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# Causal impact of masks, policies, behavior on early COVID-19 pandemic in the U.S.

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**cemmap** working paper  
CWP24/20

# CAUSAL IMPACT OF MASKS, POLICIES, BEHAVIOR ON EARLY COVID-19 PANDEMIC IN THE U.S.

VICTOR CHERNOZHUKOV, HIROYUKI KASAHARA, AND PAUL SCHRIMPF

**ABSTRACT.** This paper evaluates the dynamic impact of various policies, such as school, business, and restaurant closures, adopted by the US states on the growth rates of confirmed Covid-19 cases and social distancing behavior measured by Google Mobility Reports, where we take into consideration of people’s voluntarily behavioral response to new information of transmission risks. Using the US state-level data, our analysis finds that both policies and information on transmission risks are important determinants of people’s social distancing behavior, and shows that a change in policies explains a large fraction of observed changes in social distancing behavior. Our counterfactual experiments indicate that removing all policies would have lead to 30 to 200 times more additional cases by late May. Removing only the non-essential businesses closures (while maintaining restrictions on movie theaters and restaurants) would have increased the weekly growth rate of cases between -0.02 and 0.06 and would have lead to -10% to 40% more cases by late May. Finally, nationally mandating face masks for employees on April 1st would have reduced the case growth rate by 0.1-0.25. This leads to 30% to 57% fewer reported cases by late May, which translates into, roughly, 30-57 thousand saved lives.

## 1. INTRODUCTION

Accumulating evidence suggests that various policies in the US have reduced social interactions, and have slowed down the growth of Covid-19 infections.<sup>1</sup> An important outstanding issue is, however, how much of the observed slow down in the spread is attributable to the effect of policies per se relative to a voluntarily change in people’s behavior out of fear of being infected. This question is critical to evaluate the effectiveness of restrictive policies in the US relative to an alternative policy of just providing recommendations and information such as the one adopted by Sweden. More generally, understanding people’s dynamic behavioral response to policies and information is indispensable for properly evaluating the effect of policies on the spread of Covid-19.

This paper quantitatively assesses the impact of various policies adopted by the US states on the spread of Covid-19, such as non-essential businesses closure and mandatory face masks, paying a particular attention to how people adjust their behavior in response to policies as well as new information on cases.

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*Date:* May 29, 2020.

*Key words and phrases.* Covid-19, causal impact, masks, non-essential business, policies, behavior.

<sup>1</sup>See Courtemanche et al. (2020), Hsiang et al. (2020), Pei, Kandula, and Shaman (2020), and Abouk and Heydari (2020).

We present a conceptual framework that spells out the causal structure on how the Covid-19 spread is dynamically determined by policies and human behavior. Our approach explicitly recognizes that policies not only directly affect the spread of Covid-19 (e.g., mask requirement) but also indirectly affect its spread by changing people’s behavior (e.g., stay at home order). It also recognizes that people react to new information on Covid-19 cases and voluntarily adjust their behavior (e.g., voluntary social distancing and hand washing) even without any policy in place. Our casual model provides a framework to quantitatively decompose the growth of Covid-19 cases into three components: (1) direct policy effect, (2) policy effect through behavior, and (3) direct behavior effect in response to new information.<sup>2</sup>

Guided by the causal model, our empirical analysis examines how the weekly growth rates of confirmed Covid-19 cases are determined by policies and behavior using the US state-level data. To examine how policies and information affect people’s behavior, we also regress social distancing measures on policy and information variables. Our regression specification for case growth is explicitly driven from a SIR model and the estimated regression coefficients can be interpreted from the viewpoint of the effective reproduction number although our causal approach does not hinge on validity of a SIR model.

As policy variables, we consider state of emergency, mandatory face masks for employees in public business, stay at home order, closure of K12, closure of restaurants except take out, closure of movie theaters, and closure of non-essential business. Our behavior variables are four mobility measures that capture the intensity of visits to “transit,” “grocery,” “retail,” and “workplaces” from Google Mobility Reports. We take time trend, the lagged growth rate of cases, and the log of lagged cases as our measures of information on infection risks that affects people’s behavior. We also consider the growth rate of tests, the log number of tests, and the state-level characteristics (e.g., population size and total area) as the confounders that has to be controlled for in order to identify the causal relationship between policy/behavior and the growth rate of cases.

Our key findings from regression analysis are as follows. We find that both policies and information on past cases are important determinants of people’s social distancing behavior, where policy effects explain at around 80% or more of observed decline in four behavior variables. We also find that people dynamically adjust their behavior in response to policies and information with time lag.

There are both large policy effects and large behavior effects on case growth. The estimates from our lag cases information model imply that all policies combined would reduce the weekly growth rate of cases by around 1. Taking into account of a change in the number of tests, the weekly growth rates of infections arguably declined from around 2 in

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<sup>2</sup>The causal model is framed using the language of structural equations models and causal diagrams of econometrics (Wright (1928); Haavelmo (1944); Heckman and Vytlačil (2007); see Greenland, Pearl, and Robins (1999) for developments in computer science), with natural unfolding potential outcomes representation (Rubin (1974); Tinbergen (1930); Neyman (1925); Imbens and Rubin (2015)). As such it naturally converses in all languages for causal inference.

early March to near 0 in April. Our result suggests that total policy effects explain around one-half of this decline.

Using the estimated model, we evaluate the dynamic impact of the following counterfactual policies on Covid-19 cases: removing all policies, allowing non-essential businesses to open, and mandating face masks. The results of counterfactual experiments show a large impact of some of those policies on the number of cases. They also highlight the importance of voluntary behavioral response to infection risks for evaluating the dynamic policy effects.

Figure 1 shows how removing all policies would have changed the average growth rate of cases as well as the number of cases across states. The effect of removing policies on case growth peaks at 0.6 after two to three weeks, and then gradually declines. This decline happens because people voluntarily adjust their behavior in response to information on a higher number of cases. The estimate implies that there would have been 30-200 times more cases (10 to 100 million additional cases) by late May if all policies had never been implemented.

Figure 2 illustrates how allowing non-essential businesses open would have affected the case growth and cases. Keeping non-essential businesses open (other than movie theaters, gyms, and keeping restaurants in the “take-out” mode) would have increased the cases by  $-10\%$  to  $40\%$ . These estimates contribute to the ongoing efforts of evaluating various reopening approaches (Stock, 2020a).

