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 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 mitigating the impact of a global pandemic.

In order to detect any difference in changes in the 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, which is the US state-wide Stay-At-Home orders announced in the first quarter of 2020 at different times. In each selected state, we looked at the COVID-19 growth rate for the selected state and its comparison states reacting to the same policy at different times.

In order to investigate the potential causal relationship between reaction time and COVID-19 cases growth rate, we introduce a difference-in-difference approach to compare selected states' 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, three of the four target states - California, North Carolina, and Missouri - announced the same policy earlier in time, had relatively slower post-policy growth in COVID-19 cases compared to states that reacted with the same policy but later in time. This demonstrates that a swift Stay-At-Home order could potentially result in successfully controlling the growth of COVID-19 cases. However, the same pattern is not detected when looking at the state of New York and its comparison states, and there could be other confounding factors that contributed to the promising trend from the analysis done with the 3 other selected states, which we will address with details in the results section.

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

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

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 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 Order offered the Coronavirus an opportunity to propagate across the entire country. In this analysis, we look at the rollout and effect of the Stay-At-Home order across different regions in America.

Design

In this project, we use one of the classic causal inference frameworks - difference-in-difference analysis - to investigate whether or not an early Stay-At-Home order implementation helps curtail the increase of an airborne, infectious disease. In particular, we establish four comparison groups, and each group is composed of 3 states that have similar population, geographic proximity, and an implementation date of policy that is at least 3 days later than the treatment[4]. We aim to only differ the implementation date of Stay-At-Home order between each of the state of interest and its comparison groups to evaluate the effect of swiftness in Stay-At-Home order, and we expect the state's post-policy growth of COVID-19 cases to be slower than its comparison states that reacted later in time or did not react at all. The difference-in-difference approach minimizes the potential nationwide impact or other confounding factors.

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[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
[4] https://www.usatoday.com/storytelling/coronavirus-reopening-america-map/

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 US states have very high variance in population - from millions to tens of millions - 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 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 hope to observe the difference in the speed of increase between our 4 states of interest and their comparisons on the same timeline.

Data

In this analysis, we explore the relationship between policy reaction time and COVID-19 cases growth rate. In order to assess the effect holistically, we aim to target 4 states that are geographically apart and demographically distinctive: California, North Carolina, New York and Missouri. We select 3 comparable states (CA: Nevada, Florida, Texas, NC: Virginia, Georgia, South Carolina, NY: Pennsylvania, Maryland, Massachusetts, MO: Nebraska, Iowa, Arkansas) based on their similar population density or mobility, and growth rate trend before a Stay-At-Home order takes place. We obtained daily COVID-19 case data from the New York Times Github repository[5], and population data using the US Census Bureau collected in 2019[6], which we believe is the closest estimate of the population in 2020. Both datasets originally provided county-level information, and state-level aggregation was conducted to make the data more tailored to our research interests.

<u>Unit of Observation</u>
Below is an example of how each row in our final dataset looks like:

Date	State	Cases	Population	Cases_std	post_policy
2020-04-13	North Carolina	4788	1111761.0	43.07	True

Results

By using difference-in-difference analysis on each of the state of interest and its corresponding comparison states, we are able to provide a snapshot of the interpretation and visualization for the impact of COVID-19 related policies in 4 chosen states located in different regions in the United States where a Stay-At-Home order went into effect.

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[5] https://github.com/nytimes/covid-19-data
[6] https://www.census.gov/topics/population.html

California

The difference-in-difference plot between California and its three control states shows the difference in COVID-19 case increase speed. Specifically, Florida had their Stay-At-Home Order announced on 3/30/2020, and both Texas and Nevada had the policy implemented on 3/31/2020, which is about 10 days later than the order given in California.

Based on Figure 1, before the Stay-At-Home Order, the speed of case increase in California and other control states were close to identical. After the policy implementation on March 19th, it became salient that Florida and Nevada gained a much higher speed in COVID-19 case increase than California and Texas. Looking at Figure 2, which represents the COVID-19 increase averaged across control states, it is clear that overall, California had a faster increase in COVID-19 cases before the order. After the announcement, this difference persisted for about two weeks, starting from which the control states gained a steeper slope and the number of cases exceeded that in California. This exponentially increasing trend in COVID-19 cases extended to days after the intersection.

