The Impact of Differential Statewide Disease-Suppression Policies on Unemployment and Health/Mortality due to COVID-19

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Abstract

Importance: Understanding the impact of different SARS-CoV-2 disease-suppression policies on both health and the economy is critical to developing an effective policy response to the COVID-19 pandemic and future pandemics.

Objective: To describe the impact of disease suppression policies on unemployment measures and health/mortality measures during the first three months of the nation's COVID-19 pandemic.

Design: This study uses a panel data set of health, economic, and policy data from each of the fifty US states and Washington DC obtained from a multitude of sources including the Census, the Centers for Disease Control, the Department of Labor and individual state government websites. I utilized a correlated random effects model to determine the impact of different disease-suppression policies on both unemployment and health/mortality measures from January 26 to June 20, 2020. Data was examined on the state level and was reported weekly over the course of the five-month period.

Main Outcomes and Measures: The main outcomes of interest in this study are percent change in non-cumulative COVID-19 cases, percent change in non-cumulative deaths due to COVID-19, initial unemployment insurance claims per 100,000 people, and continued unemployment insurance claims per 100,000 people. These were the outcomes used in our correlated random effect model regressions which are the main output of this study.

Results: I found that some policies such as non-essential business closures led to less COVID-19 cases and deaths in a state, however, other policies actually had the unintended and unanticipated

effect of increasing COVID-19 cases and deaths. Enacting a non-essential business closure or the combination of gathering restrictions and food/beverage service closure led to higher continued claims of unemployment insurance. Additionally, the implementation of gathering restrictions, food/beverage service restrictions and school closures all led to higher initial claims of unemployment insurance.

Conclusions and Relevance: There are statistically significant impacts of certain disease-suppression policies individually as well as in conjunction with other policies on both health/mortality outcomes of the COVID-19 pandemic as well as unemployment claims. While some disease-suppression policies led to a reduction in cases/deaths and an increase in unemployment claims as expected, not all the coefficients have the anticipated signs. This could suggest that certain policies are not working as anticipated or that there is bias in our results.

Setting: The setting is the entire nation of the United States of America.

1.Introduction and background

The COVID-19 pandemic has presented one of the biggest threats to public health in over 100 years. Approximately 6.75 million Americans have been infected and nearly 200,000 Americans have ultimately died as a result of contracting COVID-19, and these numbers only continue to grow over time.[1] However, the prevalence of disease and the mortality rate vary dramatically by state.[1] There are many differences between U.S. states in terms of size and population which could potentially be causing some of this disparity between states, however, state-level disease suppression policies could certainly be part of the difference in COVID-19 outcomes by state.

As the pandemic has spread across the United States, the effort to mitigate the virus has largely been in the hands of state and local officials instead of national leaders.[2] This has created differing disease-suppression policies by state across the United States. These policies include stay at home orders, school closures, business closures, travel restrictions, mask mandates and more.[3] Each state has implemented these policies in slightly different ways, on different days, lasting for different amounts of time.[3] There is evidence that these policies have some impact on disease spread – masks and social distancing are proven to lessen the spread of disease and these policies encourage both practices.[4,5] If we are going to rely on policies like these in our effort to navigate the COVID-19 pandemic, it is essential that we understand the impact of the policies on the amount of COVID-19 cases in a state as well as the mortality rate in a state in order to aid public health officials in creating the most effective policy strategy.

In addition to the health impact of COVID-19, there has been a serious economic impact of the pandemic.[6] A large part of this economic impact has been because of policies that I discussed above and the shutdown of certain sectors of the economy such as schools, gyms, restaurants, bars, concert venues and more.[6] While disease-suppression policies may be aiding in preventing COVID-19 cases and deaths, they may be leading to a loss of jobs and an increase in unemployment. In an attempt to understand the full impact of disease-suppression policies, we need to investigate the economic impact – how do COVID-19 disease suppression policies impact unemployment numbers in addition to health and mortality outcomes.

