COVID-19 Policy Impact Analysis
— for public health policy maker

IDS 701

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Introduction

In light of the tragic consequences of COVID-19 pandemic, we are interested to see if the swiftness of US state policy and their reaction times have any effect in controlling the subsequent growth of new cases. Specifically, we would like to investigate if there exists a causal relationship between policy announcement and the following changes in COVID-19 cases. Given that respiratory disease such as COVID-19 has a latency period from 7 to 14 days, it is reasonable to expect that a swift stay-at-home policy could intervene in the spread of the virus as soon as possible. This is because that a smaller base number of infected patients should subsequently help slow the growth of cases at later stages, and ultimately flatten the growth curve. We aim to provide meaningful insights to future public health decision making in terms of controlling the impact of a global pandemic.

In order to detect any difference in changes in COVID-19 cases growth rate, we narrowed down our focus to the number of COVID-19 cases in 3 weeks before and after a specific COVID-19 related policy, such as a 'Stay-At-Home' or 'Mask-On' order. In each selected state, we looked at the COVID-19 growth rate for a pair of counties reacting to the same policy at different times.

In order to investigate the potential causal relationship between reaction time and COVID-19 growth rate, we introduced a difference-in-difference approach to compare selected counties' difference in pre and post policy COVID-19 cases as a way to minimize potential impact caused by other factors. Based on the analysis result, the counties we picked for the three states - California, North Carolina, and New York - announced the same policy earlier in time had relatively slower post policy growth in COVID-19 cases compared to counties that reacted with the same policy but later in time. This demonstrated that the swiftness of policy announcement could potentially result in successfully controlling the growth of COVID-19 cases.

Background

The first confirmed case of COVID-19 in the United States was reported on January 21st, 2020. Due to factors such as insufficient safety measures and educational blindspots in certain populations, the total cases have been climbing at an unstoppable rate. On January 2nd, 2021, the U.S public health agency reported close to 300,000 new cases in a single day, which was the highest single-day total since the start of the pandemic, and close to 10 times the total cases in Australia to date[1]. At the time of this writing, the number of COVID-19 cases across the entire United States has reached over 31.4 Million, constituting close to one quarter of the total cases around the globe. This pandemic gave a devastating blow to the country's economy (with some

[1] https://deadline.com/2021/01/us-tops-300000-new-cases-in-one-day-1234664162/

experts estimating a cost of over $16 Trillion dollars)[2], let alone the 560,000+ deaths count. To put that into perspective, cancer, the second leading cause of deaths, killed approximately 599,000 Americans in 2019. [3]

Since the onset of this global pandemic, countries around the world have taken a tremendous amount of effort to combat its spread. On January 23rd, 2020, the government of Wuhan, China imposed a strict lockdown policy, which prohibited all types of transport in and out of the city. While many western media argued the morality of this order and that it had severely violated the rights of the 9 million Wuhan residents, the policy proved itself effective at controlling the outbreak of the Coronavirus within the People's Republic of China. In fact, China successfully flattened its curve in less than half a year. Despite the major economic impact during the initial phase of the pandemic, China's prompt execution of its short-term and extreme social distancing measures minimized the potential long term costs on its economy and the health of its 1.4 billion citizens. On the other hand, the strategies implemented by the U.S government were relatively more relaxed. Due to the difference in the governmental systems, COVID-19 specific policies in the U.S were rolled out on a state-level instead of China's country level mandate. This meant that U.S. residents responded to different policies at different pace depending on their location (e.g. states, counties). The lack of a coherent control, as well as the lack of enforcement in these social-distancing and stay-at-home policies offered the Coronavirus an opportunity to propagate across the entire country. In this analysis, we look at the rollout and effect of the stay-in-place order across different regions in America.

Design

In this project, we use one of the classic causal inference models - difference-in-difference analysis - to investigate whether or not an early stay-in-place order implementation helps curtail the increase of an airborne, infectious disease. In particular, we establish three comparison groups, and each group is composed of two counties within the same state that have similar population and demographic characteristics, and only differ in the implementation date of stay-in-place orders.