Figure 3 show that implementing mandatory face masks on April 1st would have reduced the case growth rate by 0.1-0.25, leading to reductions of  $-30\%$  to  $-57\%$  in reported cases in late May. This roughly implies that 30-57 thousand lives would have been saved.<sup>3</sup> This finding is significant: given this potentially large benefit for reducing the spread of Covid-19, mask mandates is an attractive policy instrument especially because it involves relatively little economic disruption. Again, these estimates contribute to the ongoing efforts of designing approaches to minimize risks from reopening.

A growing number of other papers have examined the link between non pharmaceutical interventions and Covid-19 cases.<sup>4</sup> Hsiang et al. (2020) estimate the effect of policies on Covid-19 case growth rate using data from the United States, China, Iran, Italy, France, and South Korea. In the United States, they find that the combined effect on the growth rate of all policies they consider is  $-0.347$  (0.061). Courtemanche et al. (2020) use US county level data to analyze the effect of interventions on case growth rates. They find that the combination of policies they study reduced growth rates by 9.1 percentage points 16-20 days after implementation, out of which 5.9 percentage points is attributed to shelter in place orders. Both Hsiang et al. (2020) and Courtemanche et al. (2020) adopted “reduced-form” approach to estimate the total policy effect on case growth without using any social

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<sup>3</sup>As of May 27, 2020, the US Centers for Disease Control and Prevention reports 99,031 deaths in the US.

<sup>4</sup>We refer the reader to Avery et al. (2020) for a comprehensive review of a larger body of work researching Covid-19; here we focus on few quintessential comparisons on our work with other works that we are aware of.

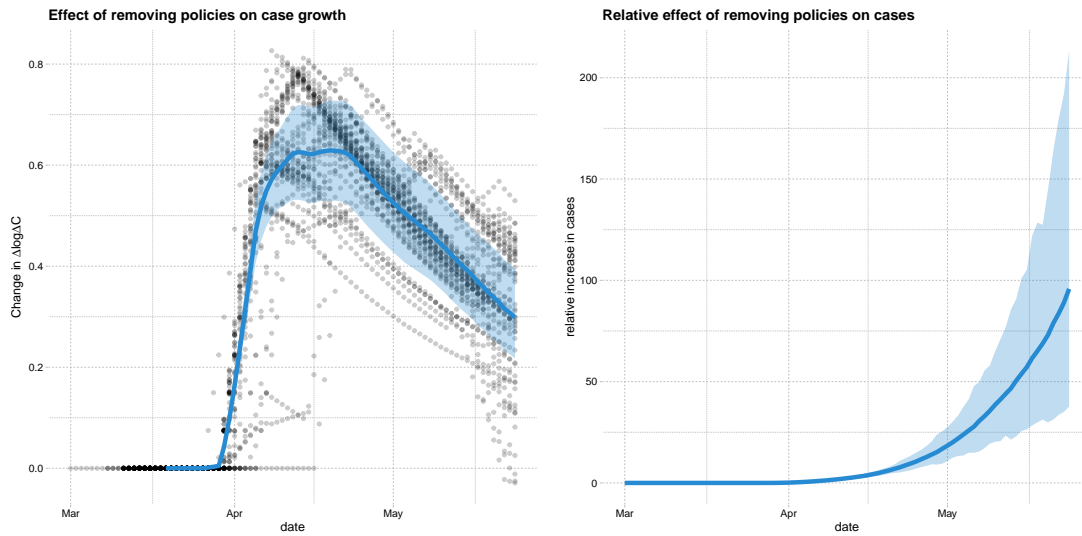


FIGURE 1. Average change in case growth and relative change in cases of removing all policies

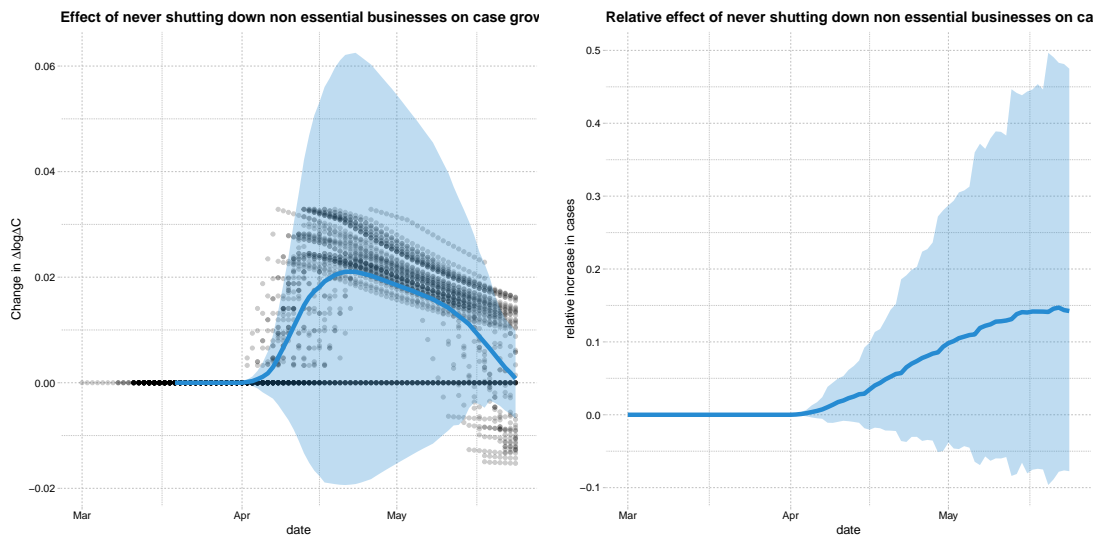


FIGURE 2. Average change in case growth and relative change in cases from leaving non-essential businesses open

distancing behavior measures. In contrast, our study highlights the role of behavioral response to policies and information.

Existing evidence for the impact of social distancing policies on behavior in the US is mixed. Abouk and Heydari (2020) employ a difference-in-differences methodology to find that statewide stay-at-home orders has strong causal impact on reducing social interactions.