Of course, there have been different policies implemented at the country level across the world. There have been studies investigating the impact of differential COVID-19 disease suppression policies at the country level.[7] This paper will add to that literature by systemically looking at different policies within the United States at the state level. Given the severity of the COVID-19 pandemic in the United States and the reliance on state level policy to combat the virus, the objective of this study is to understand the impact of COVID-19 disease suppression policies on both health and economic outcomes during the first three months of the pandemic in the United States.

2.Data and Methods

This data set was created from a variety of sources and compiled into a single data set for the period January 26 to June 20. The health and mortality data such as data about COVID-19 cases and deaths and other comorbidities such as smoking were obtained from the Centers for Disease Control Wonder tool, and it was organized by USA Facts.[8] The demographic data including state population information and density were obtained from the US Census.[9] All economic data about unemployment claims came from the US Department of Labor Office of Unemployment Insurance weekly reporting.[10] Lastly, information about disease suppression policies by state came from a data set constructed from individual state government pages that was made public on the GitHub platform.[3] Variables from each of these datasets were downloaded for the January 26 to June 20 period and aggregated to the state level with weekly values to merge with the rest of the data.

Variables

Time-Invariant Control Variables

Most of our time-invariant independent variables including population per square mile, percent white, percent of the population over 65, and percent of the population that is male were gathered from United States Census Data.[9] These variables were assumed to be relatively stable over the five-month period that this study focused on, so the values for each of these variables was added to the data set at each time period for each state. Population density and the age of the population could be incredibly important factors for the spread of COVID-19 as well as the mortality rate which is why they are included in our regressions.[1] The percent of the population that is white has also been shown to be an important indicator for the spread of COVID-19 as other race/ethnicity groups have far higher rates of COVID-19 than white people which is why the race variable is included as a control.[1] Additionally, I have included race and gender information because they could impact unemployment.

State Population

The state population data was obtained from the same data set as the health/mortality data used in this paper – the data comes from the Centers for Disease Control Wonder tool, however, it was organized by and accessed through USA Facts.[8] These state population numbers were used to make all the outcome variables per capita instead of just raw numbers– I needed the state population to be used as a denominator to fairly compare the number of cases, deaths, and unemployment claims between states.

Percent of the Population who uses Cigarettes

The percent of the population who uses cigarettes is the one health behavior that I used as a time-invariant control in this study because smoking has been associated with a higher rate of mortality from COVID-19 due to the impact on your lungs and cardiovascular health. This data was obtained from the Centers for Disease control.[11]

Tests Per 100K

I decided to include the number of COVID-19 tests performed per 100,000 people in the population because the number of tests performed could alter the number of cases reported in a given state. This could easily and possibly more accurately be seen as a time-varying variable, however, I have decided to include it here as a time-invariant variable because of data access/quality concerns.[12] This data was obtained from the Johns Hopkins Coronavirus Resource Center.[1] This variable was constructed through first gathering the total amount of tests provided in a given state at the end of our study frame, June 20, and dividing this number by the number of weeks of our study period (21). We then used state population as a denominator to determine how many tests there were per 100,000 people.

Disease-Suppression Policy Variables

All of the data for the disease-suppression policies by state came from a data set constructed from individual state government pages that was made public on the GitHub platform, however, this data was significantly changed before use.[3] This dataset includes a range of different policies, the date of implementation, the date of easing, and the date of expiration for each of the policies.[3] I categorized the list of different policies available in the GitHub dataset into eight major policy categories which are listed and defined below. Then I transformed the data into one large binary variable: for each week of our study period, I determined whether each state had implemented a policy within a specific category for at least one day of that week (coded as a 1) or not (coded as a 0). Additionally, I only counted a policy when it was a statewide mandate. The GitHub data set included government recommendations and local government mandates, however, if a policy was not statewide or mandated it was coded as a 0 in the dataset that I constructed for this paper.

Gathering Restrictions

The original data set listed gathering restrictions of various sizes as small as permitting gatherings of only five people or less to restricting gatherings of only 1,000 people or more. In this paper, I defined gathering restrictions as any formal mandate that prohibited a mass gathering of any size.

Public Mask Mandate

This variable includes any policy that mandates that individuals wear a covering over their mouth and nose when they are outside of their residence and unable to maintain six feet of distancing.

