A Study on The Effectiveness of Lock-down Measures to Control The Spread of COVID-19

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Abstract

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1. Introduction

In December 2019, an outbreak occurred in Wuhan, China involving a zoonotic coronavirus, similar to SARS coronavirus and MERS coronavirus [1]. The virus has been named Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), and the disease caused by the virus has been named the coronavirus disease 2019 (COVID-19). Since then the ongoing pandemic has infected more than 9 million people and has caused more than 467 thousand deaths worldwide.

Since the initial outbreak, several different studies have tried to estimate the number of infections [2] that stem from a single infected patient in order to predict the potential for transmission of the COVID-19 virus. In most cases, it was seen that $R_0 > 1$, implying exponential growth through infection of a vulnerable population. Original estimates placed mortality rates for individuals at high risk at 4.46 % with those suffering from cardiovascular or kidney disease having even greater susceptibility [3].

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The SARS-CoV-2 virus has no available treatment as the pathways for proliferation and pathogenesis are still unclear [4]. Current treatments are based on those effective on strains of the previous SARS coronavirus and MERS coronavirus. The SARS-CoV-2 virus is able to replicate rapidly during the asymptomatic phase and affect the lungs and respiratory tract, resulting in pneumonia, hypoxia, and acute respiratory distress [5]. Infected patients are directly dependent on external ventilation in most cases.

With the increasing pressure on the health systems due to reliance on intensive care units or non-invasive ventilation, health strategies like social distancing were implemented. The concern was to ensure the number of infected patients does not exceed the health system's ability to cope with it. It also focused on increasing the capacities of available health systems at the time.

Under the conditions at the time, with a highly pathogenic SARS-CoV-2 that is able to spread asymptotically during its incubation stage through a vulnerable population, policymakers were to contain the spread of the infection, minimize stress on the health systems and ensure public safety. This was done by issuing orders for widespread lock-down and implementing social distancing measures. All non-essential businesses and services were shut down until further notice.

Taking measures to reduce stress on the health sector and diminishing the number of infected patients is important to end the pandemic, and understanding the effectiveness of a lock-down enables the distinction of good safety measures from bad ones. Analyzing a synthetic control allows us to understand whether the decisions made were optimal and resulted in a reduction of burden on the healthcare system, and broke chain of transmission, preventing its spread and reducing the reproductive rate of the virus.

Any optimal policy considers a trade off between the benefit associated with lock-down and cost of reduced aggregate output. Aggregate output decreases as a function of the stringency of the policy, commitment from the government to maintain the level of stringency and adherence of general population. Aggregate output decreases through lower supply of labor, lower consumption and hence through lower investment, which results from investors' expectation of a lower marginal product of capital. On the other hand benefit associated with lock-down can be seen through number of life potentially saved and in curbing the pandemic early so that economic activity can be restarted early.

1.1. Our contribution

Defining how to measure these benefits.

Tools for measuring them.

Difficulty in assessing: different level of compliance, different cultural practices - hidden variables

1.2. Related Works

Other modeling approaches. SIR-F, DCM, Agent, Hybrid - not post fact A/B testing tools.

1.3. Tools

As stated above, our objective is to study the effects of government response at an aggregate level in terms of life saved, and limiting the number of cases that requires hospitalization. Such interventions can effectively be studied at a comparative level. In other words, if we have data for the evolution of aggregate outcomes, e.g. number of confirmed cases and deaths, when policy is applied in a group under study versus when the same policy is not applied in a control group. However, government policies were applied at different level across a geographic region. We do not have a mechanism to conduct a randomized trial. Hence, we consider constructing synthetic control method[6, 7, 8]. In a synthetic control set up, where observational data is available for different groups, we can construct a synthetic or virtual control group by combining measurements from alternatives (or donors). In following we provide a brief overview of Multi-dimensional Robust Synthetic Control (m-RSC) following [8].

Suppose that observations from N different geographically distinct groups or units are indexed by $i \in [N]$ in T time periods (days) indexed by $j \in [T]$. Let $k \in [K]$ be the metrics of interest (e.g. number of confirmed cases, number of deaths, number of tests conducted, etc.). By M_{ijk} we denote the ground-truth measurement of interest, and by X_{ijk}, an observation of this measurement with some noise. Let $1 \leq T_0 \leq T$ be the time instance in which our group of interest experiences an intervention, namely a government response to control the spread (e.g. stay home order, school or business closure, or mass vaccination). Without loss of generality we consider unit $i = 1$ (say, New York) and metric $k = 1$ (say, number of deaths) as our unit and metric of interest respectively.