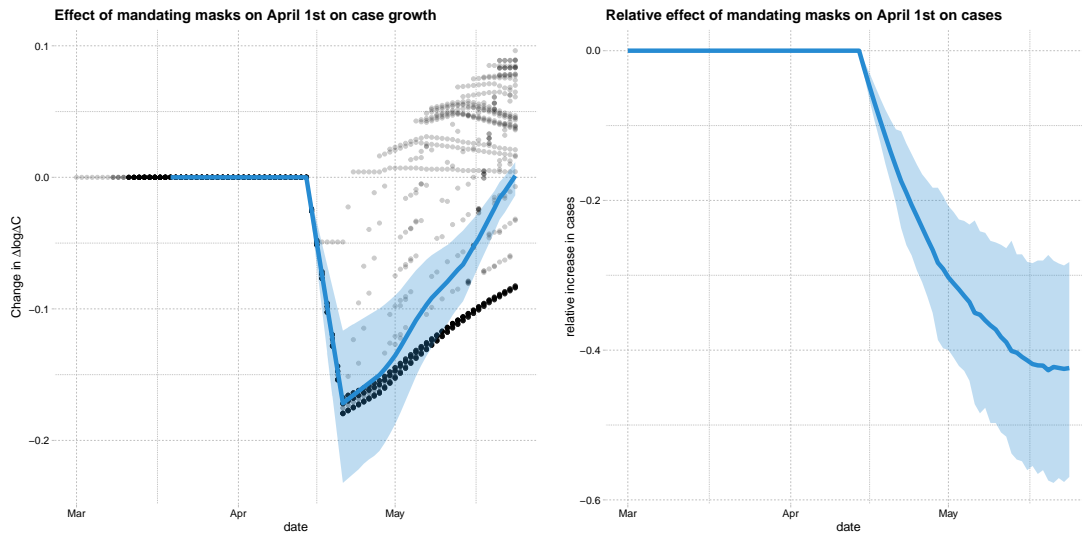


FIGURE 3. Average change in case growth and relative change in cases from mandating masks for employees on April 1st

In contrast, using the data from Google Mobility Reports, Maloney and Taskin (2020) find that the increase in social distancing is largely voluntary, and driven by information.<sup>5</sup> Another study by Gupta et al. (2020) also found little evidence that stay-at-home mandates induced distancing using mobility measures from PlaceIQ and SafeGraph. Using data from SafeGraph, Andersen (2020) show that there has been substantial voluntary social distancing but also provide evidence that mandatory measures such as stay at home order have been effective at reducing the frequency of visits outside of one's home.

Pei, Kandula, and Shaman (2020) use county-level observations of reported infections and deaths in conjunction with mobility data from SafeGraph to estimate how effective reproductive numbers in major metropolitan areas change over time. They conduct simulation of implementing all policies 1-2 weeks earlier and found that it would have resulted in reducing the number of cases and deaths by more than half. Without using any policy variables, however, their study does not explicitly analyze how policies are related to the effective reproduction numbers.

Epidemiologists use model simulations to predict how cases and deaths evolve for the purpose of policy recommendation. As reviewed by Avery et al. (2020), there exist substantial uncertainty in parameters associated with the determinants of infection rates and asymptomatic rates (Stock, 2020b). Simulations are often done under strong assumptions about the impact of social distancing policies without connecting to the relevant data (e.g., Ferguson et al., 2020). Furthermore, simulated models do not take into account that people may limit their contact with other people in response to higher transmission risks. When

<sup>5</sup>Specifically, they find that of the 60 percentage point drop in workplace intensity, 40 percentage points can be explained by changes in information as proxied by case numbers, while roughly 8 percentage points can be explained by policy changes.

such a voluntary behavioral response is ignored, simulations would produce exponential spread of disease and would over-predict cases and deaths. Our counterfactual experiments illustrate the importance of this voluntary behavioral change.

Whether wearing masks in public place should be mandatory or not has been one of the most contested policy issues, where health authorities of different countries provide contradicting recommendations. Reviewing evidence, Greenhalgh et al. (2020) recognizes that there is no randomized controlled trial evidence for effectiveness of face masks but they state “indirect evidence exists to support the argument for the public wearing masks in the Covid-19 pandemic.”<sup>6</sup> Howard et al. (2020) also review available medical evidence and conclude that “mask wearing reduces the transmissibility per contact by reducing transmission of infected droplets in both laboratory and clinical contexts.” Given the lack of experimental evidence, conducting observational studies is useful and important. To the best of our knowledge, our paper is the first empirical study that shows the effectiveness of mask mandates on reducing the spread of Covid-19 by analyzing the US state-level data. This finding corroborates and is complementary to the medical observational evidence in Howard et al. (2020).

## 2. THE CAUSAL MODEL FOR THE EFFECT OF POLICIES, BEHAVIOR, AND INFORMATION ON GROWTH OF INFECTION

**2.1. The Causal Model and Its Structural Equation Form.** We introduce our approach through the Wright-style causal diagram shown in Figure 4. The diagram describes how policies, behavior, and information interact together:

- The *forward* health outcome,  $Y_{it}$ , is determined last, after all other variables have been determined;
- The adopted policies,  $P_{it}$ , affect  $Y_{it}$  either directly, or indirectly by altering human behavior  $B_{it}$ ;
- Information variables,  $I_{it}$ , such as lagged valued of outcomes can affect both human behavior, adopted policies, and future outcome;
- The confounding factors  $W_{it}$ , which could vary across states and time, affect all other variables.

The index  $i$  describes observational unit, the state, and  $t$  describes the time.

We begin to introduce more context by noting that our main outcome of interest is the forward growth rate in the reported new Covid-19 cases; behavioral variables include proportion of time spent in transit or shopping and others; policy variables include stay-at-home order and school and business closure variables; the information variables include lagged values of outcome. We provide detailed description and time of these variables in the next section.

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<sup>6</sup>The virus remains viable in the air for several hours, for which surgical masks may be effective. Also, a substantial fraction of individual who are infected become infectious before showing symptom onset.



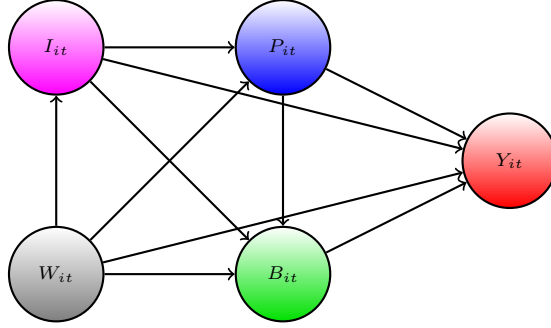


FIGURE 4. P. Wright type causal path diagram for our model.