Non-Essential Business Closure

This includes all mandates to close all non-essential businesses. This variable does not account for the fact that different states have different classifications of essential versus non-essential businesses and they vary significantly by state.

Stay at Home Order

This was defined as any mandate that requires individuals to stay at home unless participating in an essential activity. The dataset considered shelter-in-place orders to be equivalent to stay-at-home orders. This variable does not account for the fact that different states have different classifications of essential versus non-essential activities and they vary significantly by state.

School Closure

School closure was coded as any statewide mandated closure of at least all public K-12 educational institutions.

Travel Restrictions

This variable was defined as mandating quarantines for people entering the state. This could be for all people entering the state, just non-residents of the state, or those arriving from a certain state. The length of the required isolation period varies from state to state. Additionally, if there are policies where a state limits or prohibits non-residents from entering their borders at (even if they were willing to self-isolate), this variable would be coded as a 1.

Categorical Business Closure

This variable was defined as any mandate to close any category of business fully. This could include all fitness centers, casinos, personal service businesses like hair and nail salons, entertainment venues, or other category. If any of one of these categories of businesses were mandated to be closed in a given week, this variable was coded as a one for the state in that week.

Food and Beverage Business Closure

This variable was defined as the restriction or limitation of restaurants including take-out only or significantly reduced operations such as only allowing ten patrons to dine at a time. Additionally, this category includes the restriction or limitation of venues where there is the consumption of alcoholic beverages or where alcohol sales are the primary source of revenue. If either of these types of restrictions were implemented in a given week, this variable was coded as a one for the state.

Health Outcomes: Percent Change in Cases and Percent Change in Deaths

This data comes from the Centers for Disease Control Wonder tool but was accessed through USA Facts.[8] The original data set reported cumulative numbers of COVID-19 cases and deaths daily for each county in the United States.[8] I aggregated this data to the state level and created weekly values instead of daily values. The data was reported as cumulative cases/deaths in a day, so I had to transform the cumulative data into non-cumulative daily values. Additionally, I used the state population data to take the raw numbers of cases and deaths and make the variable cases/deaths per 100,000 people, so that these numbers were comparable between states.

Given that the data started in late January which was about 1.5 months before the pandemic really began to take off in the United States, the majority of the data in the first few weeks are just zeros. To combat the effect of these zeros in the regression, I transformed the cases per 100k and deaths per 100k variables into percent change in cases and percent change in deaths. I calculated the percent change from the prior week within the state.

Economic Outcomes: Initial Claims Per 100k and Continued Claims Per 100k

This data was obtained from the Department of Labor Office of Unemployment Statistics.[10] This data is reported weekly and at the state level. This data is somewhat delayed, however, I used the data in the week it was reflective of, not the week it was reported. Initial claims refer to the number of people who have filed a claim for unemployment benefits with state unemployment agencies in a given week when they haven't been filing for unemployment benefits in previous weeks.[10] The number of initial jobless claims can help us understand how many jobs are being lost in a given week. Continued claims on the other hand is the number of individuals who file a claim for unemployment benefits for additional weeks after their initial claim – these people are not included in the initial claims. The number of continued claims can help us better understand the number of people truly reliant on unemployment benefits and whether an economic change is sustained over time. I used the state population data to take the raw numbers of claims and make it claims per 100,000 people, so that these numbers were comparable between states.

Method

First, I wanted to understand what the data looks like descriptively. I calculated summary statistics for each of our time-invariant independent variables. Additionally, I created graphs to understand how cases, deaths, initial claims and continued claims per 100,000 people changed over the course of our study period.

After understanding the data descriptively, I needed to regress the health and economic outcomes on each of our policy variables in order to answer our research question using longitudinal regression techniques. I decided to use a correlated random effects or mixed effects model to keep the coefficients of our time-invariant variables – these coefficients are the same that I would find if I had performed a random effects model - while still getting the fixed effect coefficients for our time-varying independent variables. After performing a robust Hausman test for endogeneity, I determined that endogeneity was likely present in each of these models, so the fixed effects coefficients would be better in this case which is why we could not just perform a random effects regression. The fixed effects model takes into account that there are likely factors within each state that we have not included in the model that are important for our outcome and may bias our coefficients. The fixed effect model removes the effect of the time-invariant characteristics of our states so we can have an unbiased estimate of the impact of our predictors (our policy variables) on our outcome (our health and economic variables).

