How much did restricting mobility help in controlling the spread of COVID?

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Introduction

Overview

The Covid-19 pandemic has taken more than 2.5 million lives worldwide. In the U.S. alone, more than half a million people died because of it. COVID-19 is thought to spread mainly through close contact from person to person, including among people who are physically near each other (within about 6 feet).[1]

As the virus spread, many cities and other areas have implemented a shutdown policy that significantly restricted the mobility of the population. Specifically, many companies have opted for a complete work-from-home policy.

As a team of Data Scientists, we're interested in assessing the effectiveness of restricting mobility in controlling the spread of Covid-19.

Research Question

Rather than investigating the effect of social distancing on a micro and personal interaction level, we are interested in its effect on a policy level. Specifically, the Research Question we're asking is:

`How much did restricting social mobility help in controlling the spread of COVID?`

The basic causal theory we're working under can be expressed by the diagram below:

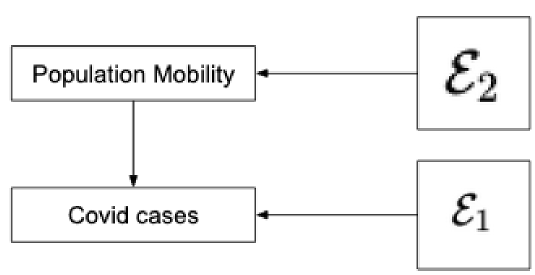

Figure 1: The Basic Causal Theory

Operationalization

To operationalize the research question, we propose the following plan for the causal models.

Firstly, we will use the New York Times Covid-19 data for the number of Covid cases per State. And we will use the COVID-19 Community Mobility Report for the population mobility scores. For the base model, we will use the "residential mobility score" as a relatively stable representative of the general population's social mobility.

Secondly, mobility have drastically different effect on the spread of the virus depending on the population density. Thus, we believe that having the raw number of cases as the outcome variable can be misleading. Therefore, we will be using the number of cases per 100,000 residents as the outcome variable to normalize the population density. The population density data will come from the COVID-19 US State Policy Database.

More formally, our base model will assume a causal relationship of the form:

$$cases\_per\_100k\_residents = \beta_0 + \beta_1 residential\_mobility\_score$$

where each data point will represent a State in the U.S., and the outcome variable will be the total number of Covid-19 cases from March 2020 to March 2021, per 100,000 residents for that state. And the independent variable will be the **average** residential mobility score of the state in the time period.

For a more advanced model, we propose to use some control variables to assess the difference mobility score makes in relation to other factors, notably we'll include whether the "Stay at Home" order is in effect and whether the face mask policy is in effect.

For the most inclusive model, we will explore all the other mobility scores, including to workplaces, parks, grocery & pharmacy, as well as retail & recreation.

The models

Data Exploration

The Linear Models

The Regression Table

Model Limitations

The Research Question under study is well suited for a time series analysis. The initial discussion and work, were poised to well take off in including a weekly average and correlation with the cases offset by couple of weeks. As per the instruction and the limited machinery in place, the team has decided to take yearly average for the states and use it in the model.

Classic Linear Model assessment

Omitted Variables

Diligently practicing mandates:

Though, State and County put restrictions, including Mask mandate, Curfew, Social distance, Quarantine, park, school and restaurant closures, how much general public abide to these mandates is a very good [Omitted] indicator that influence the total cases.

International/Non-Local Mobility:

As we all know Port of Entries like New York, San Francisco, Chicago and Seattle are the first affected places. State wide policies restricting mobility has varying effects on how close a location is to the airport or other transit points. Thus, closeness to transit stations and airport is an omitted variable.

All Percent drops are not equal:

A 10% drop in mobility is really good for sparsely populated regions to go below a certain threshold in transmitting the virus. The same cannot be applied to densely populated cities. Thus, the non-linearity in the measures taken vs impact seen is omitted.

Conclusion

References:

[1]: https://www.cdc.gov/coronavirus/2019-ncov/faq.html