The causal structure allows for the effect of the policy to be either direct or indirect – through-behavior or through dynamics; and all of these effects are not mutually exclusive. The structure allows for changes in behavior to be brought by change in policies and information. These are all realistic properties that we expect from the contextual knowledge of the problem. Policy, such as closures of schools, non-essential business, restaurants, alter and constrain behavior in strong ways. In contrast, policies, such as mandating employees to wear masks, can potentially affect the Covid-19 transmission directly. The information variables, such as recent growth in the number of cases, can cause people to spend more time at home, regardless of adopted state policies; these changes in behavior in turn affect the transmission of Covid-19.

The causal ordering induced by this directed acyclical graph is determined by the following timing sequence *within a period*:

- (1) confounders and information get determined,
- (2) policies are set in place, given information and confounders;
- (3) behavior is realized, given policies, information and confounders; and
- (4) outcomes get realized, given policies, behavior, and confounders.

The model also allows for direct dynamic effect of the information variables on the outcome through autoregressive structures, that capture persistence in the growth patterns. As further highlighted below, realized outcomes may become new information for future periods, inducing dynamics over multiple periods.

Our quantitative model for causal structure in Figure 4 is given by the following econometric structural equation model:

$$\begin{aligned}
 Y_{it}(b, p) & := \alpha' b + \pi' p + \mu' \iota + \delta_Y' W_{it} + \varepsilon_{it}^y, & \varepsilon_{it}^y & \perp I_{it}, W_{it} \\
 B_{it}(p, \iota) & := \beta' p + \gamma' \iota + \delta_B' W_{it} + \varepsilon_{it}^b, & \varepsilon_{it}^b & \perp I_{it}, W_{it}
 \end{aligned} \tag{SEM}$$

which is a collection of functional relations with stochastic shocks, decomposed into observable part  $\delta W$  and unobservable part  $\varepsilon$ . The terms  $\varepsilon_{it}^y$  and  $\varepsilon_{it}^b$  are the centered stochastic shocks that obey the orthogonality restrictions posed in these equations. (We say that  $V \perp U$  if  $EVU = 0$ ).

The policies can be modeled via a linear form as well,

$$P_{it}(\iota) := \eta' \iota + \delta'_P W_{it} + \varepsilon_{it}^p, \quad \varepsilon_{it}^p \perp I_{it}, W_{it} \quad (\text{P})$$

although our identification and inference strategies do not rely on the linearity.<sup>7</sup>

The observed variables are generated by setting  $\iota = I_{it}$  and propagating the system from the last equation to the first:

$$\begin{aligned} Y_{it} &:= Y_{it}(B_{it}, P_{it}, I_{it}) \\ B_{it} &:= B_{it}(P_{it}, I_{it}) \\ P_{it} &:= P_{it}(I_{it}). \end{aligned} \quad (\text{O})$$

The system above implies the following collection of stochastic equations for realized variables:

$$\begin{aligned} Y_{it} &= \alpha' B_{it} + \pi' P_{it} + \mu' I_{it} + \delta'_Y W_{it} + \varepsilon_{it}^y, & \varepsilon_{it}^y &\perp B_{it}, P_{it}, I_{it}, W_{it} & (\text{BPI} \rightarrow \text{Y}) \\ B_{it} &= \beta' P_{it} + \gamma' I_{it} + \delta'_B W_{it} + \varepsilon_{it}^b, & \varepsilon_{it}^b &\perp P_{it}, I_{it}, W_{it} & (\text{PI} \rightarrow \text{B}) \\ P_{it} &= \eta' I_{it} + \delta'_P W_{it} + \varepsilon_{it}^p, & \varepsilon_{it}^p &\perp I_{it}, W_{it} & (\text{I} \rightarrow \text{P}) \end{aligned}$$

which in turn imply

$$Y_{it} = (\alpha' \beta' + \pi') P_{it} + (\alpha' \gamma' + \mu') I_{it} + \bar{\delta}' W_{it} + \bar{\varepsilon}_{it}, \quad \bar{\varepsilon}_{it} \perp P_{it}, I_{it}, W_{it} \quad (\text{PI} \rightarrow \text{Y})$$

for  $\bar{\delta}' = \alpha' \delta'_B + \delta'_Y$  and  $\bar{\varepsilon}_{it} = \alpha' \varepsilon_{it}^b + \varepsilon_{it}^y$ . These equations form the basis of our empirical analysis.

**Identification and Parameter Estimation.** The orthogonality equations imply that these are all projection equations, and the parameters of SEM are identified by the parameters of these regression equation, provided the latter are identified by sufficient joint variation of these variables across states and time.

The last point can be stated formally as follows. Consider the previous system of equations, after partialling out the confounders:

$$\begin{aligned} \tilde{Y}_{it} &= \alpha' \tilde{B}_{it} + \pi' \tilde{P}_{it} + \mu' \tilde{I}_{it} + \varepsilon_{it}^y, & \varepsilon_{it}^y &\perp \tilde{B}_{it}, \tilde{P}_{it}, \tilde{I}_{it}, \\ \tilde{B}_{it} &= \beta' \tilde{P}_{it} + \gamma' \tilde{I}_{it} + \varepsilon_{it}^b, & \varepsilon_{it}^b &\perp \tilde{P}_{it}, \tilde{I}_{it}, \\ \tilde{P}_{it} &= \eta' \tilde{I}_{it} + \varepsilon_{it}^p, & \varepsilon_{it}^p &\perp \tilde{I}_{it} \end{aligned} \quad (1)$$

where  $\tilde{V}_{it} = V_{it} - W'_{it} E[W_{it} W'_{it}]^{-1} E[W_{it} V_{it}]$  denotes the residual after removing the orthogonal projection of  $V_{it}$  on  $W_{it}$ . The residualization is a linear operator, implying that (1) follows immediately from above. The parameters of (1) are identified as projection coefficients in these equations, provided that residualized vectors appearing in each of the equations have non-singular variance, that is

$$\text{Var}(\tilde{P}'_{it}, \tilde{B}'_{it}, \tilde{I}'_{it}) > 0, \quad \text{Var}(\tilde{P}'_{it}, \tilde{I}'_{it}) > 0, \quad \text{and} \quad \text{Var}(\tilde{I}'_{it}) > 0. \quad (2)$$

<sup>7</sup>This can be replaced by an arbitrary non-additive function  $P_{it}(\iota) = p(\iota, W_{it}, \varepsilon_{it}^p)$ , where (possibly infinite-dimensional)  $\varepsilon_{it}^p$  is independent of  $I_{it}$  and  $W_{it}$

Our main estimation method is the standard correlated random effects estimator, where the random effects are parameterized as functions of observable characteristic. The state-level random effects are modeled as a function of state level characteristics, and the time random effects are modeled by including a smooth trend and its interaction with state level characteristics. The stochastic shocks  $\{\varepsilon_{it}\}_{t=1}^T$  are treated as independent across states  $i$  and can be arbitrarily dependent across time  $t$  within a state.