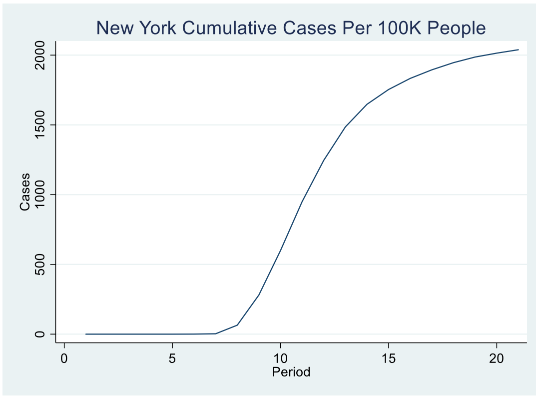
In addition to understanding the impact of each policy individually on health and economic outcomes, I wanted to understand the impact of certain policies in combination with each other on health and economic outcomes. In order to accomplish this, I included a range of interaction terms between different policy variables in the correlated random effects regression model. Additionally, I wanted to ensure that our estimates were not being biased by the fact that cases, deaths, and unemployment claims were all mostly increasing over time and in some states were leveling off towards the end of the study period. Therefore, I needed to control for period (week) and period squared to ensure that these period effects were not changing our results.

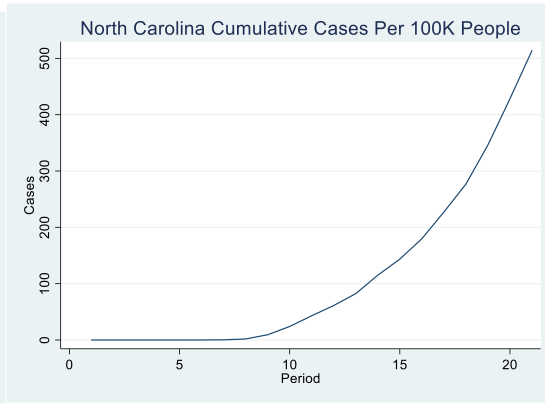
3.Results

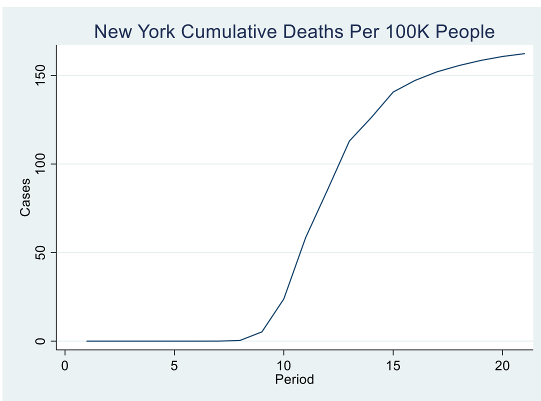
First, I wanted to understand each of the time-invariant independent variables. As shown in Table 1, there are significant differences between states on all of these measures. Population density may be the most extreme example of this as one state only has 1.2 people per square mile of area while the densest state has 9856.5 people per square mile. The large differences between each of these variables between states underscores the importance of including each of these as controls. It also indicates that there are large differences between states that I might not have accounted for and provides a strong rationale for using a fixed or mixed effects model.

