Centralized or Decentralized? A Dynamic Model on Government Task Assignment in Pandemics

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Abstract

This paper empirically studies the government task assignment problem in the context of dynamic policy implementation. We focus on effective mitigation policy design to reduce virus spread in the COVID-19 pandemics. We start by estimating a structural SIR model with regional spillover effects using indirect inference to model virus transmission. Then, we develop and estimate a dynamic game model where each U.S. state independently forms mitigation policies. Socially optimal mitigation policy is then solved by minimizing the sum of local governments' welfare loss using estimated weights on different sectors. Counterfactual analysis of centralized decision-making is conducted to compare the social welfare gain (loss) should the US adopt a mitigation policy at the federal level.

Keywords: decentralization, dynamic game, structural SIR, social welfare

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1 Introduction

The choice between decentralized decision-making and centralized decision-making plays a pivotal role in shaping public policy design. The classical insight against using decentralized decision making is the potential cost of policy spillover effect that reduces social welfare (Oates et al., 1972). In many cases, policy implementation is a dynamic process, where different regions may adopt a similar policy at different point of time. Assessing the cost of policy spillover effects in such dynamic policy implementation poses significant empirical challenges as it necessitates estimating policymakers' preferences and solving for counterfactual policy implementation, along with its consequences on social welfare. In this paper, we propose and estimate a dynamic game model to study the welfare cost of spillover effects in the context of dynamic policy implementation during the COVID-19 pandemic.

Since the outbreak of the COVID-19 pandemic in March 2020, numerous national and subnational governments have implemented mitigation policies to contain the spread of virus. These mitigation policies primarily fall into two categories: centralized and decentralized social distancing. In a centralized approach, the central government controls the policy implementation for the entire nation. Conversely, in a decentralized strategy, decision-making authority is handed over to subnational units, such as state or provincial governments. In practice, many countries, including U.S., Canada, and Australia, have opted for decentralized decision-making.[1] In addition, although some news outlets have reported coordination among certain U.S. states regarding reopening decisions,[2] there is no evidence of similar coordination when it came to the imposition of lockdowns in the U.S.

Considering the highly infectious nature of the disease, a mitigation policy enacted in one region can significantly impact other closely connected areas. For instance, if region A enforces a lockdown while neighboring region B does not, inter-regional travel

[1]For a dataset of governments' responses to COVID-19, see Hale et al. (2021).

[2]See, for example, the news report titled "New York, New Jersey and other Northeastern states form coronavirus working group to decide when to ease restrictions": https://www.cnbc.com/2020/04/13/new-york-new-jersey-and-other-northeastern-states-form-coronavirus-working-group-to-decide-when-to-ease-restrictions.html

could potentially compromise the effectiveness of the policy. Motivated by the above-mentioned policy-making challenges, this paper studies the optimal timing of mitigation policy. Given decentralized decision making realizations, we assume that regional governments do not consider the network externalities of COVID-19 transmission across regions when deciding on lockdown measures. We ask the following research questions:

1. Considering the externalities of their decisions, what's the optimal timing of lockdowns for regional governments in equilibrium?
2. What's the welfare loss/gain from the decentralized decision-making, relative to the optimal uniform policy?

To answer the aforementioned questions, we start by establishing a dynamic structural SIR model to describe the transmission of COVID-19 conditional on different levels of mitigation policies. In the model, each region has some residents who fall into the following 3 different categories at any given moment - susceptible, infected, or recovered. Each infected individual carries a risk of death in the subsequent period. Our model operates under the assumption that all individuals start as susceptible to the virus, and immunity is acquired post-recovery. Our study is primarily focused on the initial wave of the COVID-19 pandemic in the United States (the orignal strain, or the "wild type"), to avoid complications related to changes in the fundamental properties of the virus, such as the infection, reproduction and death rates. Regions, in our model, form a network, leading to potential spillover effects from one region's COVID-19 transmission to all others. The model calibrates intra-region and inter-region travel using mobility metrics from *SafeGraph*.

However, due to the inherently noisy nature of COVID-19 data during its initial outbreak, we do not directly estimate the structural SIR model. This data noise stems from a number of factors including inconsistent measurement practices early in the pandemic, limited accessibility of tests, and a significant number of false negatives, all of which could lead to a severe underestimation of the number of infections. Therefore, we use indirect inference to fit the daily death provided by the *The COVID Tracking Project*[3] and use the fitted daily death to recover the daily infectious rate of each region using the structural

[3]See https://covidtracking.com/ for details.

SIR model. Our indirect inference approach draws inspiration from Atkeson et al. (2021), albeit with a different parametric form. Specifically, we estimate the parameters of a log-normal density function with scaling and markov switching variances. To model the infection rate, We allow it to depend on mitigation policies, daily death toll, and cumulative deaths. A sieve regression is subsequently applied to estimate the COVID-19 infection rate for each region. For the empirical component of this study, our analysis narrows to seven states within the United States, i.e., Connecticut, Delaware, Massachusetts, New Jersy, New York, Pennsylvania and Rhode Island.

We use the employment index from *The Opportunity Insights Economic Tracker* program to keep track of the economics condition of each state.[4] We assume that the economic condition is strongly affected by mitigation policies, alongside the daily death and cumulative death tolls. To trace the trajectory of the employment index, we apply an autoregressive model of the first order, or AR(1). Leveraging both the structural SIR model and the employment index's law of motion, we can simulate crucial counterfactual variables that characterize COVID-19. These variables are essential for understanding the preferences of regional governments

To capture the decision-making process of regional governments regarding mitigation policy, we formulate a model of dynamic games. In this model, each regional government must balance the economic repercussions of implementing mitigation policies against the number of deaths in their region. We posit that regional governments are only concerned with the economic opportunity cost of mitigation policy and the death toll of their own region. The externalities of their decision to other regions are not taken into consideration as motivated by the electoral concern. After setting up the model, we use the observed mitigation decision made by each regional government to estimate the dynamic game model to obtain preference parameter of regional governments. Following the insights from Bajari et al. (2007), we utilize a forward simulation method to approximate value functions and construct estimates.

Finally, we plan to carry out a series of exercises to analyze welfare implications under different counterfactual policy making. First, we examine whether *centralized* decision

[4]See https://tracktherecovery.org for more details.

making improves social welfare, where in this case the central government determines the timing of a uniform lockdown policy applicable to all states. Following that, we investigate how social welfare changes where state governments internalize the spillover effects of their policies and collaborate accordingly.

Our paper is directly related to the literature of externalities, fiscal federalism and dynamic public good: our approach to the problem, i.e. decentral versus central provision is first proposed by Oates et al. (1972) and further analyzed by Banzhaf and Chupp (2012), ground water (Kuwayama and Brozović, 2013) and state gun (Knight, 2013). Also see some empirical work related to this topic (Strumpf and Oberholzer-Gee, 2002). Since regional mitigation policy is a public good to the entire nation, our paper is related to the dynamic public good literature (Fershtman and Nitzan (1991), Levhari et al. (1981), Battaglini and Coate (2007), Battaglini et al. (2014)). Compared to the existing literature, we extend the welfare analysis of externalities to a dynamic policy making process. We develop and estimate a dynamic model to quantify the welfare loss of decentralized decision making given externalities. Our empirical exercise substantiates the fact that the timing of policy execution carries significant welfare consequences. The estimation framework we adopt is dynamic game model (Bajari et al. (2007), Aguirregabiria and Mira (2007)).

Our work is also related to the literature of the economics of epidemics as well as the literature on COVID-19. There is a sizable literature in economics that analyze epidemics. Mesnard and Seabright (2009), Toxvaerd (2019), Greenwood et al. (2019), Fang et al. (2020) and Hsiang et al. (2020) provides reduced form empirical evidence that the practice of restricting human mobility (regional lock-down) in China has saved a lot of lives. Chudik et al. (2021) argues that the voluntary social distancing could be too late to containing the spread of virus. Barrios and Hochberg (2021) and Allcott et al. (2020) study people's heterogeneous risk preferences and compliances to the stay at home order.There has been a considerably amount of papers that incorporate the traditional "SIR" or "SEIR" model into neoclassical macro economics model to study the effect of COVID-19 on economy (Kaplan et al. (2020), Eichenbaum et al. (2021), Alvarez et al. (2021), Kuchler et al. (2022), Jones et al. (2021)). Other important endeavors that are related to us concerns the estimation of key parameters related to COVID-19, see Manski and Molinari

(2021) and Hortaçsu et al. (2021), Chudik et al. (2021). To the best of our knowledge, existing models do not effectively incorporate the human mobility network, nor do they research the optimal timing for local government's mitigation decisions within the context of public economics using real-world data.

The remainder of this paper is organized as follows. In Sections 2 we specify the datasets used in this paper. Section 3 provides motivation and empirical evidences for this paper and model setups. Sections 4 and 5 we estimate the structural SIR model and dynamic game model, respectively. Section 6 we provide a counter-factual analysis and Section 7 concludes.

2 Data

In this section, we introduce our main data source. Our empirical analysis focuses on a number of states within the US, namely Connecticut, Delaware, Massachusetts, New Jersey, New York, Pennsylvania, and Rhode Island. These states are presumed to have strong interconnections because of geographical proximity.

2.1 Data

2.1.1 Footage data

We use the anonymous, aggregated smartphone footage data provided by SafeGraph[5] to have a measure of effectiveness of mitigation policies. A measure of inter-state, or inter-county travel frequencies during normal times and after the start of COVID-19 pandemics. We also make use of data from PlaceIQ[6] to compare with the inter/intra-state connection results we compute from SafeGraph.

From SafeGraph, we use the *Social Distancing Metrics* dataset and within this dataset, we keep only the *origin census block group*, *date range start*, *device count*, *completely home device count*, *destination cbgs* variables. The dataset has 220 thousand observations everyday, give or take. Each row represents a origin census block group, which uses the unique 12-digit

[5]See https://docs.safegraph.com/docs/social-distancing-metrics for details.
[6]See https://github.com/COVIDExposureIndices/COVIDExposureIndices for details.