Our objective now is to estimate the trajectory of metric of interest $k = 1$ for unit $i = 1$ if no government response to control the spread had occurred.

In order to do that we will use the trajectory associated with the donor units ($2 \leq i \leq N$), and metrics $k \in [K]$. In following we make two assumptions: (1) for all $2 \leq i \leq N$, $k \in [K]$ and $j \in [T]$, we have $X_{ijk} = M_{ijk} + \epsilon_{ijk}$ where, ϵ_{ijk} is the observational noise, and (2) Same model is obeyed by $i = 1$ in pre–intervention period, i.e. for all $j \in [T_0]$ and $k \in [K]$ we have $X_{1jk} = M_{1jk} + \epsilon_{1jk}$. As described by authors in [8], in following we also assume that for unit $i = 1$, we only observe the measurement X_{1jk} for pre-intervention period, i.e. for all $j \in [T_0]$ and $k \in [K]$. Our objective is to compute a counterfactual sequence of observation M_{1jk} for the time period $j \in [T]$, and $k \in [K]$, and in specific for $T_0 \leq j \leq T$, and $k = 1$, using synthetic version of unit $i = 1$.

Define $\mathcal{M} = [M_{ijk}] \in \mathbb{R}^{N \times T \times K}$. $\mathcal{M}$ is assumed to have a few well behaved properties as required by the algorithm, namely, it must be approximately low-rank and boundedness of $|M_{ijk}|$ (for details see [8]). To check whether our model assumption holds in practice, we consider $N = 185, T = 150, K = 2$, with 185 countries as units. We consider number of confirmed cases and number of deceased as two metrics over 150 days between January 22, 2020 and June 20, 2020. For assumption to hold, data matrix corresponding to number of confirmed cases and number of deceased and their combination should be approximated by a low-rank matrix.

As shown in Figure 1, the spectrum of the top 20 singular values (sorted in descending order) for each matrix. The plots clearly support the implications that most of the spectrum is concentrated within the top 5 principal components. Same conclusion holds true when units are states of United States, and when we consider only countries in European Union.

Let $\mathcal{Z} \in \mathbb{R}^{(N-1) \times T \times K}$ corresponding to donor units, and $X_1 \in \mathbb{R}^{1 \times T_0 \times K}$ correspond to unit under intervention. We obtain $\hat{\mathcal{M}}$ from $\mathcal{Z}$ after applying a hard singular value thresholding. Subsequently, weights are learned using linear regression by computing

$$\hat{\beta} = \underset{v \in \mathbb{R}^{(N-1)}}{\arg\min} \left\| X_1 - v^T \hat{\mathcal{M}}_{T_0} \right\|_2^2$$

For every $k \in [K]$, the corresponding estimated counterfactual means for the treatment unit is then defined as

$$\hat{\mathcal{M}}_1^{(k)} = \hat{\beta}^T \hat{\mathcal{M}}^{(k)}$$

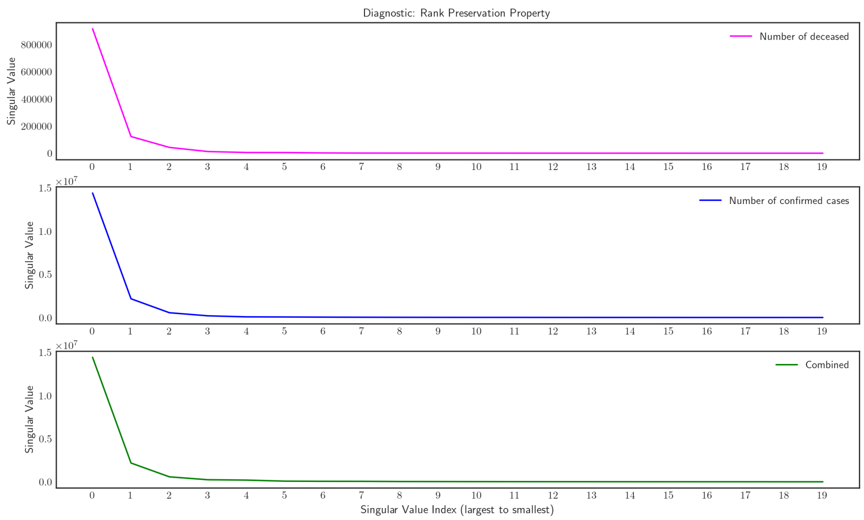

Figure 1: The Singular Value spectrum for all countries (of dimensions 185×150, showing top 20 singular values, in descending order.