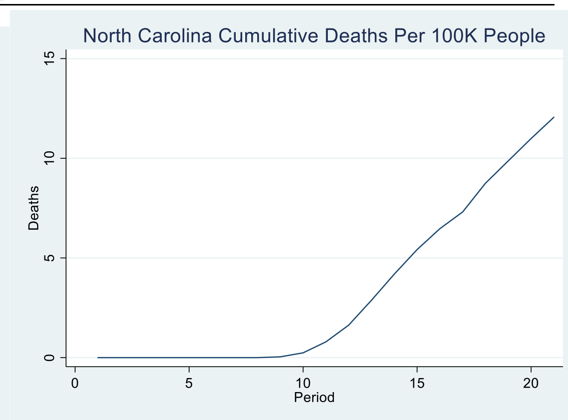
Table 1.				
Time Invariant Controls	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
People per square mile	384.4039	1364.421	1.2	9856.5
Percent of Population who use cigarettes	16.59216	3.275602	9	25.2
Percent white	78.1902	12.92414	25.6	94.6
Tests per 100k people	19456.69	6712.183	10392	40231
Percent of population that is over 65	16.40392	1.944218	11.1	20.6
Percent of population that is male	49.29608	.7867614	47.2	52
State population	6440402	7312838	578759	4.00e+07

Next, I wanted to visualize each of my outcome variables and how they change over the course of the study period. Given that we were analyzing data from all fifty states plus Washington DC, it was not feasible to examine the pattern over time for each of the states. Instead, I elected to look at a few examples. First, I examined a state with high COVID-19 prevalence, New York. Additionally, as a student at the University of North Carolina, I also selected the state of North Carolina to examine as a more common case.

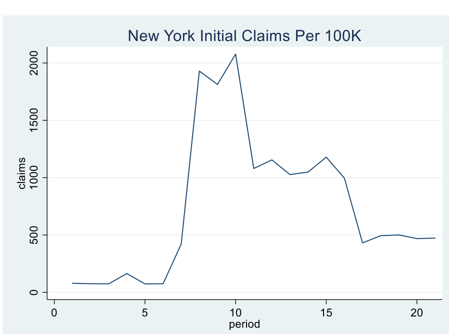


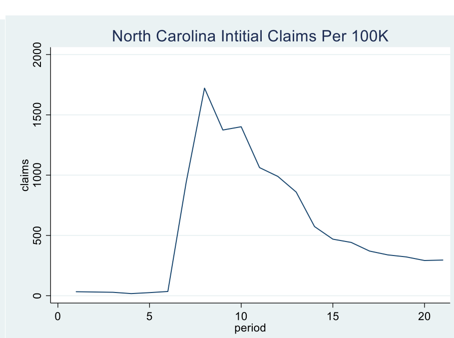


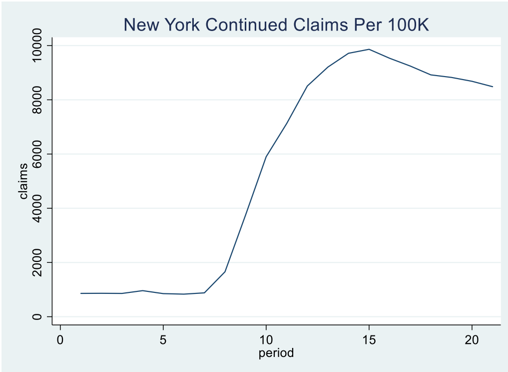


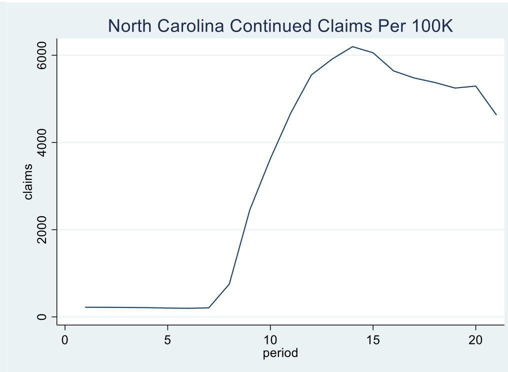


Both the graphs for cumulative deaths and cumulative cases per 100,000 people in New York show that starting in about the 10th week of the study period, there was a sharp increase in cases and deaths. Starting in about the 15th week of the study period, this increase began to flatten and cases and deaths were rising at a much slower pace than before. In North Carolina, the pattern is slightly different. Similar to New York, in about the 10th week of the study period, cases and deaths in North Carolina began to rise, however, not as sharply as in New York and the rise stayed fairly consistent throughout the study period.