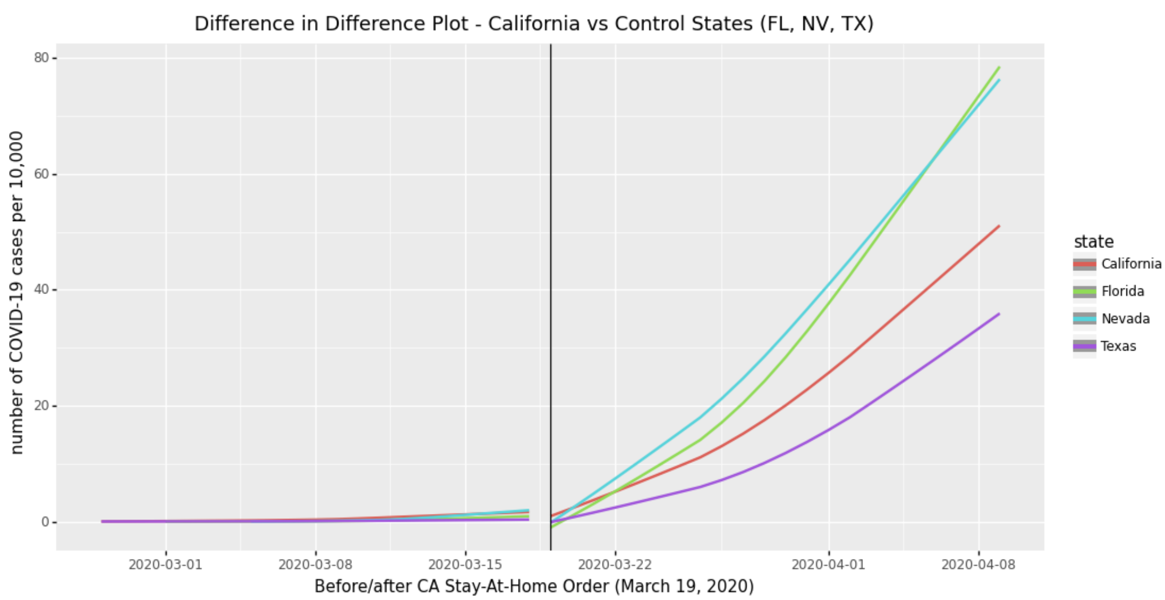

Figure 1: California vs. control states, individual level

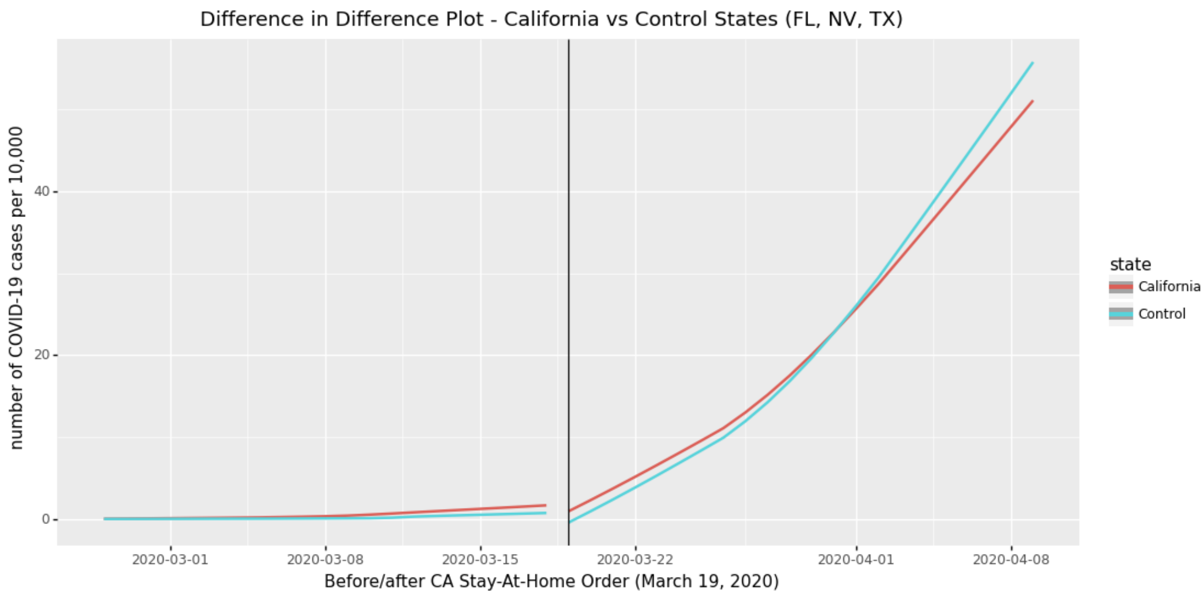

Figure 2: California vs. control states, overall average

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.[7] The order also banned gatherings of more than 10 people and directed everyone to physically stay at least six feet apart from others. Around the same time but slightly later, VA, GA, and SC announced similar Stay-At-Home policies (3/30/2020, 4/3/2020, 4/7/2020, respectively).