2. Methods

2.1. Overview

As described in Section 1, we use m-RSC to construct a synthetic control for the treatment unit using data from multiple control units or donor group using pre-intervention period data. The synthetic control is then used for estimating the counterfactual in the post-intervention period. In our setup intervention date is typically the date when a stay-home order or lock-down was declared for the treatment unit. However, government policy may have been applied over time with different level of stringency measures.

To understand this we use stringency and policy indices data from OxCGRT [9], which records the strictness of policies that restrict people's behavior and includes 8 different measures - e.g. school and workplace closure, cancellation of public events, restrictions on gathering size etc. Figure 2, shows the plot of stringency index, with mobility data.

It can be observed that the level of lock-down varies over time and geographic region. We use this information in two different ways. First we choose the maximum level of index, first increased level of restriction index, and 14 days after the maximum level of index as various intervention dates

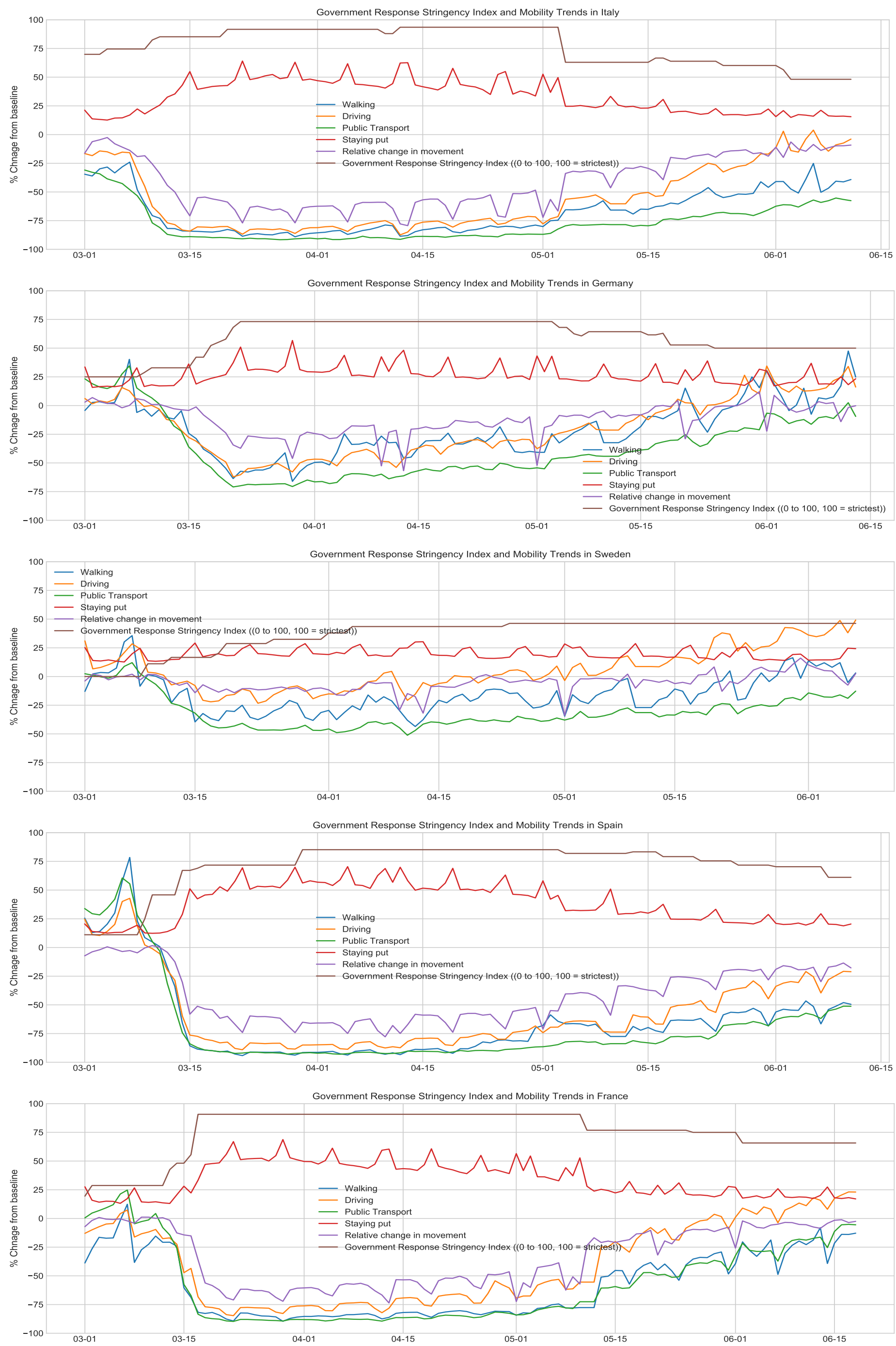

Figure 2: Stringency index, and Mobility Trends in (a) Italy (b) Germany (c) Sweden (d) Spain (e) France.

and compare their effects. Second, we combine this information with mobility data to select the control groups for a treatment unit as discussed below.

In order to understand the effect of stringency on a treatment unit for a metric, we need to select a donor group where level of stringency was different or adherence to stringency was different. Since, there was a degree of stringency measures and adherence to such measures at different level - under any possible choice of donor group, we acknowledge, that we will be underestimating the counterfactual - i.e. what would have been without any stringency measures. To estimate the degree of adherence to lock-down measures, we use mobility data from Apple, Google and Facebook. Apple mobility data provides a relative volume of directions requests per region, sub-region or city compared to a baseline volume - i.e. percentage change over time from the baseline including weekly seasonality. Facebook data provides the relative percentage of population that is staying in the same place and also the percentage of population that moved from a region to another. In Facebook data, to quantify how much people move around measure is derived by counting the number of level-16 Bing tiles (which are approximately 600 meters by 600 meters in area at the equator) they are seen in within a day. Assuming $U_{d,r}$ is the set of eligible users in region r on day d, and $tiles(u)$ is