Unlike the graphs for health outcomes, the graphs for the economic outcomes for New York and North Carolina had almost the identical shape. For initial claims: between approximately the 5th and 10th week of the study period, initial unemployment claims rose sharply, but they decreased to only slightly higher than the pre-pandemic levels by about the 15th week of the study period. For continued claims: claims began to rise in about the 7th week of the study period but began to decrease slowly in about the 15th week of the study period.

Table 2. Percent Change in Non-Cumulative Cases Per 100k

	Random Effects Coefficients	Fixed Effects Coefficients (Within)	Test for Endogeneity p (Difference)
People per Square Mile	-.0130589	-	-
Cigarette Use	6.701556	-	-
Percent White	-.5028005	-	-
Tests Per 100k	-.0014302	-	-
Percent Over 65	-2.846138	-	-
Percent Male	-3.717125	-	-
Period	-	-32.37896	0.0403**
Period Squared	-	.0868474	0.0506*
Gathering Restrictions	-	-62.42161	0.4988
Public Masks	-	-67.77934	0.3356
School Closure	-	57.68653	0.6308
Stay at Home Order	-	-91.34791	0.6345
Food Service Restriction	-	-127.3063	0.1482
Travel Restriction	-	-211.2734*	0.4832
Non-Essential Business	-	-263.6615***	0.0002***
Categorical Business	-	-41.01456	0.4934
I: Masks and Stay Home	-	-19.97715	0.9747
I: Masks and Gathering	-	40.03059	0.3208
I: Masks and Travelling	-	140.7875*	0.1195
I: Masks and NE Business	-	-97.12117	0.2084
I: Gather and Stay Home	-	-	-
I: Gathering and Travel	-	132.3187	0.2048
I: Gathering and Food	-	26.72129	0.7344

I: Gathering and School	-	-92.27005	0.8611
I: Food Restrict and Mask	-	-	-
I: Food and Stay Home	-	-14.90967	0.8550
I: Food and NE Business	-	-	-
I: School and Travel	-	-48.84773	0.2746
I: Stay Home and Travel	-	-19.77811	0.9138
N= 1071 p-value < 0.1 = * p-value < 0.05 = ** p-value < 0.01 = ***			

Table 2 shows the impact of each of the policies and policy combinations on the percentage change in non-cumulative COVID-19 cases. The table shows that policies mandating travel restrictions and non-essential business closures showed statistically significant and negative impacts on the non-cumulative cases in a state. Instituting a non-essential business closure led to a 263.6615 percent decrease in COVID-19 cases and enacting a travel restriction led to a -211.2734 decrease in COVID-19 cases in a state. Table 2 also showed that the interaction between a mask mandate and a travelling restriction had a coefficient that was statistically different than zero (140.7875), however, it shows that instituting this combination of policies led to an increase in COVID-19 cases which is the opposite of the anticipated effect. Additionally, Table 2 shows that the variable for enacting a non-essential business closure mandate is potentially endogenous.

Table 3. Percent Change in Non-Cumulative Deaths Per 100k

	Random Effects Coefficients	Fixed Effects Coefficients (Within)	Test for Endogeneity p-value (Difference)
People per Square Mile	.0339061**	-	-
Cigarette Use	2.185679	-	-
Percent White	-.0282489	-	-
Tests Per 100k	.0001837	-	-
Percent Over 65	-4.609606	-	-
Percent Male	-33.75854	-	-
Period	-	-183.6572***	0.4520
Period Squared	-	5.146754***	0.5656
Gathering Restrictions	-	-113.2066	0.5982
Public Masks	-	-218.6425	0.4378
School Closure	-	203.9754*	0.7746
Stay at Home Order	-	38.18446	0.8887
Food Service Restriction	-	-51.80203	0.9490
Travel Restriction	-	100.0266	0.8361
Non-Essential Business	-	-220.0156*	0.1398
Categorical Business	-	155.7352	0.1986