A secondary estimation method is the fixed effects estimator, where  $W_{it}$  includes latent (unobserved) state level effects  $W_i$  and and time level effects  $W_t$ , which must be estimated from the data. This approach is much more demanding on the data and relies on long cross-sectional and time histories. When histories are relatively short, large biases emerge and they need to be removed using debiasing methods. In our context debiasing materially change the estimates, often changing the sign.<sup>8</sup> However, we find the debiased fixed effect estimates are qualitatively and quantitatively similar to the correlated random effects estimates. Given this finding, we chose to focus on the latter, as a more standard and familiar method, and report the former estimates in the supplementary materials for this paper.<sup>9</sup>

**2.2. Information Structures and Induced Dynamics.** We consider three examples of information structures:

(I1) Information variable is time trend:

$$I_{it} = \log(t).$$

(I2) Information variable is lagged value of outcome:

$$I_{it} = Y_{i,t-\ell}.$$

(I3) Information variables include trend, lagged and integrated values of outcome:

$$I_{it} = \left( \log(t), Y_{i,t-\ell}, \sum_{m=1}^{\infty} Y_{i,t-\ell m} \right)',$$

with the convention that  $Y_{i,t} = 0$  for  $t \leq 0$ .

The first information structure captures the basic idea that, as individuals discover more information about covid over time, they adapt safer modes of behavior (stay at home, wear masks, wash hands). Under this structure, information is common across states and exogenously evolves over time, independent of the number of cases. The second structure arises for considering autoregressive components and captures people's behavioral response to information on cases in the state they reside. Specifically, we model persistence in growth  $Y_{it}$  rate through AR(1) model, which leads to  $I_{it} = Y_{i,t-7}$ . This provides useful *local*, state-specific, information about the forward growth rate and people may adjust their behavior to safer modes when they see a high value. We model this adjustment via the term  $\gamma' I_t$  in

<sup>8</sup>This is cautionary message for other researchers intending to use fixed effects estimator in the context of Covid-19 analysis. Only debiased fixed effects estimators must be used.

<sup>9</sup>The similarity of the debiased fixed effects and correlated random effects served as a useful specification check. Moreover, using the fixed effects estimators only yielded minor gains in predictive performances, as judging by the adjusted  $R^2$ 's, providing another useful specification check.

the behavior equation. The third information structure is the combination of the first two structures plus an additional term representing the (log of) total number of new cases in the state. We use this information structure in our empirical specification. In this structure people respond to both global information, captured by trend, and local information sources, captured by the local growth rate and the total number of cases. The last element of the information set can be thought of as local stochastic trend in cases.

All of these examples fold into a specification of the form:

$$I_{it} := I_{it}(I_{i(t-\ell)}, Y_{i(t-\ell)}, t), \quad t = 1, \dots, T, \quad (\text{I})$$

with the initialization  $I_{i0} = 0$  and  $Y_{i0} = 0$ .<sup>10</sup>

With any structure of this form, realized outcomes may become new information for future periods, inducing a dynamical system over multiple periods. We show the resulting dynamical system in a causal diagram of Figure 5. Specification of this system is useful for studying delayed effects of policies and behaviors, and in considering the counterfactual policy analysis.

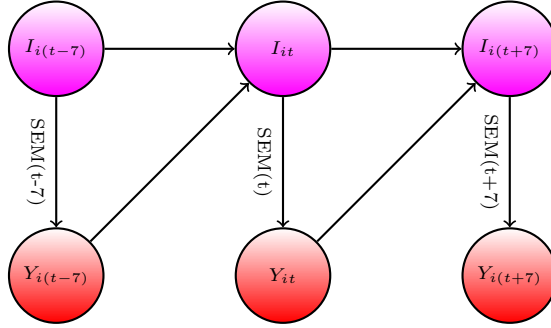


FIGURE 5. Dynamic System Induced by Information Structure and SEM

**2.3. Outcome and Key Confounders via SIR Model.** Letting  $C_{it}$  denotes cumulative number of confirmed cases in state  $i$  at time  $t$ , our outcome

$$Y_{it} := \Delta \log(\Delta C_{it}) := \log(\Delta C_{it}) - \log(\Delta C_{i,t-7}) \quad (\text{3})$$

approximates the weekly growth rate in new cases from  $t - 7$  to  $t$ .<sup>11</sup> Here  $\Delta$  denotes the differencing operator over 7 days from  $t$  to  $t - 7$ , so that  $\Delta C_{it} := C_{it} - C_{i,t-7}$  is the number of new confirmed cases in the past 7 days.

We chose this metric as this is the key metric for policy makers deciding when to relax Covid mitigation policies. The U.S. government’s guidelines for state reopening recommend that states display a “downward trajectory of documented cases within a 14-day period”

<sup>10</sup>The initialization is appropriate in our context for analyzing pandemics from the very beginning, but other initializations could be appropriate in other contexts.

<sup>11</sup>We may show that  $\log(\Delta C_{it}) - \log(\Delta C_{i,t-7})$  approximates the average growth rate of cases from  $t - 7$  to  $t$ .

(White House, 2020). A negative value of  $Y_{it}$  is an indication of meeting this criteria for reopening. By focusing on weekly cases rather than daily cases, we smooth idiosyncratic daily fluctuations as well as periodic fluctuations associated with days of the week.

Our measurement equation for estimating equations (BPI→Y) and (PI→Y) will take the form:

$$Y_{it} = \theta' X_{it} + \delta_T \Delta \log(T)_{it} + \delta_D \frac{T_{it} \Delta D_{it}}{\Delta C_{it}} + \epsilon_{it}, \quad (\text{M})$$

where  $i$  is state,  $t$  is day,  $C_{it}$  is cumulative confirmed cases,  $D_{it}$  is deaths,  $T_{it}$  is the number of tests over 7 days,  $\Delta$  is a 7-days differencing operator,  $\epsilon_{it}$  is an unobserved error term, where  $X_{it}$  collects other behavioral, policy, and confounding variables, depending on whether we estimate (BPI→Y) or (PI→Y). Here

$$\Delta \log(T)_{it} \text{ and } \delta_D \frac{T_{it} \Delta D_{it}}{\Delta C_{it}}$$

are the key confounding variables, derived from considering the SIR model below. We describe other confounders in the empirical section.