FIPS code for the Census Block Group. *Device count* denotes number of devices seen in their panel during the date range whose home is in *census block group*. Home is defined as the common nighttime location for the device over a 6 week period where nighttime is 6 pm - 7 am. Any census block groups where the count < 5 are not included. Out of the *device count*, *completely home device count* is the number of devices which did not leave the geohash-7 (153m $\times$ 153m) region. in which their home is located during the time period. Each *destination cbgs* contains a dictionary in which the keys are a destination census block groups and value is the number of devices with a home in census block group that stopped in the given destination census block group for >1 minute during the time period. Destination census block group will also include the origin census block group.

For robustness purpose, we also use the exposure indices derived from PlaceIQ movement data produced by Glaeser et al. (2020). They produced a state-level location exposure index (LEX): Among smartphones that pinged in a given state today, what share of those devices pinged in each state at least once during the previous 14 days? The daily state-level LEX is a 51-by-51 matrix in which each cell reports, among devices that pinged today in the column state, the share of devices that pinged in the row state at least once during the previous 14 days, i.e.,

$$LEX_{ij} = \frac{\text{\#devices pinned in state i in the past 14 days among denominator}}{\text{\#devices pinned in state j today}}$$

2.1.2 Epidemiological data

We use the tested, confirmed and death data released mainly from state health departments. We impute the missing or inaccessible data using data from *The COVID Tracking Project*[7]. They collect, cross-check, and publish COVID-19 data from 56 US states and territories in three main areas: testing, patient outcomes, and, via *The COVID Racial Data Tracker*, racial and ethnic demographic information. Because of measurement problems mentioned by Manski and Molinari (2021). We believe the daily deaths data are the most reliable variable. To avoid interpreting measurement changes as underlying structural changes observed in the data, we smooth the daily death number by interpolating out-

[7] See https://covidtracking.com/ for details.

liers before bring this data to estimation.

2.1.3 Economic Indicators

The economic indicators that we use are from *The Opportunity Insights Economic Tracker* program,[8]. Specifically, we use daily unemployment rates across different geographical locations and industries (see also Chetty et al. (2020) for some papers based on the dataset). Unemployment rates is based on the weekly unemployment insurance claims counts and rates (as a share of the 2019 labor force).

2.1.4 Government Intervention

Mitigation and re-open policies are also used for estimation. Data provided by Killeen et al. (2020) contains the dates that counties (or states governing them) took measures to mitigate the spread by restricting gatherings, including *stay at home*, *>50 gatherings*, *>500 gatherings*, *public schools restaurant dine-in*, *entertainment/gym*, *federal guidelines*, *foreign travel ban*. They also include those intervention rollback dates in the dataset. Any type of restaurant or gym reopening was taken as the rollback date (for example, the county could have reopened at 25% capacity and only outdoor, all the way to business as usual. The data does not distinguish the reopen levels along this dimension.)

3 Empirical Evidences

Here we show preliminary empirical patterns of how COVID-19 spreads temporally and geographically. Additionally, we show that mitigation policies have strong impact on virus transmission.

Figure 1 shows the geographical pattern of patients with confirmed coronavirus disease in US across time starting from March 10 to March 30. We can see clearly that COVID-19 spreads through economically and geographically connected regions, this motivates that different regions should have their own time lines in terms of combating the virus. Moreover, the human activity network is crucial in disease transmission.

[8]See https://tracktherecovery.org.

Figure 2 shows the cross state border activities for 13 state pairs (from PlaceIQ). This is measured by state-level location exposure index (LEX): the share of those devices pinged in each state at least once during the previous 14 day among smartphones that pinged in a given state today. The size of the squares represents the size of the indexes. We see that externalities across different states pairs are different. This motivates the idea that when making decisions, states are facing a network externalities with different heterogeneous impact. For example, New Jersey and New York are more closely connected than other states due to the highly active cross-border transportation.

Figure 3 shows a time line of 45 states ordering stay at home order. While most of the states declare the quarantine rule in late March, the timeline lasts as long as 20 days. This gives us enough exogenous variation to investigate the effect of lockdown policies to disease transmission.

Figure 4 County-level data shows the pattern of social distancing before and after the stay at home order. This ratio is measured by the share of mobile devices which did not leave home. The completely-stay-at-home ratio does not change much between February 2/03/2020 - 3/02/2020, but increases uniformly across the country between 3/02/2020 - 3/30/2020. This is necessary but not sufficient to show a causal relation between a lockdown policy and lower commute levels. It could be people started to be more informed of this disease and voluntarily stay in quarantine.

3.1 Reduced-Form Evidence

To further confirm the effect of mitigation policy, we present some reduced-form empirical figure to support that government's mitigation policy has substantial effect on people's moving patterns. We find that the mitigation policy issued by state governments decreased people's activity. Moreover, we also find that one state's mitigation policy decreases the number of people who travel to adjacent states.

To test the effect of state government's mitigation policy, we first construct a panel dataset consisting of several activity indices and confirmed COVID-19 cases. We plot the activity index against a time window 30 days before and after a certain mitigation policy is implemented. When plotting the graph, we controlled for the effect of confirmed cases on people's willingness to engage in social activities. We also controlled for state fixed effects, the effect of each day of a week, as well as holidays.

Figure 6a shows how each state's first mitigation policy affects percentage change of people staying at home while figure 6b shows how each state's stay at home order affects percentage change of people staying at home in each states. We only distinguish first state action and stay at home order because many states issue many mitigation policies at a same day, making it hard to distinguish the effect of them.

To test a the effect of mitigation policy on inter-state travel, we changed the dependent variable to be a constructed measure of interstate travel index $LEX^{m}_{m',t}$ provided by PlaceIQ. $LEX_{m,t}$ is constructed to be the inter-state travel frequency index from a state m to state m'. m' is the state that has the most cross-border travel with state m. For example, if $m = NY$, then $m' = NJ$. Figure 7a shows the results for the impact of each state's first mitigation policy.

We also conduct a falsification test to show that state m's mitigation policy will not affect the movement from state m to m'. To do that, we construct another index LEX^{m}_{t} that is the LEX index for people travel from state other than m to m. Figure 7b shows the effect by using NY as an example.

4 Structure SIR

Time is discrete and is denoted as $t = 0, 1, 2....$ There are M heterogeneous regions that we denote each of them as $m \in \{1, 2, 3, ...M\}$. At each point of time t, each region has a population of n^{m}_{t} with initial mass of n^{m}_{0} in each region. The total population at each point of time is $N_t = \sum_{r}^{M} n^{m}_{t}$ with initial population $N_0 = \sum_{r}^{M} n^{m}_{0}$. We normalize the number of individuals in each state by the population. On the one hand, because we do not have daily population data, and the overall population change is small compare to its scale. On the other hand, as will become clear later, we only care about the transition coefficients.

4.1 State Variables

We classify our state variables ($\mathbf{X}_t$) into 2 groups. The first group is COVID-19 ($\mathbf{D}_t$) related while the other group is economic related ($\mathbf{E}_t$).

First we introduce the COVID-19 ($\mathbf{D}_t$) related state variables. At any given point of time, each individual in each region can be one of the 4 types: susceptible, infected or recovered, and dead. We specify the definition of the 4 states as follows (each as a fraction of regional population at time t):

- Susceptible (s_t^m): individuals that have not been exposed to the virus. This group are those who will never be tested positive.
- Infected (i_t^m): individuals that are infected. We include both symptomatic patients and asymptomatic ones in this group. This group becomes infectious, i.e., people have close contact with this group will likely be infected. The fraction of this group is extremely hard to measure, taking into account the test-taker ratio and false negative rates of the tests. The number of this group is not comparable to any established metric in data sets to our best knowledge.
- Recovered (r_t^m): Infected individuals that have recovered and we assume they have immunity thereafter[9].
- Dead (d_t^m): individuals that are dead because of COVID-19 infection. In some states, these individuals must also have COVID-19 listed on the death certificate to count as a COVID-19 death. When states post multiple numbers for fatalities, the metric includes only deaths with COVID-19 listed on the death certificate, unless deaths among cases is a more reliable metric in the state. Although the reported number of this group can still be biased[10], it is more reliable than the infected measure.

[9]Although this is obviously not true in the long run, in this paper we only consider the first wave and the variant of COVID, that is, the SARS-COV-2. In such a short amount of time it is therefore reasonable to assume the immunity still holds.

[10]COVID-19-caused death is tricky to define, and it has been updated over time. See for example https://cdn.ymaws.com/www.cste.org/resource/resmgr/2020ps/Interim-20-ID-01_COVID-19.pdf and https://www.mass.gov/news/department-of-public-health-updates-covid-19-death-definition

Hence in each region, we have the following equality holds:

$$1 = s_t^m + i_t^m + r_t^m + d_t^m$$

There are two absorbing states of the Markov chain: recovered and dead. Hence, in the end everyone will be in either of these two states.

Now we introduce the economic related state variables $\mathbf{E}_t$ that contains a measure of economic condition during the COVID-19 pandemic. Let E_t^m be the economic related state variables from region m, which is the relative unemployment level for each state.

4.2 Action Space

At $t = 0$, M_0 regions of the economy is hit by a deadly virus. Each of the M_0 regions has total infected population s_0^m so the virus starts to spread.