From the difference-in-difference plots regarding COVID-19 cases for North Carolina and its comparison states (VA, GA, SC) below, we can see that NC and its comparison states exhibited relatively similar COVID-19 cases growth trend before the *NC Statewide Stay at Home order* announced in Mar 27, 2020, both at the individual-state level (below left) and at the 3-control state-averaged level (below right). However, in the following 3 weeks after the order was announced, the comparison states (both individual and overall) showed a faster COVID-19 cases growth trend than that in NC. This potentially suggests that faster implementation of the same policy could lead to slower COVID-19 growth rate. It is also important to note that because the Stay-At-Home policies in VA, GA, and SC went into effect within only 10 days following the NC announcement, it would be more convincing to conclude that there was a strong causal relationship between policy reaction time and COVID-19 growth rate if we perform similar comparisons during a longer timeframe and on different types of policies.

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7 https://www.ncdhhs.gov/news/press-releases/governor-cooper-announces-statewide-stay-home-order-until-april-29

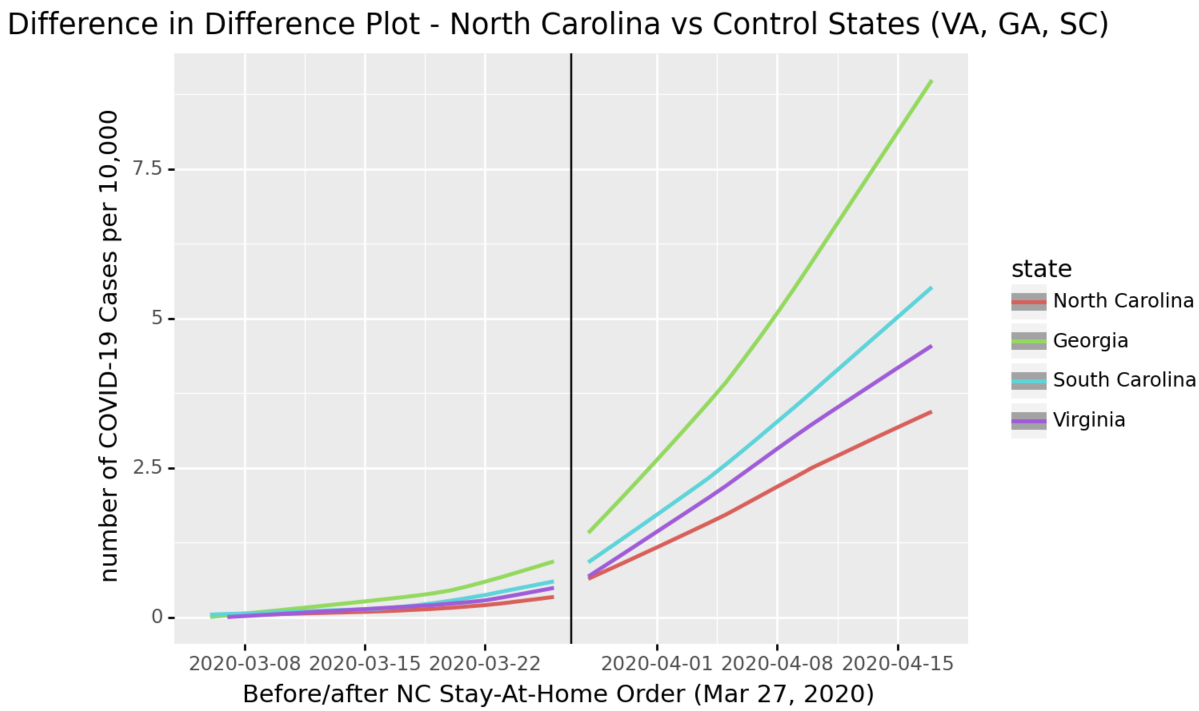

Figure 3: North Carolina vs. control states, individual level

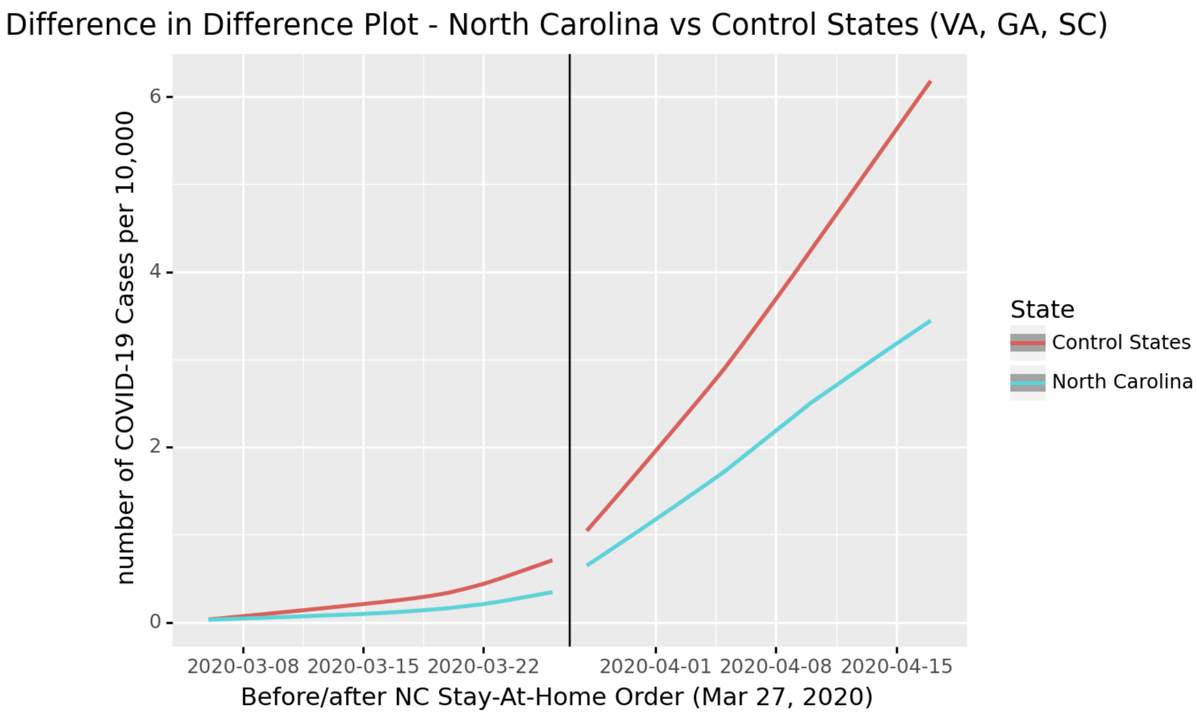

Figure 4: North Carolina vs. control states, overall average

Missouri

In Missouri, Governor Mike Parson has issued a Stay-At-Home order for the state in response to the coronavirus pandemic that went into effect on April 6, 2020. This order states that Missourians should avoid leaving their homes unless necessary.[8] In terms of choosing the comparison states for Missouri, we used a slightly different approach from the 2 experiments above. Instead of picking 3 control states that implemented the same policies at a later time, the 3 control states we choose for Missouri, which are Nebraska, Iowa, and Arkansas, never announced any Stay-At-Home order at all. However, we do believe that it is still valid to compare Missouri and the 3 chosen states since we followed the same criteria as selecting our control states for the other 2 experiments discussed above.

Based on visual inspection from the difference-in-difference plots below, we can easily see that before the Stay-At-Home order announcement in Missouri on April 6, both MO and its comparison states exhibited a similar COVID-19 cases growth trend. However, starting 2 weeks after the implementation of the policy, we can see that the COVID-19 cases growth rate for MO started to level off, while the trend for the comparison states stayed the same. Therefore, we can conclude that compared to not having any policy implemented at all, there was moderately strong evidence showing that a Stay-At-Home order could potentially slow down the trend of COVID-19 cases growth rate.