Our main estimating equation (M) is motivated by a variant of a SIR model, where we incorporate a delay between infection and death instead of a constant death rate, and we add confirmed cases to the model. Let  $S$ ,  $I$ ,  $\mathcal{R}$ , and  $D$  denote the number of susceptible, infected, recovered, and dead individuals in a given state or province. Each of these variables are a function of time. We model them as evolving as

$$\dot{S}(t) = -\frac{S(t)}{N} \beta(t) I(t) \quad (4)$$

$$\dot{I}(t) = \frac{S(t)}{N} \beta(t) I(t) - \frac{S(t-\ell)}{N} \beta(t-\ell) I(t-\ell) \quad (5)$$

$$\dot{\mathcal{R}}(t) = (1 - \pi) \frac{S(t-\ell)}{N} \beta(t-\ell) I(t-\ell) \quad (6)$$

$$\dot{D}(t) = \pi \frac{S(t-\ell)}{N} \beta(t-\ell) I(t-\ell) \quad (7)$$

where  $N$  is the population,  $\beta(t)$  is the rate of infection spread,  $\ell$  is the duration between infection and death, and  $\pi$  is the probability of death conditional on infection.<sup>12</sup>

Confirmed cases,  $C(t)$ , evolve as

$$\dot{C}(t) = \tau(t) I(t), \quad (8)$$

where  $\tau(t)$  is the rate that infections are detected.

Our goal is to examine how the rate of infection  $\beta(t)$  varies with observed policies and measures of social distancing behavior. A key challenge is that we only observed  $C(t)$  and

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<sup>12</sup>The model can easily be extended to allow a non-deterministic disease duration. This leaves our main estimating equation (9) unchanged, as long as the distribution of duration between infection and death is equal to the distribution of duration between infection and recovery.

$D(t)$ , but not  $I(t)$ . The unobserved  $I(t)$  can be eliminated by differentiating (8) and using (5) and (7) as

$$\frac{\ddot{C}(t)}{\dot{C}(t)} = \frac{S(t)}{N} \beta(t) + \frac{\dot{\tau}(t)}{\tau(t)} - \frac{1}{\pi} \frac{\tau(t) \dot{D}(t)}{\dot{C}(t)}. \quad (9)$$

We consider a discrete-time analogue of equation (9) to motivate our empirical specification by relating the detection rate  $\tau(t)$  to the number of tests  $T_{it}$  while specifying  $\frac{S(t)}{N} \beta(t)$  as a linear function of variables  $X_{it}$ . This results in

$$\underbrace{\frac{Y_{it}}{\dot{C}(t)}} = \underbrace{X'_{it} \theta}_{\frac{S(t)}{N} \beta(t)} + \underbrace{\delta_T \Delta \log(T)_{it}}_{\frac{\dot{\tau}(t)}{\tau(t)}} + \underbrace{\delta_D \frac{T_{it} \Delta D_{it}}{\Delta C_{it}}}_{\frac{1}{\pi} \frac{\tau(t) \dot{D}(t)}{\dot{C}(t)}},$$

which is equation (M), where  $X_{it}$  captures a vector of variables related to  $\beta(t)$ .

**STRUCTURAL INTERPRETATION.** In the early pandemics, when the number of susceptibles is approximately the same as the entire population, i.e.  $S_{it}/N_{it} \approx 1$ , the component  $X'_{it} \theta$  is the projection of infection rate  $\beta_i(t)$  on  $X_{it}$  (policy, behavioral, information, and confounders other than testing rate), provided the stochastic component  $\epsilon_{it}$  is orthogonal to  $X_{it}$  and the testing variables:

$$\beta_i(t) S_{it}/N_{it} = X'_{it} \theta + \epsilon_{it}, \quad \epsilon_{it} \perp X_{it}.$$

### 3. DECOMPOSITION AND COUNTERFACTUAL POLICY ANALYSIS

**3.1. Total Change Decomposition.** Given the SEM formulation above, we can carry out the following decomposition analysis, after removing the effects of confounders. For example, we can decompose the total change  $E\tilde{Y}_{it} - E\tilde{Y}_{io}$  in the expected outcome, measured at two different time points  $t$  and  $o = t - \ell$  into sum of three components:

$$\begin{aligned} \underbrace{E\tilde{Y}_{it} - E\tilde{Y}_{io}}_{\text{Total Change}} &= \underbrace{\alpha' \beta' (E\tilde{P}_{it} - E\tilde{P}_{io})}_{\text{Policy Effect via Behavior}} \\ &+ \underbrace{\pi' (E\tilde{P}_{it} - E\tilde{P}_{io})}_{\text{Direct Policy Effect}} \\ &+ \underbrace{\alpha' \gamma' (E\tilde{I}_{it} - E\tilde{I}_{io}) + \mu' (E\tilde{I}_{it} - E\tilde{I}_{io})}_{\text{Dynamic Effect}} \\ &=: \text{PEB}_t + \text{PED}_t + \text{DynE}_t, \end{aligned} \quad (10)$$

where the first two components are immediate effect and the third is delayed or dynamic effect.

In the three examples of information structure given earlier, we have the following form for the dynamic effect:

$$(I1) \quad \text{DynE}_t = \gamma\alpha \log \ell + \mu \log \ell,$$

$$(I2) \quad \text{DynE}_t = \sum_{m=1}^{t/\ell} (\gamma\alpha + \mu)^m (\text{PEB}_{t-m\ell} + \text{PED}_{t-m\ell}),$$

$$(I3) \quad \begin{aligned} \text{DynE}_t &= \sum_{m=0}^{t/\ell} ((\gamma\alpha)_2 + \mu_2 + (\gamma\alpha)_3 + \mu_3)^m ((\gamma\alpha)_1 \log \ell + \mu_1 \log \ell) \\ &+ \sum_{m=1}^{t/\ell} ((\gamma\alpha)_2 + \mu_2 + (\gamma\alpha)_3 + \mu_3)^m (\text{PEB}_{t-m\ell} + \text{DPE}_{t-m\ell}) \\ &+ \sum_{m=1}^{t/\ell-1} ((\gamma\alpha)_3 + \mu_3)^m (\text{PEB}_{t-(m+1)\ell} + \text{DPE}_{t-(m+1)\ell}). \end{aligned}$$

The effects can be decomposed into (a) delayed policy effects via behavior by summing terms containing  $PEB$ , (b) delayed policy effects via direct impact by summing terms containing  $DPE$ , and (c) pure behavior effects, and (d) pure dynamic feedback effects.