To avoid the quickly spread of the virus, the government can impose policy to control the spread. The measures that regional governments can do is to impose different degrees of social distancing, such as mandatory statewide capacity, gathering limits and physical distancing requirements and mask requirements. Specifically, we assume that the social distancing decision is a discrete decision that has a total $L + 1$ possible actions, i.e. $l_t^m \in \{0, l_1, l_2, ...l_L\}$, each of which is assumed to match a specific observed policy of regional governments. Denote $\mathbf{L}_t$ as a vector of actions that all states issue. For the purpose of estimation, we assume the actions are ordinal, meaning l_i is less effective than l_j if $l_i < l_j$

4.3 Transition density of COVID-19 Related State Variables

For the 2 different sets of state variables, we use different empirical strategies to capture them. For the COVID-19 related state variables $\mathbf{D}_t$ we build a simple empirical oriented structural SIR model to capture the transition of $\mathbf{D}_t$. And we non-parametrically estimate the transition of economic state variables conditional on the disease state variables. The underlying assumption is that disease transmission process is unaffected by the economic state variables $\mathbf{E}_t$. This is an fairly strong assumption because one can argue that both disease and economic state variables are jointly determined by individual behavior. One could build up a model to capture them together, but because the focus here is not to characterize specific channels between virus transmitting and economic activity, we adopt this reduced form way to model the transition of state variables.

Specifically, we consider a basic SIR structure with regional spillover effect. The following equations fully describe the transition between each COVID-19 related state variables

$$\Delta s_{t+1}^m = -\lambda_{m,m}(l_t^m)\beta^m(l_t^m)\frac{s_t^m}{1-d_t^m}i_t^m - \sum_{m'\neq m}\lambda_{m,m'}(l_t^{m'})\beta^{m'}(l_t^{m'})i_t^{m'}\frac{s_t^m}{1-d_t^m} \tag{1}$$

$$\Delta i_{t+1}^m = \lambda_{m,m}(l_t^m)\beta^m(l_t^m)\frac{s_t^m}{1-d_t^m}i_t^m + \sum_{m'\neq m}\lambda_{m,m'}(l_t^{m'})\beta^{m'}(l_t^{m'})i_t^{m'}\frac{s_t^m}{1-d_t^m} - \gamma i_t^m \tag{2}$$

$$\Delta r_{t+1}^m = (1-\nu)\gamma i_t^m \tag{3}$$

$$\Delta d_{t+1}^m = \nu\gamma i_t^m \tag{4}$$

where $\lambda_{m,m'}(l_t^m)$ describes the intra/inter state mobility from m' to m, and $\beta^m(l_t^m)$ captures the infection rate (up to a constant). γ is the rate at which agents who are infected stop being infectious and hence stop transmitting the disease. ν is the fatality rate[11]. We need to also account for the fact that people tend to actively avoid meeting when situation gets worse. We argue that this avoidance (which lowers the contact rate) could be captured by assuming a parametric structure for λ_t^m, which has a time trend or depends linearly on aggregate death number. For simplicity, we do not add this extra variation in the following exercise. To solve the model using full-information we need to solve for a 4-variable diffusion process, which is beyond this paper.

[11]We could allow for γ and ν to be regional dependent and it would only affect our estimation by increasing the errors.

Rewrite (3) and (4), we have

$$\begin{aligned}
i_t^m &= \frac{1}{\nu\gamma}\Delta d_{t+1}^m \\
r_t^m &= \frac{1-\nu}{\nu} d_t^m \\
s_t^m &= 1 - d_t^m - \frac{1-\nu}{\nu} d_t^m - i_t^m = 1 - \frac{1}{\nu} d_t^m - \frac{1}{\nu\gamma}\Delta d_{t+1}^m
\end{aligned}$$

Put (1)-(4) in a matrix form,

$$\begin{pmatrix} -\lambda_{1,1}(l_t^1)i_t^1 & -\lambda_{1,2}(l_t^2)i_t^2 & \cdots & -\lambda_{1,M}(l_t^M)i_t^M \\ -\lambda_{2,1}(l_t^1)i_t^1 & -\lambda_{2,2}(l_t^2)i_t^2 & \cdots & -\lambda_{2,M}(l_t^M)i_t^M \\ \vdots & \vdots & \ddots & \vdots \\ -\lambda_{M,1}(l_t^1)i_t^1 & -\lambda_{M,2}(l_t^2)i_t^2 & \cdots & -\lambda_{M,M}(l_t^M)i_t^M \end{pmatrix} \cdot \begin{pmatrix} \beta^1(l_t^1) \\ \beta^2(l_t^2) \\ \vdots \\ \beta^M(l_t^M) \end{pmatrix} = \begin{pmatrix} \Delta s_{t+1}^1 / \frac{s_t^1}{1-d_t^1} \\ \Delta s_{t+1}^2 / \frac{s_t^2}{1-d_t^2} \\ \vdots \\ \Delta s_{t+1}^M / \frac{s_t^M}{1-d_t^M} \end{pmatrix}$$

The idea here is to use d_t^m, Δd_t^m to recover state variables i_t^m, r_t^m,s_t^m and Δs_{t+1}^m. We calibrate λ from the Safegraph mobility data. Specifically, we calculate the inter and within region mobilit index for each pair of region $m \in \{1, 2, ...M\}$ and $m' \in \{1, 2, ...M\}$ t. Then we calculate the average $\lambda_{m,m'}(l)$ for each state pair under a specific policy l. This is without loss of generality because any other variations of λ is loaded into the COVID-19 transmission sequence $\{\beta\}$ that we estimate.

Because λ are calibrated from data, the COVID-19 transmission rate sequence $\{\beta^m(l_t^m)\}$ can be solved from the above matrix equality for each region at each point of time t. Note that in this structure SIR model we assume that we can not directly observe the suspected, infected or recovered population, which as discussed above, is more or less the reality.

4.4 Parametrization

There are a few parameter we need to calibrate before we proceed to estimation. Following Atkeson et al. (2021), we let the parameter γ be the daily rate at which agents who are infected stop being infectious, that is, γ is the transition from the state i to the state r or d. We hereby call it the recovery rate. Estimates for COVID-19 continue to be updated as new data comes in. Values of incubation period between 2 and 14 (by ECDC), and remain infectious for another 5-10 days are considered in the literature [12], which correspond to a rate γ between $1/5$ and $1/10$. In this paper, we use the lowest infectious time period 5 for mild cases, that is, $\gamma = 1/5$. We discuss sensitivity of our results to this parameter below.

We denote the fatality rate from the disease by ν. That is, ν is the fraction of infected agents who stop transmitting the disease because they died. Measurement of the fatality rate of the disease is difficult because of incomplete measurement of the number of infected people and of the number of deaths from COVID-19. Even a place with tested rate approaching 1 could have yielded a biased fatality rate measurement because of type 1 and type 2 errors in testing. There is a wide range of estimates of this parameter. Early estimates of the fatality rate among infected people from the Diamond Princess cruise ship in which both infections and fatalities were well measured are in the range of 1.3% (Russell et al., 2020). Recent estimates of the infection fatality rate obtained from trends in the case fatality rate and testing data worldwide and in the United States lie in the range of 0.5% and 1.2% (Levin et al., 2020) respectively. A study on estimating infection fatality rate in NYC between March 1-May 16, 2020 gives an IFR of 1.45% (Yang et al., 2021). We consider values of ν= 1% as our baseline value and 1.4% as an alternative value.

4.4.1 Auxiliary Model

So far, randomness does not play any role in our model. To make our transition of state variables non-trivial, it seems natural to make our structural SIR a stochastic differential system. The reason we don't do that here is two-fold: First, solving for a four-variable diffusion process can be hard, in addition, you need assumptions that guarantees the 'reducibility' of the system (Aït-Sahalia, 2002, 2008) to have a close-form transition density. The second reason is we want to control the source of error so that it only comes from the channel of daily death data, which we trust the most. To get a good estimate of $d^m(t)$, Δd_t^m and $\Delta^2 d_t^m$, we consider the following Markov Chain regime-switching model as our auxiliary model and conduct indirect inference (Gourieroux et al., 1993). We consider the parametric form of a lognormal density because it provides a good approximation to our

[12] e.g, Zaki and Mohamed (2021), see also CDC website https://www.who.int/news-room/commentaries/detail/criteria-for-releasing-covid-19-patients-from-isolation

daily death data.

Consider an auxiliary model for daily death like this:

$$\Delta D_t = \frac{c}{t\sigma\sqrt{2\pi}} \cdot \exp(-\frac{(\log t - \mu)^2}{2\sigma^2} + \sigma_{k_t}\epsilon_t$$

where ΔD_t is the daily death without normalization. $c > 0$ is the scale parameter, $\sigma > 0$ is the variation parameter, μ is the location parameter.

k_t here is the regime at time t, ϵ_t are i.i.d. and standard Gaussian. One rationale for this auxiliary model is we observe a mean-zero process after taking a difference with the daily death data. We add-in more flexibility in volatility of this process by allowing parameters to vary by regimes, which can be justified by different stages of disease transmission.

The set of parameters that we need to estimate is the following,

$$\theta = \left\{c, \mu, \sigma, \sigma_1, \sigma_2, q_{i,j}^k\right\}$$

Given the regime-switching equation, we could write the likelihood, i.e.

$$\begin{aligned}\log \mathcal{L}\left(\Delta D_t^{\text{Data}} \mid \Delta D^{t-1, \text{Data}}, k_t, \theta\right) &= \log \mathcal{L}\left(\Delta D_t^{\text{Data}} \mid k_t, \theta\right) \\ = -\frac{1}{2}\log(2\pi) - \log\left(\sigma_{k_t}\right) &- \frac{\left(\Delta D_t^{\text{Data}} - \frac{c}{t\sigma\sqrt{2\pi}} \cdot \exp(-\frac{(\log t-\mu)^2}{2\sigma^2}\right)^2}{2\sigma_{k_t}^2}\end{aligned}$$

It follows that the likelihood function for ΔD^{Data} is

$$\mathcal{L}\left(\Delta D^{\text{Data}} \mid \theta\right) = \prod_{t=t_0}^{T} \sum_{k_t=1}^{x} \left[\mathcal{L}\left(\Delta D_t^{\text{Data}} \mid \Delta D^{t-1, \text{Data}}, k_t, \theta\right) p\left(k_t \mid \Delta D^{t-1, \text{Data}}, \theta\right)\right]$$