As mentioned earlier, given that COVID-19 has about 7 to 14 days of latency period, we use daily-new-cases data covering a time frame of three weeks before and after the date of implementation to better capture the situation of COVID-19 spread. Due to the fact that counties have very high variance in population - some have thousands while some with half million - we normalize the total number of COVID-19 cases to the number of cases in every 10,000 people. Besides, given that the difference in implementation date is the treatment variable we are trying

[2] https://news.harvard.edu/gazette/story/2020/11/what-might-covid-cost-the-u-s-experts-eye-16-trillion/
[3] https://www.cdc.gov/nchs/fastats/deaths.htm

to observe, we use standardized dates that represent the number of days before and after policy, with the date of implementation as the origin. By doing so, we would be able to observe the difference in the speed of increase between two counties on the same timeline.

Data

In this analysis, we explore the relationship between policy reaction time and COVID-19 cases growth rate for selected counties in 3 states: California, North Carolina, and New York. In each state, we select 2 comparable counties (CA: San Francisco and Los Angeles, NC: Mecklenburg and Wake, New York: Suffolk and Nassau) based on their similar population density and growth rate trend before a specific policy takes place.

<u>Unit of Observation</u>

Below is an example of how each row in our final dataset looks like:

Date	County	State	Cases	Population	Cases_std	Treated
2020-04-13	Wake	North Carolina	476	1111761.0	4.281496	1

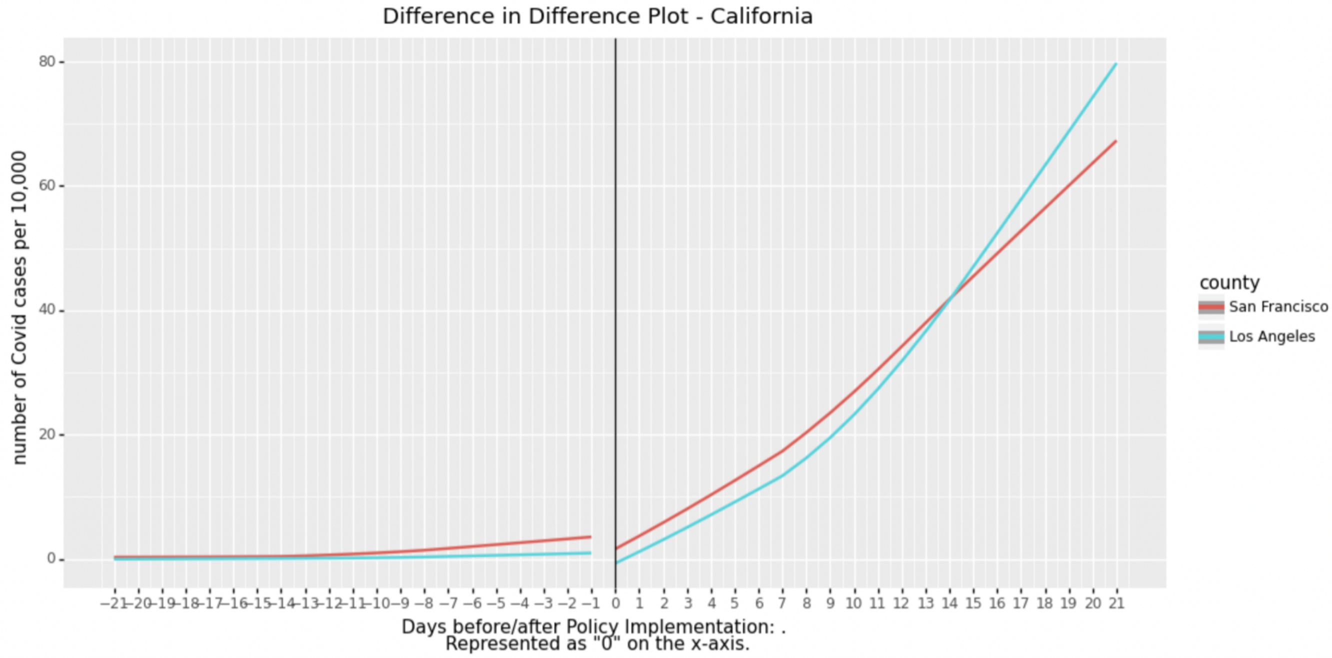
* Treated = 0: pre-policy announcement; Treated = 1: post-policy announcement