**3.2. Counterfactuals.** We also consider simple counterfactual exercises, where we examine the effects of setting a sequence of counterfactual policies for each state:

$$\{P_{it}^*\}_{t=1}^T, \quad i = 1, \dots, N.$$

We assume that the SEM remains invariant, except of course for the policy equation.<sup>13</sup> Given the policies we propagate the dynamic equations:

$$\begin{aligned} Y_{it}^* &:= Y_{it}(B_{it}^*, P_{it}^*, I_{it}^*), \\ B_{it}^* &:= B_{it}(P_{it}^*, I_{it}^*), \\ I_{it}^* &:= I_{it}(I_{i(t-1)}^*, Y_{i(t-1)}^*, t), \end{aligned} \quad (\text{CEF-SEM})$$

with the initialization  $I_{i0}^* = 0$ ,  $Y_{i0}^* = 0$ ,  $B_{i0}^* = 0$ ,  $P_{i0}^* = 0$ . In stating this counterfactual system of equations, we make the following invariance assumption

**INVARIANCE ASSUMPTION.** The equations of (CF-SEM) remain exactly of the same form as in the (SEM) and (I). That is, under the policy intervention  $\{P_{it}^*\}$ , that is, parameters and stochastic shocks in (SEM) and (I) remain the same as under the original policy intervention  $\{P_{it}\}$ .

Let  $\mathcal{P}Y_{it}^*$  and  $\mathcal{P}Y_{it}$  denote the predicted values, produced by working with the counterfactual system (CEF-SEM) and the factual system (SEM):

$$\begin{aligned} \mathcal{P}Y_{it}^* &= (\alpha'\beta' + \pi')P_{it}^* + (\alpha'\gamma' + \mu')I_{it}^* + \bar{\delta}'W_{it}, \\ \mathcal{P}Y_{it} &= (\alpha'\beta' + \pi')P_{it} + (\alpha'\gamma' + \mu')I_{it} + \bar{\delta}'W_{it}. \end{aligned}$$

In generating these predictions we make the assumption of invariance stated above.

<sup>13</sup>It is possible to consider counterfactual exercises in which policy responds to information through the policy equation if we are interested in endogenous policy responses to information. Although this is beyond the scope of the current paper, counterfactual experiments with endogenous government policy would be important, for example, to understand the issues related to the lagged response of government policies to higher infection rates due to incomplete information.

Then we can write the difference into the sum of three components:

$$\begin{aligned}
\underbrace{\mathcal{P}Y_{it}^* - \mathcal{P}Y_{it}}_{\text{Predicted CF Change}} &= \underbrace{\alpha' \beta' (P_{it}^* - P_{it})}_{\text{CF Policy Effect via Behavior}} \\
&+ \underbrace{\pi' (P_{it}^* - P_{it})}_{\text{CF Direct Effect}} \\
&+ \underbrace{\alpha' \gamma' (I_{it}^* - I_{it}) + \mu' (I_{it}^* - I_{it})}_{\text{CF Dynamic Effect}} \\
&=: \text{PEB}_{it}^* + \text{PED}_{it}^* + \text{DynE}_{it}^*.
\end{aligned} \tag{11}$$

Similarly to what we had before, the counterfactual dynamic effects take the form:

$$(I1) \quad \text{DynE}_{it}^* = \gamma \alpha \log \ell + \mu \log \ell,$$

$$(I2) \quad \text{DynE}_{it}^* = \sum_{m=1}^{t/\ell} (\gamma \alpha + \mu)^m (\text{PEB}_{i(t-m)\ell}^* + \text{PED}_{i(t-m)\ell}^*),$$

$$\begin{aligned}
(I3) \quad \text{DynE}_{it}^* &= \sum_{m=0}^{t/\ell} ((\gamma \alpha)_2 + \mu_2 + (\gamma \alpha)_3 + \mu_3)^m ((\gamma \alpha)_1 \log \ell + \mu_1 \log \ell) \\
&+ \sum_{m=1}^{t/\ell} ((\gamma \alpha)_2 + \mu_2 + (\gamma \alpha)_3 + \mu_3)^m \left( \text{PEB}_{i(t-m)\ell}^* + \text{DPE}_{i(t-m)\ell}^* \right) \\
&+ \sum_{m=1}^{t/\ell-1} ((\gamma \alpha)_3 + \mu_3)^m \left( \text{PEB}_{i(t-(m+1)\ell}^* + \text{DPE}_{i(t-(m+1)\ell}^* \right).
\end{aligned}$$

The effects can be decomposed into (a) delayed policy effects via behavior by summing terms containing *PEB*, (b) delayed policy effects via direct impact by summing terms containing *DPE*, and (c) pure behavior effects, and (d) pure dynamic feedback effects.

#### 4. EMPIRICAL ANALYSIS

**4.1. Data.** Our baseline measures for daily Covid-19 cases and deaths are from The New York Times (NYT). When there are missing values in NYT, we use reported cases and deaths from JHU CSSE, and then the Covid Tracking Project. The number of tests for each state is from Covid Tracking Project. As shown in Figure 23 in the appendix, there was a rapid increase in testing in the second half of March and then the number of tests increased very slowly in each state in April.

We use the database on US state policies created by Raifman et al. (2020). In our analysis, we focus on 7 policies: state of emergency, stay at home, closed nonessential businesses, closed K-12 schools, closed restaurants except takeout, close movie theaters, and mandate face mask by employees in public facing businesses. We believe that the first five of these policies are the most widespread and important. Closed movie theaters is included because it captures common bans on gatherings of more than a handful of people. We also include mandatory face mask use by employees because its effectiveness on slowing down Covid-19 spread is a controversial policy issue (Howard et al., 2020; Greenhalgh et al., 2020). Table 1 provides summary statistics, where  $N$  is the number of states that have ever implemented the policy. We also obtain information on state-level covariates from Raifman



et al. (2020), which include population size, total area, unemployment rate, poverty rate, and a percentage of people who are subject to illness.