Given the initial condition $p\left(k_{t_0-1} = 1 \mid \Delta D^{t_0-1, \text{Data}}, \theta\right) = 1/2$, the predictive probability of regime, $p\left(k_t \mid \Delta D^{t-1, \text{Data}}, \theta\right)$, can be updated recursively through Hamilton (1989) 's filter as

$$p\left(k_t \mid \Delta D^{t-1, \text{Data}}, \theta\right) = \sum_{k_{t-1}=1}^{2} q_{k_t,k_{t-1}} p\left(k_{t-1} \mid \Delta D^{t-1, \text{Data}}, \theta\right)$$

and

$$p\left(k_t \mid \Delta D^{t,\text{ Data}}, \theta\right)=\frac{\mathcal{L}\left(\Delta D_t^{\text{Data}} \mid \Delta D^{t-1,\text{ Data}}, k_t, \theta\right) p\left(k_t \mid \Delta D^{t-1,\text{ Data}}, \theta\right)}{\sum_{k_t=1}^{X}\left[\mathcal{L}\left(\Delta D_t^{\text{Data}} \mid \Delta D^{t-1,\text{ Data}}, k_t, \theta\right) p\left(k_t \mid \Delta D^{t-1,\text{ Data}}, \theta\right)\right]}$$

Let $p(\theta)$ be the prior pdf. Specifically, we take $p(\theta)$ to be uniform distribution for a and σ_{k_t}, and the Dirichlet distribution for the elements of left stochastic matrix $\mathcal{Q}_k$. It follows that the log posterior density function of θ is

$$\log p\left(\theta \mid \Delta D^{\text{Data}}\right)=\log \mathcal{L}\left(\Delta D^{\text{Data}} \mid \theta\right)+\log p(\theta)-\log p\left(\Delta D^{\text{Data}}\right)$$

where $p\left(\Delta D^{\text{Data}}\right)$ is the marginal data density (MDD).

This proposed auxiliary model is to fully capture ΔD_t using the existing ΔD_t^{data}. We rely heavily on ΔD_t^{data} to estimate our auxiliary model because we believe the daily increased death sequence is a relatively reliable data source during COVID-19 pandemic time.

However, on top of using the death data, we also incorporate information from confirmed case data to enhance our estimates in the auxiliary model. To achieve this, we reference the literature to obtain upper and lower bounds for the infectious rate. These bounds are then employed as supplementary information within our auxiliary model.

More specifically, because we could always back out the infected sequence i_t^m by using a death sequence according to our structure SIR model. Therefore, during the estimation, we first calculate upper bound and lower bound of infected population at each period t ($i_t^{m,upper}$ and $i_t^{m,lower}$) using the same method as Manski and Molinari (2021). Then we impose the restriction that the our model implied sequence of infected population must be within the upper and lower bound of infected population for 95% of the time, i.e. or $Pr\left[\hat{i_t^m} \in [i_t^{m,lower}, i_t^{m,upper}]\right] \geq 95\%$ where

$$\hat{d_t^m}=\frac{1}{\nu\gamma}\Delta\hat{d_t^m}$$

and Δd_t^m comes from our one period ahead prediction using date $\Delta D^{t-1,Data}$ given a set of parameters $\hat{\theta}=\left\{\hat{c}, \hat{\mu}, \hat{\sigma}, \hat{\sigma}_1, \hat{\sigma}_2, \hat{q}_{i,j}^k\right\}$.

Both $i_t^{m,upper}$ and $i_t^{m,lower}$ are calculated using the methods proposed in Manski and Molinari (2021). The information are used as moment inequalities to bound our estimates. In our estimation of the Manski and Molinari (2021) bounds for infection rate, we let sensitivity take values between 0.6 to 0.9 and let specificity be 1[13], i.e., there is no false positives.

4.4.2 Counter-factual COVID-19 Transmission

Estimating a dynamic game model requires simulating COVID-19 state variables given different counter-factual policy implementations. Based on the structural SIR model specified in equations 1 and the specified inter-region activity function λ, we still need to put structure on how the COVID-19 transmission rate dependent on mitigation policy l.

Specifically, we assume that the COVID-19 transmission rate of state m at time t is an function of state policies (dummies) and number of daily death Δd_t^m and cumulative death d_t^m, using the polynomials of the death regressors up to order 3 as the sieve basis function, i.e.,

$$\beta_t^m = \alpha_1^m \mathbb{1}(l_t^m = 0) + \alpha_2^m \mathbb{1}(l_t^m = FSA) + \alpha_3^m \mathbb{1}(l_t^m = SAH) + \boldsymbol{\alpha}_4^m \mathbf{P}(\log d_t^m) + \boldsymbol{\alpha}_5^m \mathbf{P}(\log \Delta d_t^m),$$

where $\mathbf{P}(\cdot)$ denotes the vector of the polynomial basis. We first estimate parameters $\{\alpha^m\}$ for each region separately using sieve regression, then we compare the model predicted transmission rate $\hat{\beta}_t^m$ and the actual transmission rate computed from the SIR model $\{\beta_t^m\}$. Figure 9a and 9b examines the model-fit.

With the structural model of transmission rate and calibrated inter-region mobility index given mitigation policy, we can simulate the counter-factual disease transmission at any point time t for any region m using the structural SIR model.

[13]The sensitivity and specificity of tests for COVID-19 on the tested sub-population are P(test positive | tested, infected) and P(text negative | tested, not infected) respectively.

4.5 Transition of the Economic State Variable

After fully describing the transition density of COVID-19 related state variables, we describe how we get the transition density of economic related state variables $\mathbf{E}_t = (E_t^1, \cdots, E_t^M)$. The economic state variable that we consider describes the employment condition for each region taken from the *The Opportunity Insights Economics Tracker* program. Given the assumption that economic state variable is affected by the disease situation, we propose a parametric model to estimate the transition density for $\mathbf{E}_t$ for each region with an assumption that the epidemiological state variables are not affected by economic state variables. Specifically, we assume that the employment condition (E_t^m) evolves according to the following parameterized AR(1) transition density:

$$E_t^m = \rho^u E_{t-1}^m + \rho_u^d \Delta d_t^m + \sum_k \rho_u^l \mathbf{1}(l^m = k) + e_t^m \tag{5}$$

where Z_t consists of d_t^m, and Δd_t^m. Δd_t^m is fitted value from the auxiliary model. e_t^m is an error term. In practice, all COVID-19 state variables are logged. We pool all regions together in the estimation.

Table 1 shows the results of the estimation. We intuitively find that more strict mitigation policies and higher daily death have negative impacts on employment condition. The regression has a high R-square, meaning that the AR1 model can approximate the transition of economics state well.

Putting together with our results on the COVID transition $p(\Delta\mathbf{d}_t, \mathbf{d}_t \mid \Delta\mathbf{d}_{t-1}, \mathbf{d}_{t-1}, \mathbf{L}_t)$, we have specified the transition density of all state variables $p(\mathbf{X}_t|\mathbf{X}_{t-1}, \mathbf{L}_t)$. Note again that the structural of our SIR model makes it sufficient to carry only two COVID state variables.

5 Dynamic Game

In this section, we setup the dynamic game for each regional governments. In the setup, we treat each regional government as an independent decision maker. In the model, each regional government's decision on mitigation policies can depend on, COVID scenarios, economics conditions and other governments' decisions.

Each regional governments seek to minimized the present discounted cost from the disease of their own region described as below:

$$\min_{l_t^m \in \{0, l_1, \ldots l_L\}} \quad \sum_{t=0}^{\infty} \delta^t \left[\pi(E_t^m, \Delta d_t^m, l_t^m) + \xi_t^m(l^m)\right] \tag{6}$$

subject to the law of motion of state variables $p(\mathbf{X}_t | \mathbf{X}_{t-1}, \mathbf{L}_t)$. δ is a discount rate. We denote the deterministic part of the per period payoff of regional government m as $\pi(E_t^m, \Delta d_t^m, l_t^m)$. $\xi_t^m \sim N(0, 1)$ is a choice specific i.i.d. random shock.

Here, we assume that each regional government forms a correct belief on the transition of all state variables. That is to say, regional governments have rational expectation on the future disease propagation and the evolution of economy during the pandemic.

The the deterministic part of the per period payoff $\pi(E_t^m, \Delta d_t^m, l_t^m)$ captures the trade-off of economic activity and death from the disease. More specifically, it takes the form as follows

$$\pi(E_t^m, d_t^m, l_t^m) = \underbrace{\theta_e E_t^m}_{\text{loss of economics activity}} + \underbrace{\theta_d \Delta d_t^m}_{\text{cost of death}} + \underbrace{\sum_i^L \theta_p^i \mathbf{1}\{l_t^m = l_i\}}_{\text{cost of implementing mitigation policies}}$$

The first part of π captures the loss of economic activity. E_t^m contains a measure of employment condition. The second term measures the cost of death. The last term is a regional specific cost of implementing social distancing. The current setup of the each region's decision problem does not depend on other regions. This is motivated by the electoral concern, i.e. the regional leaders are primarily responsible for regional population. We believe this is a reasonable assumption given the US political institution.

5.1 Equilibrium

We consider pure-strategy Markov Perfect Equilibrium. That is to say, regional governments play Markovian strategies. The equilibrium policy is a function of payoff relevant state variables.

Let $\sigma^m(\mathbf{L}|\mathbf{X})$ be the region m's belief about the possibility of having action profile $\mathbf{L}$

when the realized state is $\mathbf{X}$. Denote $\sigma = (\sigma^1, ..., \sigma^M)$

We now formally define an equilibrium here:

Equilibrium 1 *A pure-strategy Markov Perfect Equilibrium is a collection of belief and strategies* $(\sigma, \mathbf{L}) = (\sigma^1, ..., \sigma^M, l^1, ...l^M)$ *if:*

- *All players use Markovian strategies;*
- *For all m, l^m is a best response to $\mathbf{L}^{-m}$ given the belief σ^m at each state $X \in \mathcal{X}$;*
- *For all m, the belief σ^m is consistent with the strategy $\mathbf{L}$,*

Equilibrium needs not be unique in this dynamic context. However, following Bajari et al. (2007), we assume the data observed are generated by a single MPE profile $\mathbf{L}$. And since the per-period payoff function $\pi(\mathbf{L}_t, \mathbf{X}_t, \xi_i^m)$ satisfies the Monotone Choice assumption stated in Bajari et al. (2007), we can estimate $Pr(l_t^m|\mathbf{X}_t)$ given the distribution knowledge of ξ_t^m.