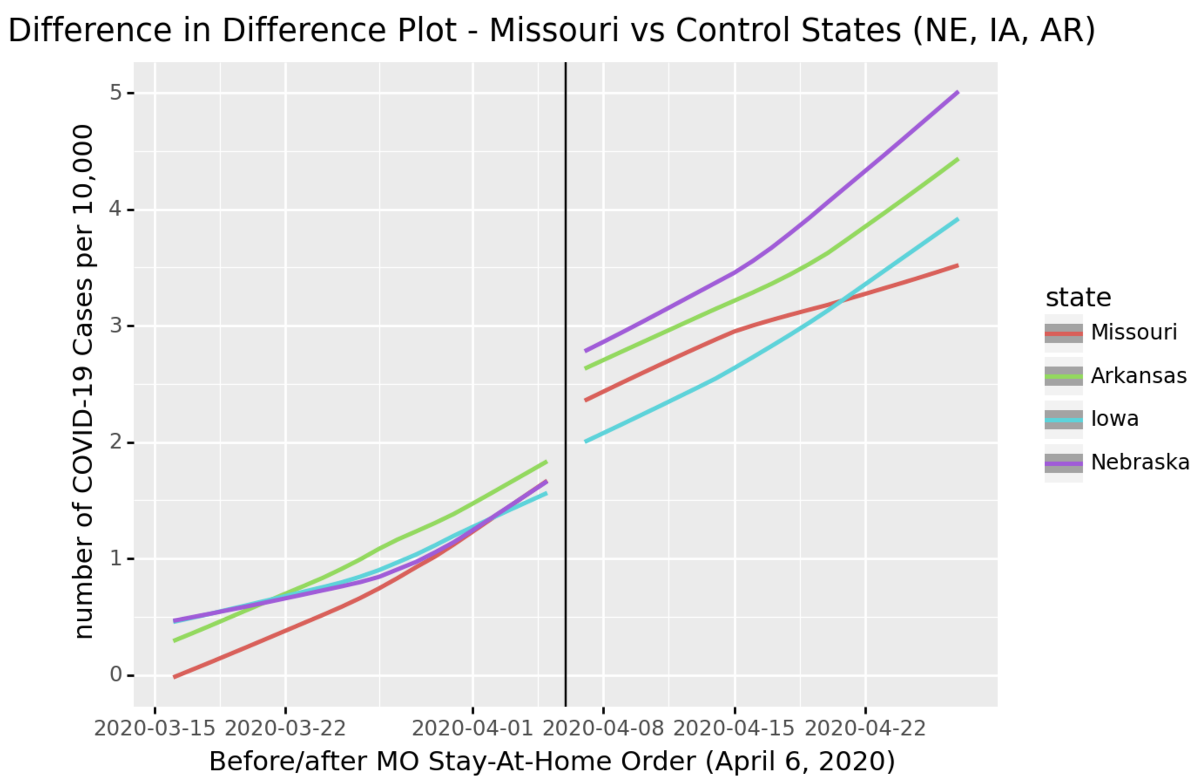

Figure 5: Missouri vs. control states, individual level

[8] https://governor.mo.gov/priorities/stay-home-order

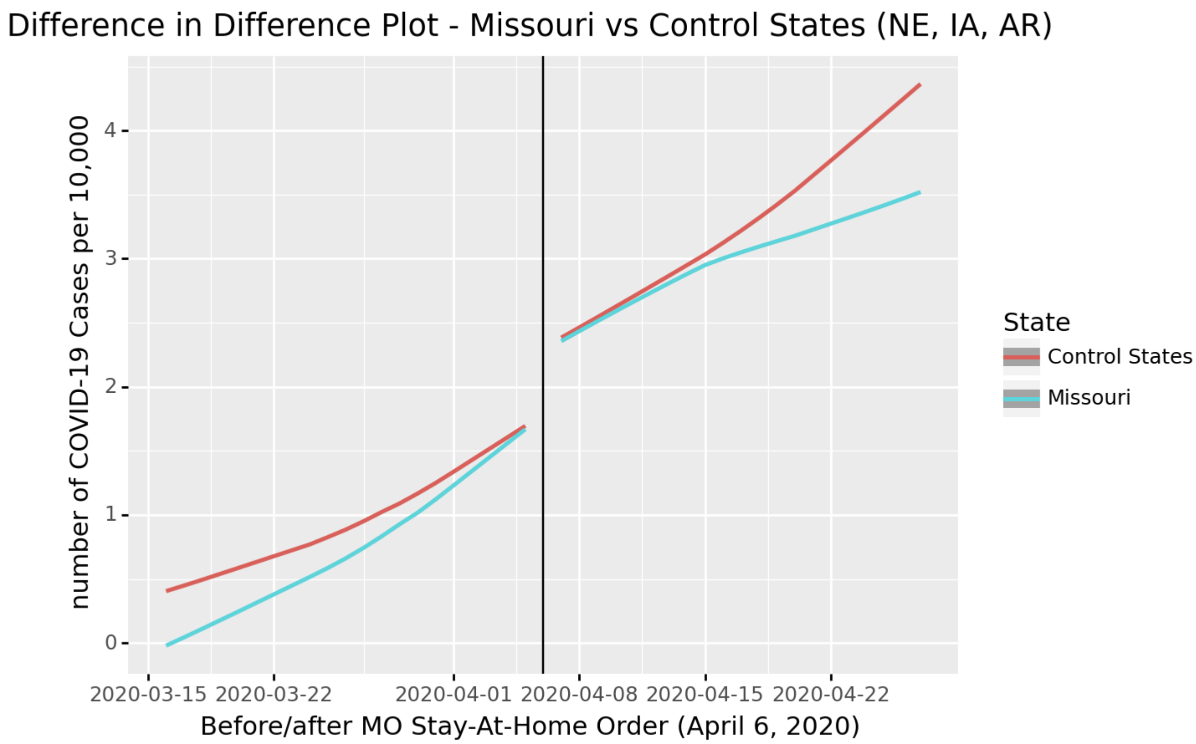

Figure 6: Missouri vs. control states, overall average

New York

The difference-in-difference plots below depict the COVID-19 increase trends for New York state and its comparison states (Pennsylvania, Maryland and Massachusetts) before and after the Stay-At-Home order went into effect. Prior to the policy date, we can observe a clear parallel trend which indicates these four states have similar COVID-19 cases growth trends. After the policy date, while all four states' COVID-19 cases increased rapidly, these four states' growth trends exhibited different behaviors and the previous parallel trends did not remain.

Compared to New York, Pennsylvania and Maryland's Stay-At-Home policies were effective on April 1st, 2020 and March 30th, 2020, respectively. On the contrary to our hypothesis, Pennsylvania and Maryland's case growth speeds were slower than New York's. We think this discrepancy is caused by some uncontrolled variables. For example, compared to Pennsylvania and Maryland, New York, especially New York City, has higher international traffic. The huge number of visitors from all over the world could potentially increase New York's COVID-19 case growth speed. Another possible reason for this discrepancy is that the policy delay is only 9 to 10 days. Due to the incubation period of COVID-19, these reaction time differences may be too short to reflect significant results. Massachusetts did not implement any Stay-At-Home restrictions until April 24th, 2020. While all four states' cases increased after the policy date, Massachusetts had a significantly faster case growth rate than the rest of the states. Figure 8 demonstrates Massachusetts, Maryland and Pennsylvania combined as control states. The result still doesn't meet our expectation due to the low COVID-19 cases growth rate in Pennsylvania and Maryland. To conclude, the result of difference-in-difference analysis in the state of New York does not support our hypothesis. While our results show that longer policy reaction time, such as the situation in Massachusetts, could lead to faster COVID-19 case growth rate, they could also fall short in showing a correlation between short periods of delay and a faster growth rate of COVID-19 cases.