the number of tiles visited by a given user u in $U_{d,r}$, total number of tiles visited for that region is given by $totaltiles(U_{d,r}) = \sum_{u \in U_{d,r}} min(tiles(u), 200)$. Change in Movement measure is then the difference between a baseline and value on day d for average number of $totaltiles(U_{d,r})$. Similarly, Stay Put metric is calculated as the percentage of eligible people who are only observed in a single level-16 Bing tile during the course of a day on an average compared to a baseline. Finally, Google Community Mobility Report provides a percent change in visits to places like grocery stores and parks within a geographic area from baseline.

It can be seen from Figure 2, that the adherence and stringency level do not correspond. For example, in Sweden, with increasing level of government measures between March - April, there has not been any significant change in proportion of people staying put or moving between regions. Similarly, in other places, it can be observed that while government measures remain at the same level over April, number of people staying put at one place starts declining.

How are we combining these indexes? How we have selected donor an example here. Method for running the mRSC.

2.2. Data Source

We use following three sources of data as described in Table 1:

Data source	Description
Daily update from JHU [10]	We use this data to derive metric for units: i.e. number of confirmed cases and number of deceased for each day and geographic locations.
Facebook Movement Range Maps [11]	The relative percentage of population that is staying put and also the percentage of population that moved from a region to another. We use this data in selection of donor units.
Apple Mobility Trends[12]	Relative volume of directions requests per region, sub-region or city compared to a baseline volume, categorized by Driving, Walking or Public Transport. We use this data in selection of donor units.
OxCGRT [9]	Strictness of policies that restrict people's behavior, 8 measures combined to provide a score between 0 and 100, where 100 being most stringent. We use this data in selection of donor units.
Google Community Mobility Report [13]	Percent change in visits to places like grocery stores and parks within a geographic area. We use this data in selection of donor units.

Table 1: Data Source

3. Results

3.1. United States

US - compare prediction models data vs. Synthetic control projection vs actual by state by start and end of lock-down dates (what are the control group in each cases)

3.2. Italy

3.3. India

India - 4 stages of lock-down - effect of each stages - results on prediction by Synthetic control

3.4. Australia

4. Discussion and Concluding Remarks

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