5.2 CCP estimation

An important insight from the dynamics game estimation literature is that Conditional Choice Probability can be estimated outside of the main estimation process. The idea is that given the choices made by the players (regional government) must be optimal, we can directly estimate the conditional choice probability as a function of all relevant state variables.

Formally, denote $\mathbf{L}(\mathbf{X}_t)$ as the conditional choice probability as a function of all the state variables. We estimate the policy function using the ordered-Probit model. The dependent variable is the observed policy choice for each day, which is chosen from an ordered set $\{0, FSA, SAH\}$. Explanatory variables are (logged): E_t^m, Δd_t^m, d_t^m, $\sum_{m' \neq m} \Delta d_t^{m'}$, $\sum_{m' \neq m} d_t^{m'}$. Other regions' state variables are grouped together when entering the policy function of region m, following Ryan (2012). Additionally, We include the total population of the region.

Table 2 reports the result. We find that the R-square of the CCP estimation is high (larger than 0.9) meaning that the implementation of mitigation policy can be well explained by the set of state variables. Additionally, we find that the number of daily death and cumulative death in a region pushes the government toward implementing mitigation policies which is intuitive.

5.3 Value function approximation

We approximate value function through forward simulation a la Bajari et al. (2007). They key idea is that we can approximate value functions by simulating the value function forward for enough long periods with the help of the estimated conditional choice probability. The validity of this method relies on an accurately estimated conditional choice probability (CCP) function and forward simulations that cover enough different potential equilibrium paths.

Let $V(\mathbf{X};\mathbf{L};\theta)$ denote the value function of firm i at state $\mathbf{X}$, where Markov strategy $\mathbf{L}$ is used by all m. Then we have

$$V(\mathbf{X};\mathbf{L};\theta) = \mathbb{E}\left[\sum_{t=0}^{T} \beta^t \pi\left(\mathbf{L}(\mathbf{X}_t,\xi_t),\mathbf{X}_t,\xi_t^m;\theta\right)) |\mathbf{X}_0 = \mathbf{X};\theta\right]$$

where T and β should be chosen s.t. value function after T periods is sufficiently small, e.g. $\beta = 0.98$ and $T = 120$. Because we have in total 546 unique state realizations observed in the data, we approximate value function for all of them.

Therefore, a single simulated path of play can be obtained by the following:

1. Starting at state $\mathbf{X}_0 = \mathbf{X}$, draw private shock ξ_o^m from $N(0,1)$ for each m.

2. Pick an action l_0^m from any Markov strategy profile $\mathbf{L}(\mathbf{X}_0,\xi_0)$ (or any other deviations of it) and the resulting profits $\pi\left(\mathbf{L}(\mathbf{X}_0,\xi_0),\mathbf{X}_0,\xi_0^m;\theta\right))$.

3. Draw a new state $\mathbf{X}_1$ using the estimated transition density $\mathbf{P}$.

4. Repeat above steps for T periods.

Because one simulation path contains randomness. We averaging G different paths of play to obtain an estimate of $V(\mathbf{X};\mathbf{L};\theta)$ given any strategy profiles.

One simplification that is mentioned in Bajari et al. (2007) is that when the parameter θ enters into the payoff function linearly, one can first simulate the future state variables and shocks then multiply with parameters to get value functions. This method can alleviate the computation burden. Importantly, we can use the linearity simplification because the way θ enters into the profit function linearly.

5.4 Estimator

Given the equilibrium definition, the strategy profile $\mathbf{L}$ is a MPE if and only if $\forall m$, $\forall \mathbf{X}$, and $\forall$ alternative Markov policies l',

$$V\left(\mathbf{X}; l', \mathbf{L}_{-m}; \theta\right) \leq V\left(\mathbf{X}; l, \mathbf{L}_{-m}; \theta\right)$$

Intuitively, this means that the all other strategies will not generate a larger value as compared to the policy strategy profile $\mathbf{L}$, since $\mathbf{L}$ is on the equilibrium path.

Given this intuition, we can form the following estimator (Bajari et al. (2007), henceforth the BBL estimator)

$$\hat{\theta}^{BBL} = \underset{\theta}{\operatorname{argmin}} \sum_{\mathbf{X}} \sum_{l'} \max\{\left(V\left(\mathbf{X}; l', \mathbf{L}_{-m}; \theta\right) - V\left(\mathbf{X}; l, \mathbf{L}_{-m}; \theta\right)\right)^2, 0\}$$

The idea here is that deviation strategies $\mathbf{L}'$ should generate lower values for the decision maker. To obtain a reasonable estimator, we follow Sweeting (2013) to construct a reasonable deviation strategy $\mathbf{L}'$. Specifically, we perturbate the cutoffs in the conditional choice probability function we obtained shown in table 2 because cutoffs in a ordered Probit regression directly determnines the policy choice.

5.5 Estimates

Estimates coming.

6 Counterfactual Analysis

We plan to conduct two counterfactual analyses. The first one is to calculate the optimal timing of mitigation policy given our estimates. While the second is to hypothesize a central government that can decide the regional mitigation policies for each region.

6.1 Optimal Timing

We consider a social planner who seeks to minimize the present discounted loss described as below

$$\min_{l_t^m \in \{0, l_1, \ldots l_L\}} \quad \sum_{t=0}^{\infty} \delta^t \left[\sum_m \pi^p(E_t^m, d_t^m, l_t^m) \right]$$

where $\pi(E_t^m, d_t^m, l_t^m)$ is a per period utility that the social planner derives. It is the same per period utility function as the regional government.

$$\pi(E_t^m, d_t^m, l_t^m) = \hat{\theta}'_e E_t^m + \hat{\theta}'_d f(d_t^m) + \sum_i^L \hat{\theta}_p^i \mathbf{1}\{l_t^m = l_i\}$$

In the per period utlity function, $\hat{\theta}'_e$, $\hat{\theta}'_d$ and $\hat{\theta}_p^i$ are estimates from the previous estimation step. We seek to solve this single player dynamic problem and find the policy function that minimizes the present discounted value of the social planner.

The idea here is that the social planner takes into account the spillover nature of the infectious disease. We also plan to compare the social planner's welfare with the welfare derived from the observed mitigation policy scheme.

Estimates coming.

7 Conclusion

In this paper, we revisit classical decentralization problem in the context of the COVID-19 pandemic. We study the consequence of different mitigation policies on social welfare from centralized and decentralized decision-making. To our best knowledge, we are the first to put local governments' decisions in a dynamic game framework and compare the cost and benefit of decentralization.