I: Masks and Stay Home	-	140.6107*	0.4232
I: Masks and Gathering	-	75.82981	0.3603
I: Masks and Travelling	-	70.78217	0.2859
I: Masks and NE Business	-	-44.18033	0.6700
I: Gather and Stay Home	-	-	-
I: Gathering and Travel	-	80.71191	0.8556
I: Gathering and Food	-	78.73639	0.9807
I: Gathering and School	-	-80.96026	0.4510
I: Food Restrict and Mask	-	-	-
I: Food and Stay Home	-	-88.83216	0.7529
I: Food and NE Business	-	-	-
I: School and Travel	-	-194.7028	0.6996
I: Stay Home and Travel	-	-32.65923	0.5575
N = 1071 p-value < 0.1 = * p-value < 0.05 = ** p-value < 0.01 = ***			

Table 3 shows the impact of each of the policies and policy combinations on the percentage change in non-cumulative COVID-19 deaths. The table shows that none of the policies had a highly statistical significant coefficient; all the p-values were above 0.05, however there were some coefficients that were significant at the 0.1 level. Table 5 indicates that policies mandating non-essential business closures led to a 220 percent decrease in COVID-19 deaths in a state. Similar to the COVID-19 cases regression results, mandating school closures and the combination of a stay at home order and public mask mandate actually led to an increase in deaths due to COVID-19 which is the opposite of what I hypothesized.

Table 4. Initial Claims Per 100k

	Random Effects Coefficients	Fixed Effects Coefficients (Within)	Test for Endogeneity p-value (Difference)
People per Square Mile	-.0140363	-	-
Cigarette Use	.9810091	-	-
Percent White	-6.780755***	-	-
Tests Per 100k	-.0033465	-	-
Percent Over 65	-14.56267	-	-
Percent Male	-21.63415	-	-
Period	-	91.82077***	-
Period Squared	-	-6.418428***	-
Gathering Restrictions	-	774.8104***	0.6425
Public Masks	-	.4663219	0.1992
School Closure	-	482.1248***	0.1308
Stay at Home Order	-	-210.896	0.7941
Food Service Restriction	-	763.7649***	0.0022***
Travel Restriction	-	342.5898**	0.4109
Non-Essential Business	-	-19.68615	0.9093
Categorical Business	-	-18.47782	0.5510
I: Masks and Stay Home	-	-173.2679	0.9968

I: Masks and Gathering	-	-259.7634	0.1585
I: Masks and Travelling	-	-3.88152	0.9185
I: Masks and NE Business	-	145.9716	0.6095
I: Gather and Stay Home	-	-	-
I: Gathering and Travel	-	-253.6703*	0.1756
I: Gathering and Food	-	-434.3405***	0.1693
I: Gathering and School	-	-378.5426***	0.2701
I: Food Restrict and Mask	-	-	-
I: Food and Stay Home	-	92.68854	0.6056
I: Food and NE Business	-	-	-
I: School and Travel	-	-316.7845**	0.2113
I: Stay Home and Travel	-	45.91307	0.0346**
N = 1071 p-value < 0.1 = * p-value < 0.05 = ** p-value < 0.01 = ***			

Table 4 shows the impact of each of the policies and policy combinations on initial claims per 100,000 people. The table shows that policies mandating gathering restrictions, food/beverage service closures, school closures and travel restrictions have statistically significant, strong, and positive impacts on initial claims in state. Instituting each of these policies led to between a 300 and 800 increase in initial claims. All of these coefficients were highly statistically significant and large indicating a large impact of enacting these policies on initial claims. Additionally, the interaction terms between gathering restrictions and food/beverage service restrictions, gathering restrictions and school closures, gathering restrictions and travel restrictions, school closures and travel restrictions have statistically significant coefficients, however, the coefficients are all negative. This would indicate that because these policies were instituted, initial unemployment claims actually went down which is the opposite of what I hypothesized.

