: United States." Google, https://www.gstatic.com/covid19/mobility/2022-04-03_US_Mobility_Report_en.pdf.
2. "Cartographic Boundary Files - Shapefile." United States Census Bureau, https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html.
3. "Monthly Transportation Statistics." U.S. Department of Transportation Bureau of Transportation Statistics, https://data.bts.gov/Research-and-Statistics/Monthly-Transportation-Statistics/crem-w557.
4. Eby, K. (2022, May 5). *Coronavirus timeline: Tracking major moments of covid-19 pandemic in San Francisco Bay Area*. ABC7 San Francisco. Retrieved May 9, 2022, from https://abc7news.com/timeline-of-coronavirus-us-covid-19-bay-area-sf/6047519/.
5. Katella, K. (2021, March 9). *Our Pandemic Year—A COVID-19 Timeline*. Yale Medicine. Retrieved May 9, 2022, from https://www.yalemedicine.org/news/covid-timeline.
6. Rosenberg, M. (n.d.). Schools Spend the Summer Fixing Up Their Buildings. *The New York Times*. Retrieved May 9, 2022, from https://www.nytimes.com/1999/09/05/nyregion/schools-spend-the-summer-fixing-up-their-buildings.html.