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Figures

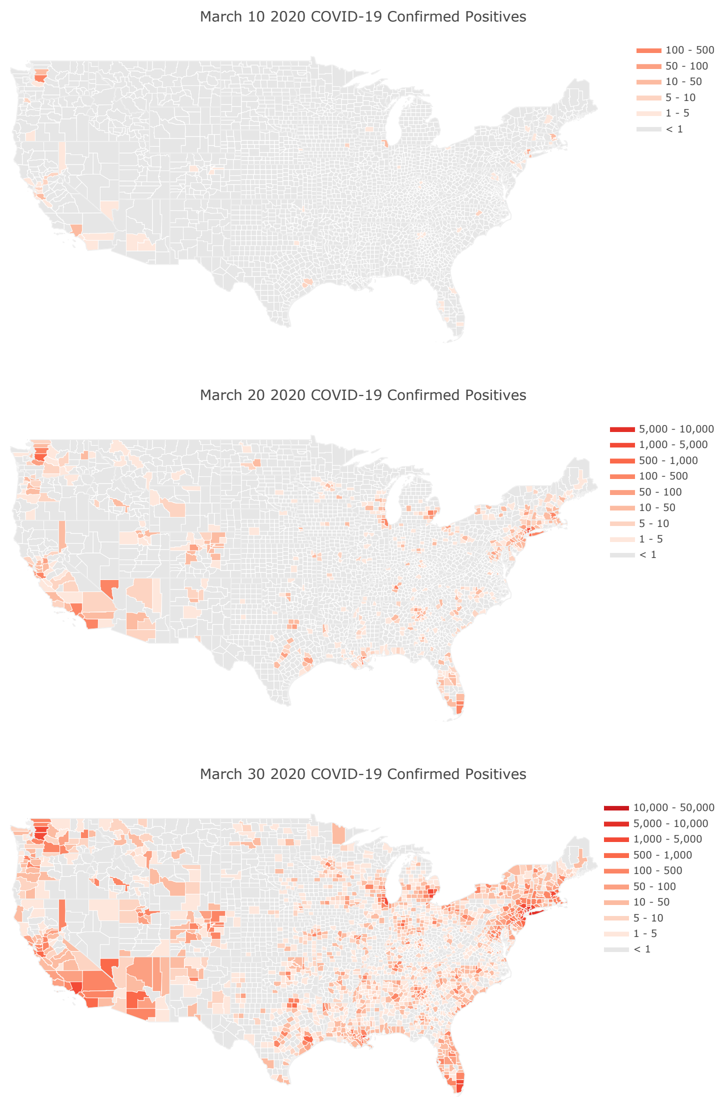


Figure 1: Confirmed Cases in US at Different Point of Time

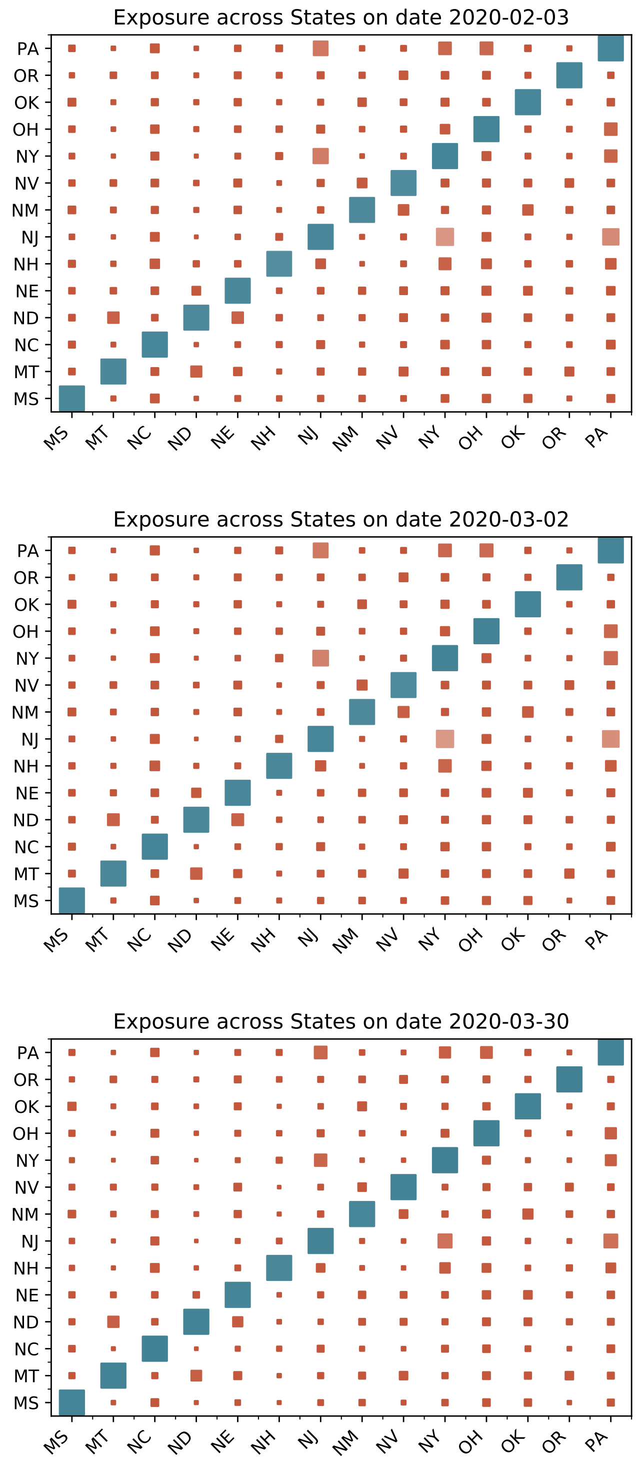


Figure 2: Cross State Border Activities by State Pairs at Different Point of Time