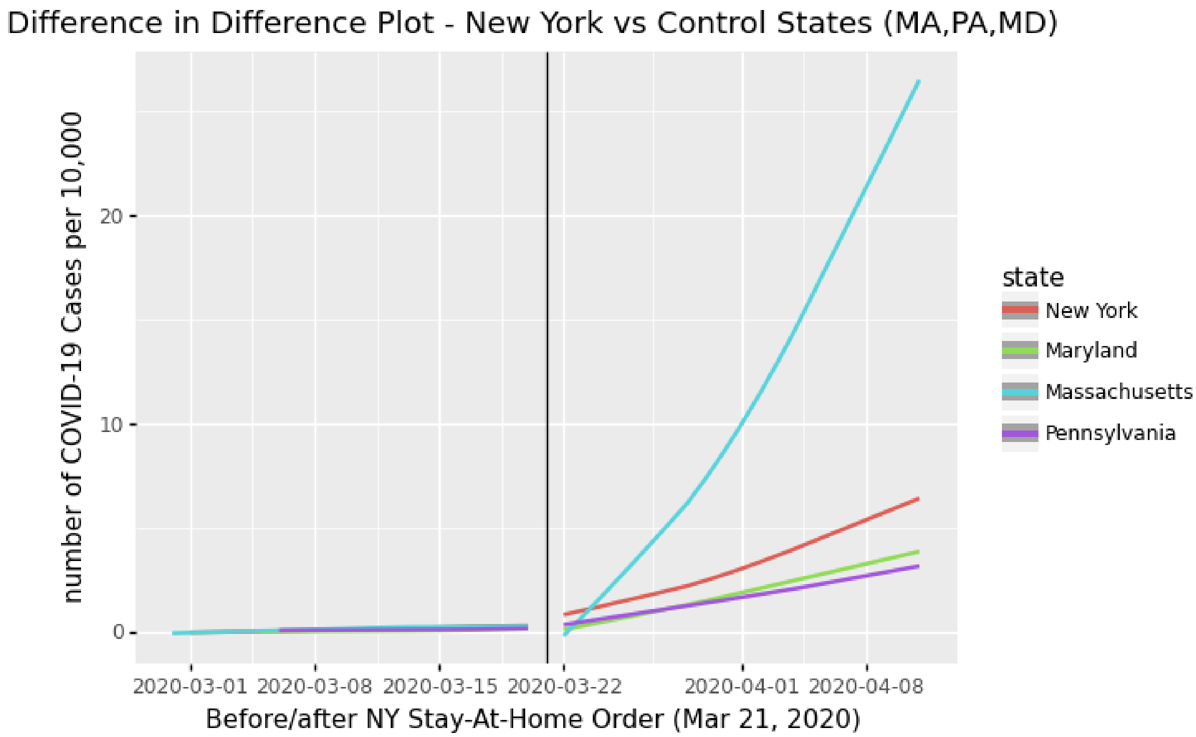

Figure 7: New York vs. control states, individual level

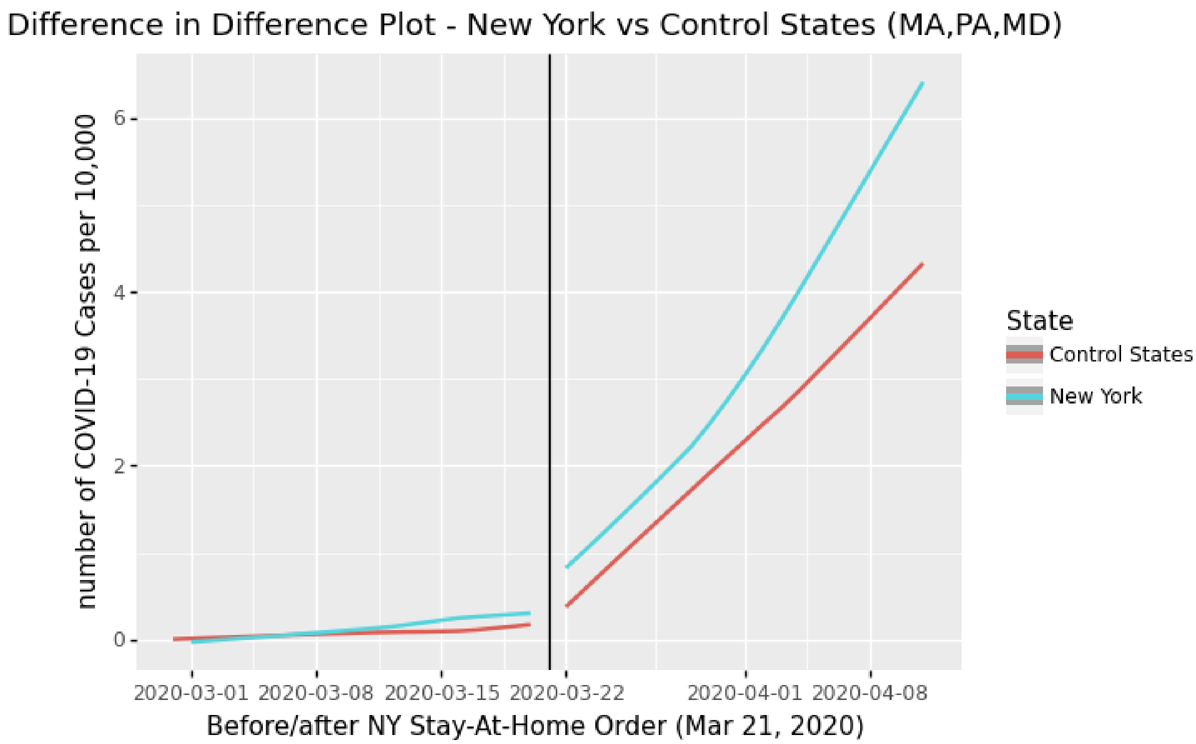

Figure 8: New York vs. control states, overall average

Conclusions

Undoubtedly, the year of 2020 would not be annotated in history without the COVID-19 pandemic. Given the immense toll on the economy and human lives, it is essential to understand public-health best-practices for such infectious pandemics. There have been both numerous national and international efforts in implementing policies for better containment and mitigation of the virus. This analysis focuses on the effect of an early implementation of Stay-At-Home policy in different regions across the United States. Specifically, we observe the importance of an early intervention by looking at the change in new COVID-19 cases in every 10,000 people in a 6-week-span.