Results

By using difference-in-difference analysis on each state, we can provide a visualization for the impact of COVID-19 stay-in-place policy in different counties where policy went into effect.

California

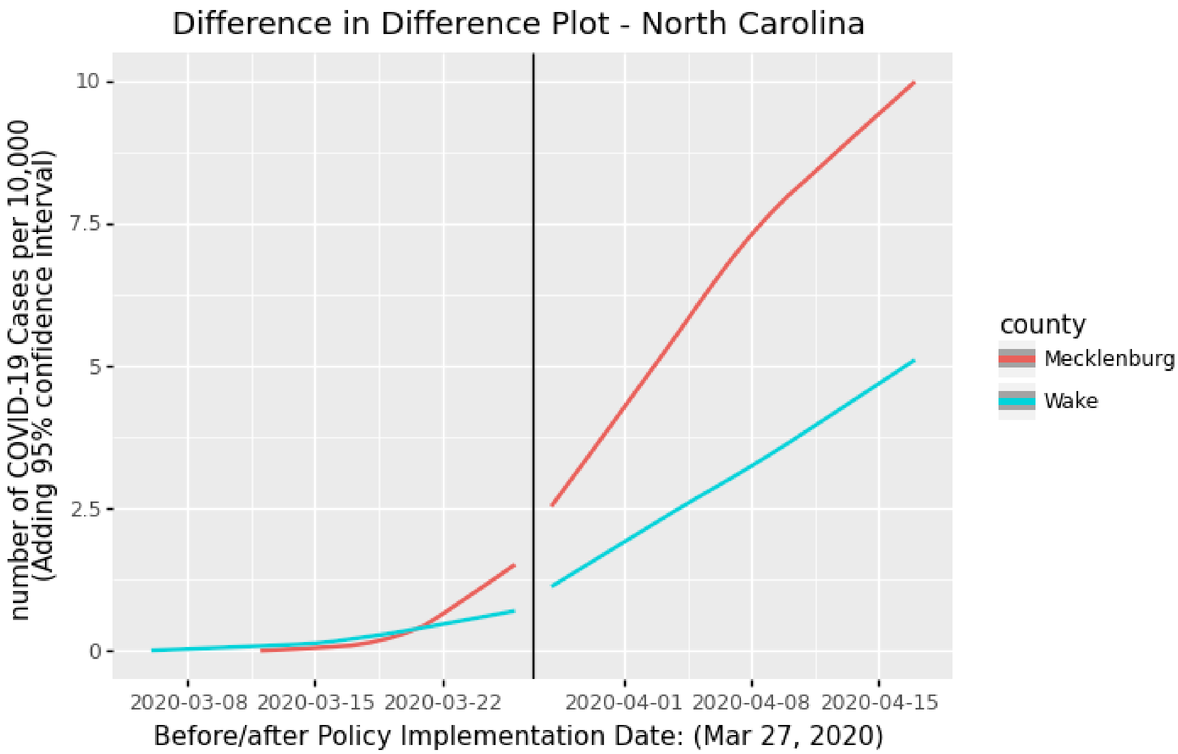
The difference-in-difference plot between San Francisco and Los Angeles county shows the difference in COVID-19 case increase speed. Before the stay-in-place order, the speed of case increase in San Francisco was higher than that of Los Angeles given the steeper slope. After an earlier policy implementation, however, we see that about two weeks later, the number of cases in the two counties became the same, starting from which LA county gained a steeper slope and the number of cases exceeded that in San Francisco. This exponentially increasing trend in COVID-19 cases extended to days after the intersection.