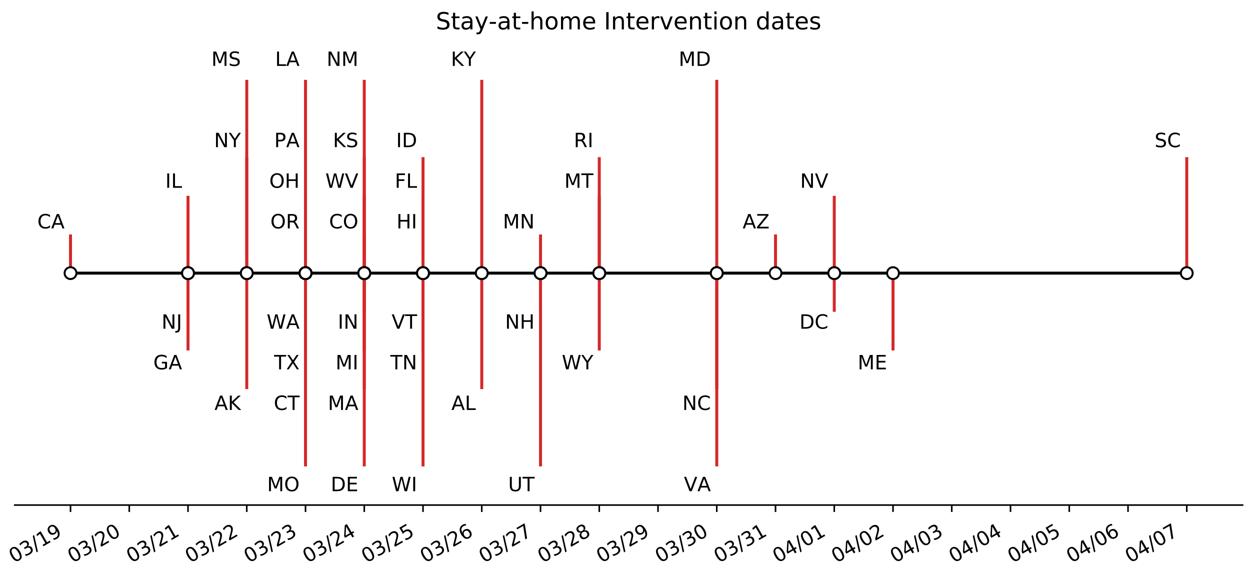


Figure 3: Timing of Observed State lock-down Order by Time in US

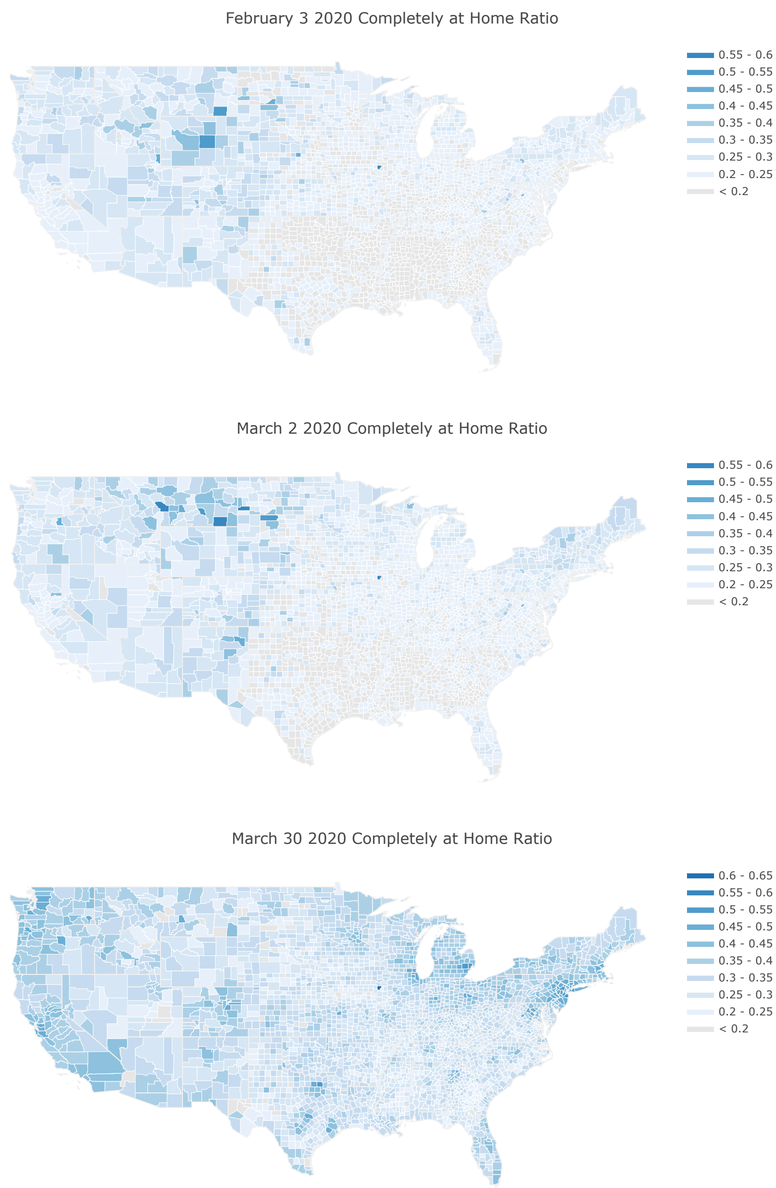


Figure 4: Social Distancing in US at Different Point of Time

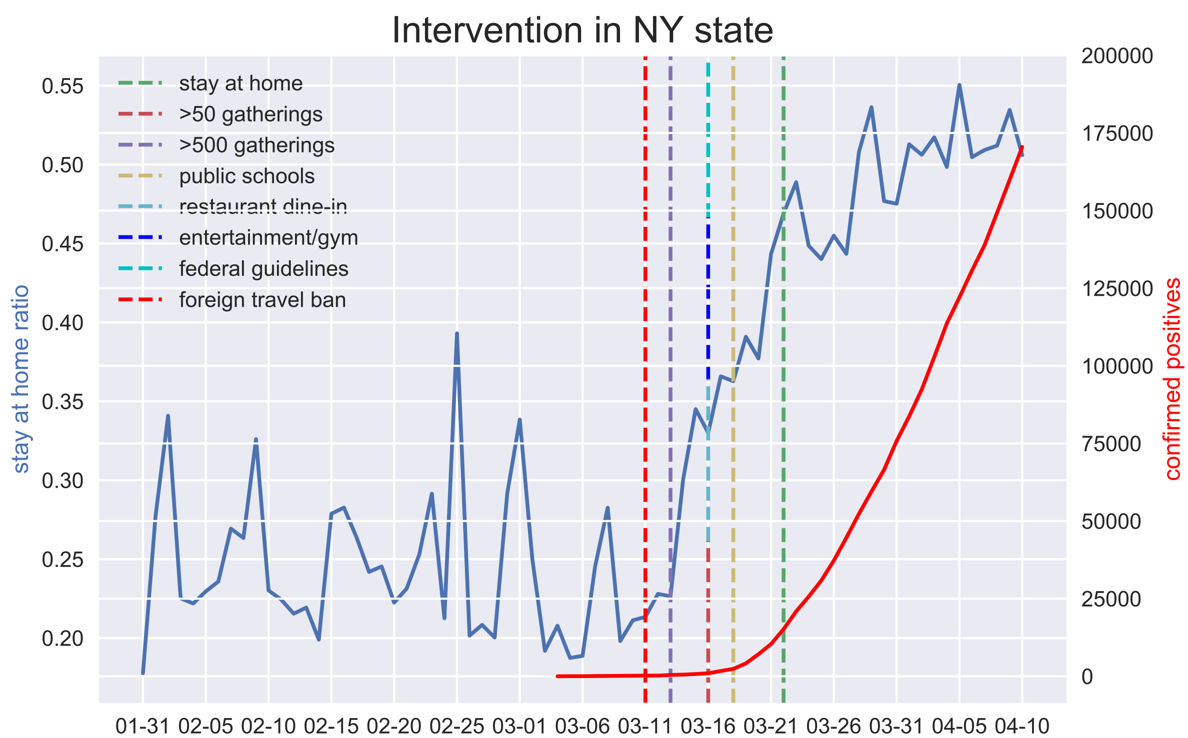
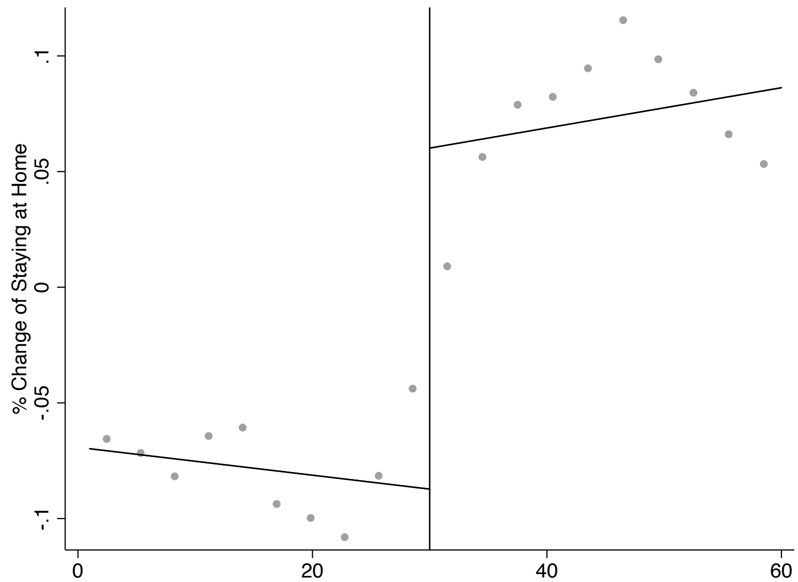
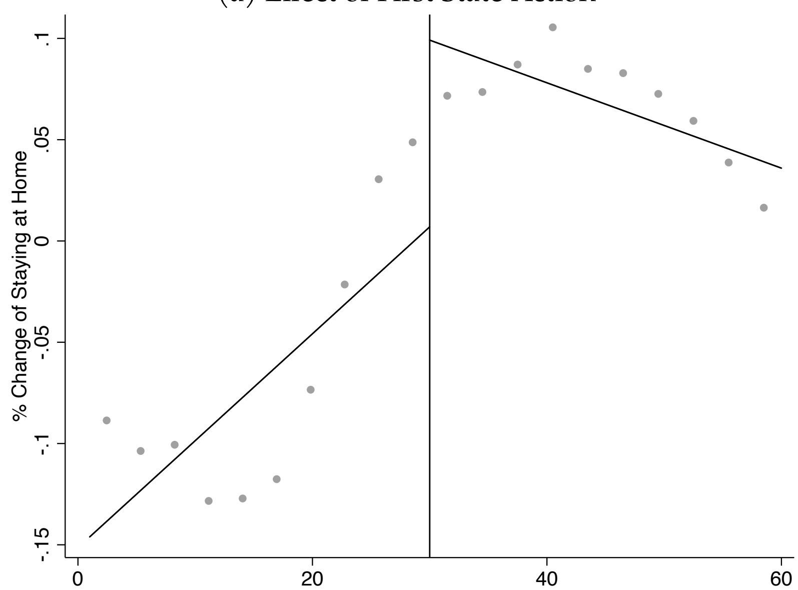


Figure 5: Lock-down Policy and Stay-at-home in NY



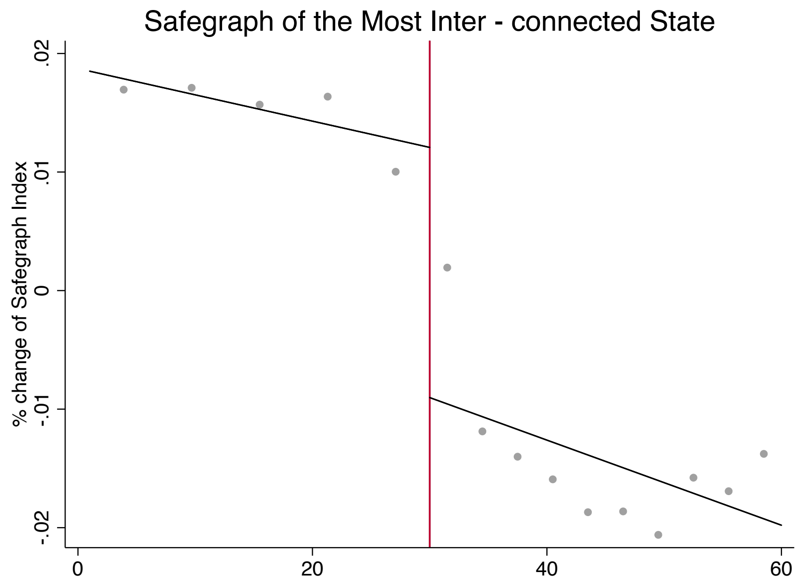
(a) Effect of First State Action



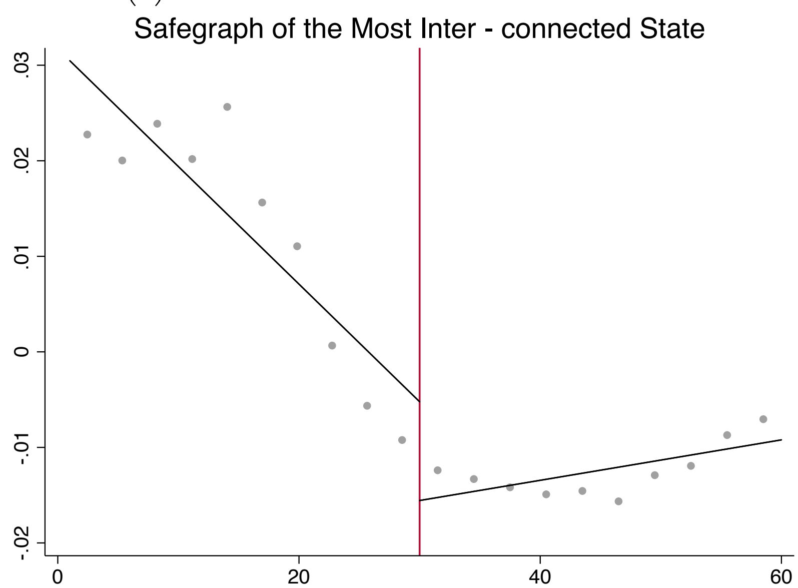
(b) Effect of Stay At Home Order

Figure 6: Effect of Different Mitigation Policies on % Change of Stay at Home

Notes: the dependent variable here is the percentage change of people who stay at home. The vertical line in figure 6a is the time when first mitigation policy is issued. The vertical line in figure 6b is the time when stay at home order is issued. We group the observations before and after the policy into 10 bins each and fit a line on it. When plotting the graph, we controlled for the effect of confirmed cases on people's willingness to engage in social activities. We also controlled for state fixed effects, the effect of each day of a week, as well as holidays.



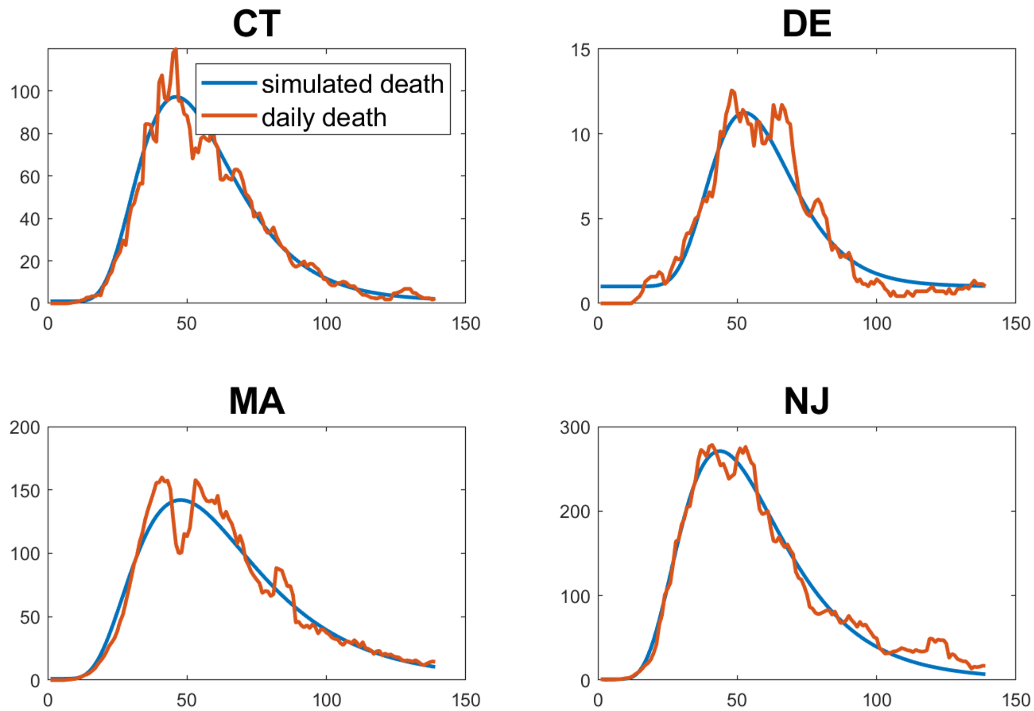
(a) Effect of First State Action on LEX Index