As indicated in the previous section, our analysis suggested that the Stay-At-Home policy had certain effects on COVID-19 growth rates. However, the effects vary across the selected treatment groups and some results were less convincing than the other. For instance, the difference-in-difference analysis for California illustrated that the growth rate slowed down and was outpaced by its control states approximately 10 days post implementation. In Missouri, this effect was even more conspicuous, where the pre and post behaviors were completely different between Missouri and its control states. This particular comparison could make a strong argument for our hypothesis since it represented an ideal experiment where a policy was never implemented in the control states. On the other hand, despite a seemingly diverging pattern, the pre-treatment growth rate was already lower in North Carolina compared to its control states. In this case, our data and analysis did not provide enough evidence to conclude the policy effective. To further understand the causal relationship between policy implementation time and COVID-19 growth rate, a more rigorous analysis with more data is required.

Additionally, even though our analysis uncovered varying levels of effects of the Stay-At-Home order, we cannot be completely certain about its causality and the absence of other confounding factors. Therefore, it is imperative to note the limitation of our analysis, which we have classified into five categories below:

Timing related

The officially claimed incubation period for COVID-19 is between 2-14 days. An ideal difference-in-difference experiment would select control groups in which the target policy is either not implemented, or there is a gap large enough for which the policy could generate observable effects. In the United States, the state-wide Stay-At-Home orders were mostly implemented between mid March to early April. Therefore, the mandate implementation gap between our treatment and control groups might not be long enough to observe any true causal effect, if any. This limit is observed across all 4 analyses. For instance, the policy implementation gap between California and its control groups was approximately 10 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.

Unit of Analysis related

Even though we initially proposed to perform a county-level analysis, we quickly encountered challenges with data collection and other limitations specified in this section, which become more problematic on county-level. Therefore, we pivoted to doing state-level analysis. However, by upscaling the unit of analysis, we also risked losing statistical power, and the results become more sensitive to small variations and unobserved variables.

Policy related

There were many different policies that commenced within the first quarter after the first COVID-19 case was reported. One of which was the mask mandate which was deemed helpful in battling the spread of the virus. For example, New Jersey's Stay-At-Home order started on March 21st, 2020[9] and its mask order started on April 10th[10]. This implied that there could be an overlapping effect and our difference-in-difference analysis could not effectively isolate the causal effect of the Stay-At-Home order alone.

[9] https://www.nj.gov/governor/news/news/562020/20200320j.shtml

[10] https://www.nj.gov/governor/news/news/562020/20200408e.shtml

Testing related
In the initial stage of COVID-19, the lack of resources and knowledge about the diseases limited our ability to carry out comprehensive and accurate diagnosis. Therefore, the data recorded might not reflect the true cases number. In fact, many places and around the world were able to confirm more COVID-19 cases as the result of more accessible testing ability and more reliable diagnostic protocols. We suspect that this behavior was present in the analysis of the Missouri state and its control states, represented as an abrupt increase in the number of cases.

COVID-19 related
Unlike the topic studied in other policy effectiveness analysis such as opioid control and alcohol regulation related policies, the infectious nature of COVID-19 implies that its growth would generally be exponential if control measures are not adequately carried out in the early stage. Therefore, any policies implemented after the initiation of this explosive growth were mere efforts to slow down the growth and would not generate any significant short term effect.

This also puts a contradictory challenge on how control groups could be selected. More concretely, we tried to pick states that are geographically closer to our treatment group to maximize comparability. However, states that are closer to each other would also experience similar growth rates and likely rolled out restrictions simultaneously (North Carolina and Virginia, New York and New Jersey), which may hinder a meaningful comparison.

Next Steps

Analyzing only 4 selected states and their comparisons 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 a Stay-At-Home order implementation. If the limitations mentioned above can be properly addressed, we would be able to capture more accurately what an early 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.