North Carolina

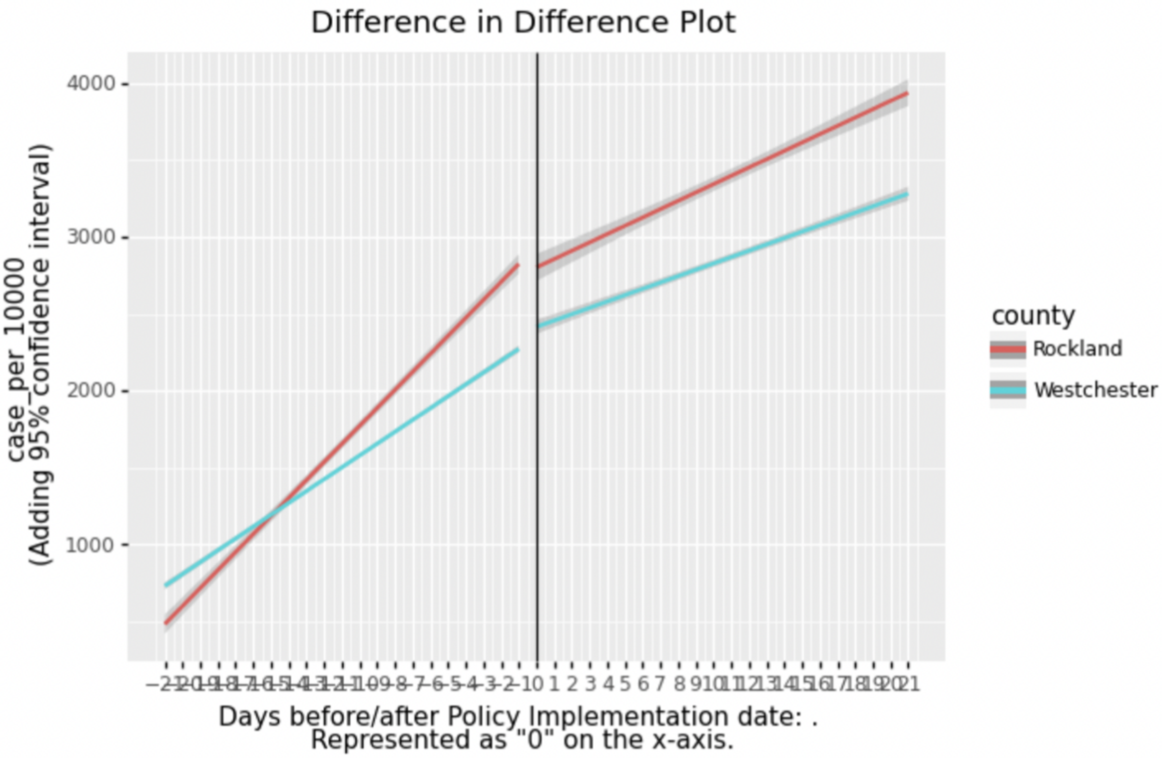
On March 27, 2020, Governor Roy Cooper ordered people in the state of North Carolina to stay at home except to visit essential businesses to slow the spread of the COVID-19 coronavirus. The Order also banned gatherings of more than 10 people and directed everyone to physically stay at least six feet apart from others.

From the difference-in-difference plot regarding the two selected counties in North Carolina below, we can see that the two counties - Mecklenburg County and Wake County - exhibited relatively similar COVID-19 cases growth trend before the *NC Statewide Stay at Home Order* announced in Mar 27, 2020, but Mecklenburg County shows a faster increasing growth trend than Wake County in the following 3 weeks after the order was announced. This potentially suggests that faster implementation of the same policy could lead to slower COVID-19 growth rate. However, because it was announced in the form of a statewide policy, this result is not conclusive unless we acquire more data in the specific response time to this Stay At Home order for each state.