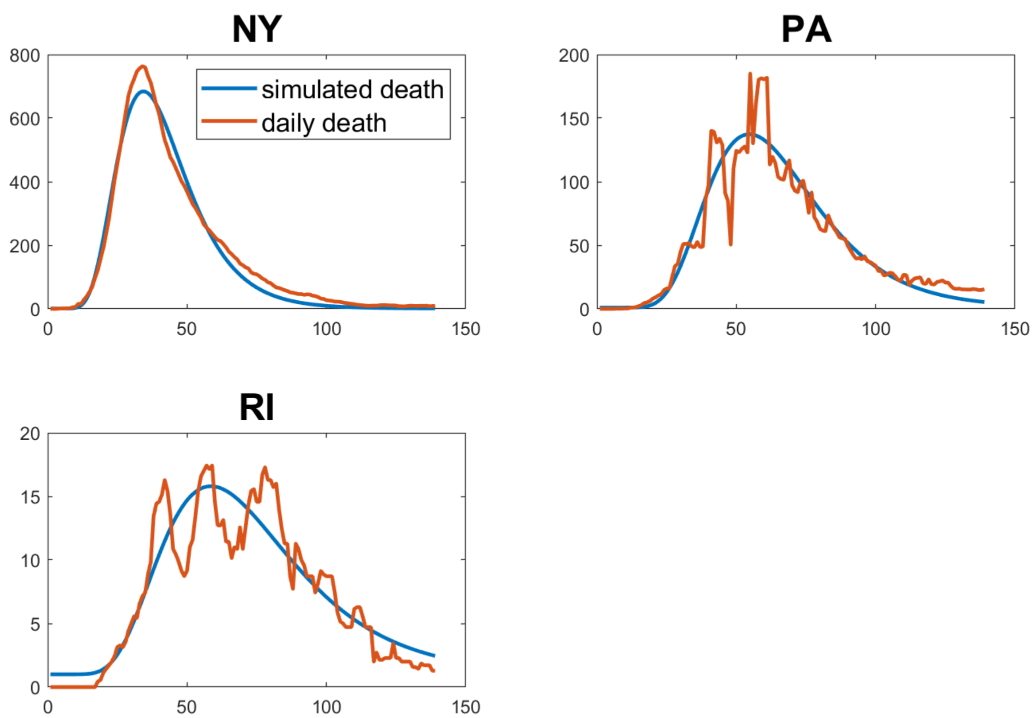
(b) Placebo Effect of First State Action on LEX Index

Figure 7: Effect of Different Mitigation Policies on % Change of LEX Index

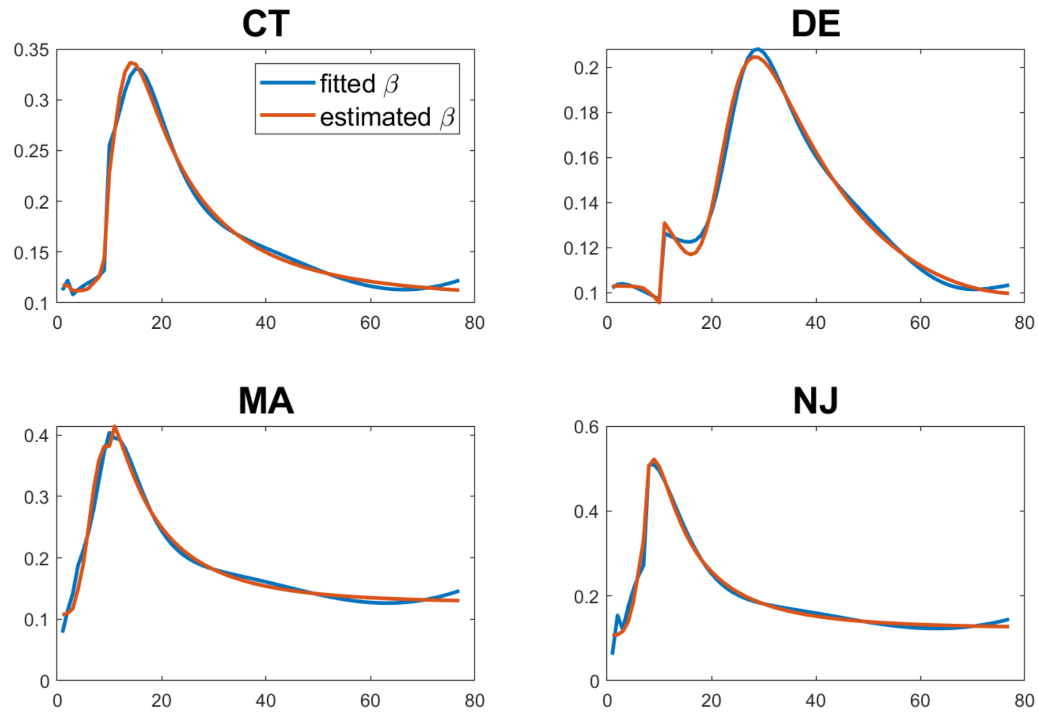
Notes: the dependent variable here is the LEX index. Figure 7a picks a state m' that is the most closely connected state to m for all m. Figure 7b picks LEX indeces from NY to all other states m'. The left vertical line is when the state m' issues a mitigation policy. The difference between 2 vertival lines are 14 days. we group the observations before and after the policy into 10 bins each and fit a line on it. When plotting the graph, we controlled for the effect of confirmed cases on people's willingness to engage in social activities. We also controlled for state fixed effects, the effect of each day of a week, as well as holidays.



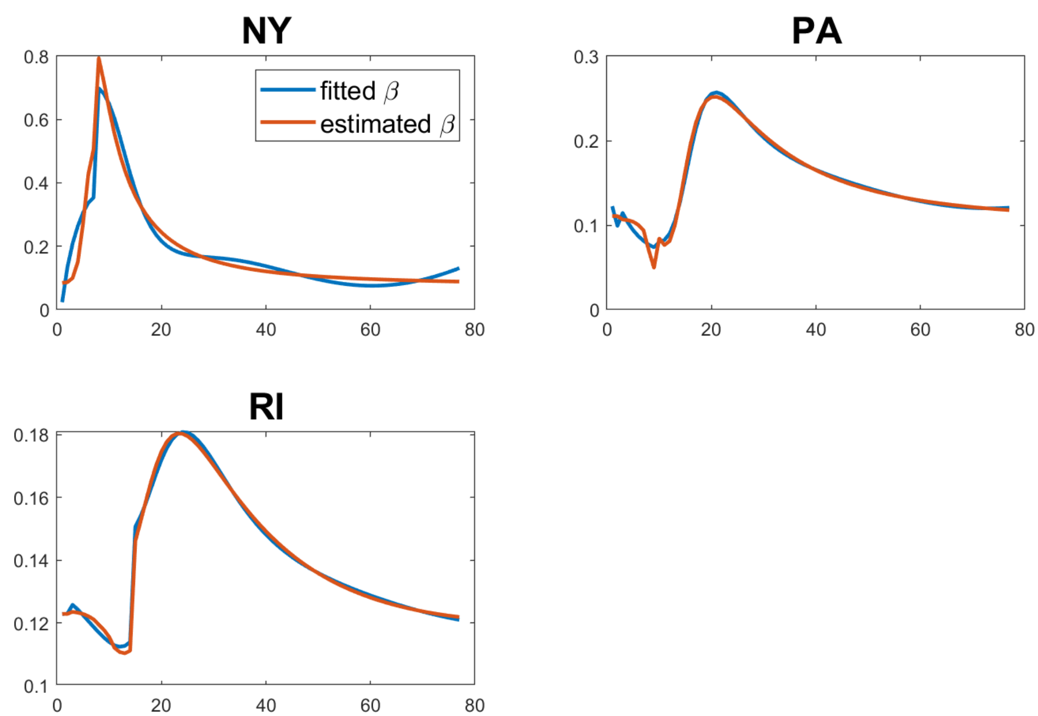
(a) Simulation of the Daily Death from the Auxillary Model for Connecticut, Delaware, Massachusetts and New Jersy



(b) Simulation of the Daily Death from the Auxillary Model for New York, Pennsylvania and Rhode Island



(a) Estimated and fitted infection rate for Connecticut, Delaware, Massachusetts and New Jersy



(b) Estimated and fitted infection rate β_t^m for New York, Pennsylvania and Rhode Island

Tables

Table 1: Transition Density of Economics State Variable

	Employment Condition
Lagged Unemployment Condition	0.957***
	(0.002)
Lagged Daily Death	-0.0007***
	(0.00012)
Mitigation Policy=0	0
	(.)
Mitigation Policy=1	-0.005***
	(0.002)
Mitigation Policy=2	-0.012***
	(0.002)
Constant	-0.005***
	(0.002)
R-square	1
Observations	539

Notes: The dependent variable is the relative state of employment to mid-January from *The Opportunity Insights Economics Tracker* program. We use Daily Death estimates from the auxiliary model detailed in subsection 4.4.1.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Estimates of Conditional Choice Probability

	Mitigation Policy
Employment Condition	76.88***
	(19.49)
Daily Death	1.632*
	(0.847)
Cumulative Death	4.080***
	(1.286)
Sum Daily Death	2.103***
	(0.726)
Sum Cumulative Death	1.043
	(1.258)
Logged Population	0.297
	(0.209)
cutoff1	13.08***
	(4.250)
cutoff2	18.28***
	(4.631)
R-square	0.915
Observations	546

Notes: We use an ordered-Probit model to estimate the Conditional Choice Probability (CCP). The dependent variable is the implementation of mitigation policy. Daily Death and Cumulative Death are estimates from the auxiliary model detailed in subsection 4.4.1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$