Table 5. Continued Claims Per 100k

	Random Effects Coefficients	Fixed Effects Coefficients (Within)	Test for Endogeneity p-value (Difference)
People per Square Mile	.2614025**	-	-
Cigarette Use	56.61864	-	-
Percent White	-14.86224	-	-
Tests Per 100k	.027728	-	-
Percent Over 65	71.54594	-	-
Percent Male	584.785***	-	-
Period	-	206.2547***	-
Period Squared	-	-.0881186	-
Gathering Restrictions	-	-514.1399*	0.6654
Public Masks	-	-37.06918	0.0823*

School Closure	-	324.9313	0.9969
Stay at Home Order	-	1066.049	0.5397
Food Service Restriction	-	-393.6606	0.3702
Travel Restriction	-	220.53	0.6837
Non-Essential Business	-	718.6473***	0.0195**
Categorical Business	-	263.3255	0.2599
I: Masks and Stay Home	-	101.2349	0.0003***
I: Masks and Gathering	-	518.8499	0.0498**
I: Masks and Travelling	-	-392.2414	0.4006
I: Masks and NE Business	-	489.2891	0.3917
I: Gather and Stay Home	-	-	-
I: Gathering and Travel	-	-196.0344	0.8768
I: Gathering and Food	-	1213.01***	0.8537
I: Gathering and School	-	102.8677	0.8754
I: Food Restrict and Mask	-	-	-
I: Food and Stay Home	-	352.8617	0.7731
I: Food and NE Business	-	-	-
I: School and Travel	-	324.6268	0.5351
I: Stay Home and Travel	-	137.506	0.3762
N = 1071 p-value < 0.1 = * p-value < 0.05 = ** p-value < 0.01 = ***			

Table 5 shows the impact of each of the policies and policy combinations on continued claims per 100,000 people. The table shows that policies mandating non-essential business closures and the combination of gathering restrictions and food/beverage service closures have statistically significant, strong, and positive impacts on continued claims in state. Instituting a non-essential business closure led to a 718.6473 increase in continued claims and enacting both a gathering restriction and a restriction on food/beverage businesses led to a 1213.01 increase in continued claims. Both of these coefficients were highly statistically significant and very large indicating a large impact of enacting these policies on continued claims.

4.Discussion

There was certainly an impact of some of the policies and combinations of policies on our health and economic outcomes. Non-essential business closures and travel restrictions in particular had a statistically significant and expected impact on multiple of our dependent variables of interest. The results help us to see that not all policies enacted are having a strong impact on outcomes, but some do and we should focus more resources and attention on discerning which policies are the most important and effective if disease-suppression policies are going to be the main lever for mitigating the COVID-19 pandemic. Additionally, we can see that all of the policies that led to a statistically significant reduction in COVID-19 cases or deaths also led to an increase in unemployment initial claims or continued claims. While of course it makes sense for public health officials to primarily consider health outcomes in the policies they make, it needs to be acknowledged that this may have adverse economic effects. While this shouldn't stop public health officials from enacting life-saving legislation, it should be an indicator that other policies need to be adopted in conjunction to ensure that those who are losing their jobs as a result of the pandemic are able to provide for their families and live at an acceptable standard.

In addition to these takeaways, one of the main surprising findings from this analysis was that some of the signs of the coefficients in each of my regressions were not what I expected. While the fixed effects model was able to get rid of the omitted variable bias of the time-invariant variables that exist due to state level population factors and more, it was not able to get rid of potential bias that is time-varying. It is possible that the severity of the virus in each given state is what sparked the establishment of more serious disease-suppression policies in each state, so instead of the disease severity being a response to the policy, the policies are a response to disease severity in the state. This could create biased results as our regression doesn't include the potentially important variable of disease severity that is time varying. This could certainly be addressed with future research to try to determine if these coefficients were accurate.

Additionally, this study had a narrow focus in that it looked at a state government's decisions to create a policy. I did not go further to examine the enforcement or uptake of the policy in the general public. I didn't examine mobility data to see if there was backlash to certain policies being implemented or any measures of how regularly people were wearing masks. I also didn't look at local government directives which has been another major source of disease-suppression policies during the COVID-19 pandemic. This could all be the subject of further research and investigation to better understand the impact of disease suppression policies on health and economic outcomes during the COVID-19 pandemic.

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