New York

The difference-in-difference plot below depicts the COVID-19 increase trends for Rockland county and Westchester county before and after the "stay at home" order went into effect. While we can clearly observe that the case growth rate decreased after the policy was implemented, the parallel pattern of these two states' case growth trends did not change. Unlike North Carolina, although New York also published state-level executive orders, all counties in New York reacted rapidly because New York had both the highest case counts *and* the highest positive test rate at that time. Therefore this plot potentially implies that if the policy reaction time were the same, we would expect to see a consistent parallel trend both before and after the implementation date.



Conclusions

Undoubtedly, the year of 2020 would not be annotated in history without COVID-19. Given the immense toll on the economy and human lives, it is essential to understand public-health best-practices for such infectious pandemics. This analysis explores the effect of an early implementation of stay-in-place policy in California, North Carolina, and New York. Specifically, we observe the importance of an early action by looking at the change in speed of increase in new COVID-19 cases in 6-week-span in every 10,000 people.

The difference-in-difference analysis in California shows that San Francisco, which had a stay-in-place order implemented earlier, had a slower increase in new COVID-19 cases compared to its counterpart, Los Angeles, which had an exponential growth trend in new cases about two weeks after the implementation of the order.

By using the difference-in-difference approach, our analysis has shown that an early stay-in-place policy in California was very likely to be effective in terms of curtailing new COVID-19 case increase.

The result for North Carolina shows that Wake county exhibited a slower COVID-19 cases growth after the announcement of the Stay at Home Order than Mecklenburg county. However, the situation is different here since the order was announced in the form of a statewide policy instead of a county specific one. Therefore, although we would very much like to conclude that the slower growth in COVID-19 cases in Wake county was due to its faster reaction time, we would not be able to do so unless we acquired more information on how quickly each county reacted to the Stay-At-Home Order. Alternatively, we may compare counties such as Durham, which had similar policy implemented earlier, to the rest of the counties in the state to detect if there is a causal effect between response time and subsequent COVID-19 growth rate.

Similar to North Carolina, the result from the difference-in-difference analysis in New York demonstrates a slower COVID-19 cases growth after the Stay-At-Home Order went into effect. However, in contrast to California and North Carolina, counties in New York reacted to the Governor's executive order quickly and simultaneously due to the severity of the Coronavirus. Since these two counties reacted to the state-wide policy around the same time, they also exhibited a parallel trend of the COVID-19 growth rate after the implementation of the policy.

Limitations

It is imperative to note that our analysis is not done without limitations. First, the policy implementation gap between San Franciscio and Los Angeles was three days, and whether or not this short window period is strictly causal to the difference in the speed of increase we see two weeks later cannot be rigorously answered.

For the state of North Carolina, COVID-19 cases data were only available after March 12, 2020 for Mecklenburg county, so only about 2.5 weeks of data were captured in the pre-policy analysis for Mecklenburg county. In addition, since the policy we investigate was announced at the state level, we can conclude that the slower growth rate in Wake county compared to Mecklenburg county was due to the faster reaction time in the former one only after we acquire more detailed information of the specific timing of when this policy was implemented in both counties.

Furthermore, the statistics for COVID-19 cases may not reflect what the actual situation was for the first couple of weeks due to limited testing resources in the early stage of the outbreak.

Next Steps

Comparing only two counties in the three selected states also means that the statistical power of our analysis is relatively weak. Confounder variables that we do not observe can be the true drivers for the difference in the speed of increase, instead of the date of stay-in-place order implementation. Thus, our next steps would be to group counties within the states that had policy implementation prior to others, and treat the former as the treatment, latter as the control. By comparing the difference or the lack thereof in COVID-19 cases increase between the treatment and control groups, we would be able to capture more accurately what an ealy policy can bring to help slow the spread of a global pandemic.

Nevertheless, this analysis opens up a window for investigating practices for infection prevention and control of epidemic and provides a paradigm of analysis that can be useful for other preliminary policy impact analysis.