	N	Min	Median	Max
State of emergency	51	2020-02-29	2020-03-11	2020-03-16
Date closed K 12 schools	51	2020-03-13	2020-03-17	2020-04-03
Stay at home shelter in place	42	2020-03-19	2020-03-28	2020-04-07
Closed movie theaters	49	2020-03-16	2020-03-21	2020-04-06
Closed restaurants except take out	48	2020-03-15	2020-03-17	2020-04-03
Closed non essential businesses	43	2020-03-19	2020-03-25	2020-04-06
Mandate face mask use by employees	36	2020-04-03	2020-05-01	2020-05-11

TABLE 1. State Policies

We obtain social distancing behavior measures from “Google COVID-19 Community Mobility Reports” (LLC, 2020). The dataset provides six measures of “mobility trends” that report a percentage change in visits and length of stay at different places relative to a baseline computed by their median values of the same day of the week from January 3 to February 6, 2020. Our analysis focuses on the following four measures: “Grocery & pharmacy,” “Transit stations,” “Retail & recreation,” and “Workplaces.”<sup>14</sup>

In our empirical analysis, we use weekly measures for cases, deaths, and tests by summing up their daily measures from day  $t$  to  $t - 6$ . We focus on weekly cases because daily new cases are affected by the timing of reporting and testing, and are quite volatile as shown in Figure 20 in the appendix. Similarly, reported daily deaths and tests are subject to high volatility. Aggregating to weekly new cases/deaths/tests smooths out idiosyncratic daily noises as well as periodic fluctuations associated with days of the week. We also construct weekly policy and behavior variables by taking 7 day moving averages from day  $t - 14$  to  $t - 21$ , where the delay reflects the time lag between infection and case confirmation. The four weekly behavior variables are referred as “Transit Intensity,” “Workplace Intensity,” “Retail Intensity,” and “Grocery Intensity.” Consequently, our empirical analysis uses 7 days moving averages of all variables recorded at daily frequencies.

Table 2 reports that weekly policy and behavior variables are highly correlated with each other, except for the “masks for employees” policy. High correlations may cause multicollinearity problem and potentially limits our ability to separately identify the effect of each policy or behavior variable on case growth but this does not prevent us from identifying the aggregate effect of all policies and behavior variables on case growth.

**4.2. The Effect of Policies and Information on Behavior.** We first examine how policies and information affect social distancing behaviors by estimating a version of (PI→B):

$$B_{it}^j = (\beta^j)' P_{it} + (\gamma^j)' I_{it} + (\delta_B^j)' W_{it} + \varepsilon_{it}^{bj}$$

<sup>14</sup>The other two measures are “Residential” and “Parks.” We drop “Residential” because it is highly correlated with “Workplaces” and “Retail & recreation” at correlation coefficients of -0.99 and -0.98 as shown in Table 2. We also drop “Parks” because it does not have clear implication on the spread of Covid-19.

TABLE 2. Correlations among Policies and Behavior

	residential	transit	workplaces	retail	grocery	closed K-12 schools	stay at home	closed movie theaters	closed restaurants	closed businesses	masks for employees	state of emergency
residential	1.00											
transit	-0.95	1.00										
workplaces	-0.99	0.93	1.00									
retail	-0.98	0.93	0.96	1.00								
grocery	-0.81	0.83	0.78	0.82	1.00							
closed K-12 schools	0.90	-0.80	-0.93	-0.87	-0.65	1.00						
stay at home	0.73	-0.75	-0.74	-0.70	-0.72	0.70	1.00					
closed movie theaters	0.83	-0.76	-0.85	-0.81	-0.69	0.88	0.78	1.00				
closed restaurants	0.85	-0.79	-0.85	-0.84	-0.70	0.84	0.74	0.88	1.00			
closed businesses	0.73	-0.70	-0.73	-0.71	-0.70	0.66	0.80	0.75	0.75	1.00		
masks for employees	0.29	-0.32	-0.31	-0.24	-0.22	0.41	0.36	0.39	0.32	0.21	1.00	
state of emergency	0.84	-0.75	-0.85	-0.82	-0.45	0.92	0.63	0.81	0.79	0.60	0.37	1.00

Each off-diagonal entry reports a correlation coefficient of a pair of policy and behavior variables.

where  $B_{it}^j$  represents behavior variable  $j$  in state  $i$  at  $t - 14$ .  $P_{it}$  collects the Covid related policies in state  $i$  at  $t - 14$ . Confounders,  $W_{it}$ , include state-level covariates, the growth rate of tests, the past number of tests, and one week lagged dependent variable which may capture unobserved differences in policies across states.

$I_{it}$  is a set of information variables that affect people's behaviors at  $t - 14$ . Here, and throughout our empirical analysis, we focus on two specifications for information. In the first, we assume that information is captured by a trend and a trend interacted with state-level covariates, which is a version of information structure (I1). We think of this trend as summarizing national aggregate information on Covid-19. The second information specification is based on information structure (I3), where we additionally allow information to vary with each state's lagged growth of new cases,  $\text{lag}(\Delta \log \Delta C, 7)$ , and lagged log new cases,  $\text{lag}(\log \Delta C, 14)$ .

Table 3 reports the estimates. Across different specifications, our results imply that policies have large effects on behavior. School closures appear to have the largest effect, followed by restaurant closures. Somewhat surprisingly, stay at home and closure of non essential businesses appear to have modest effects on behavior. The effect of masks for employees is also small. However, these results should be interpreted with caution. Differences between policy effects are generally statistically insignificant; except for masks for employees, the policies are highly correlated and it is difficult to separate their effects.

TABLE 3. The Effect of Policies and Information on Behavior ( $PI \rightarrow B$ )

	<i>Dependent variable:</i>							
	Trend Information				Lag Cases Information			
	workplaces	retail	grocery	transit	workplaces	retail	grocery	transit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
masks for employees	1.149 (1.100)	-0.613 (1.904)	-0.037 (1.442)	0.920 (2.695)	0.334 (1.053)	-1.038 (1.786)	-0.953 (1.357)	1.243 (2.539)
closed K-12 schools	-14.443*** (3.748)	-16.428*** (5.323)	-14.201*** (3.314)	-16.937*** (5.843)	-11.595*** (3.241)	-13.650*** (4.742)	-12.389*** (3.190)	-15.622*** (6.046)
stay at home	-3.989*** (1.282)	-5.894*** (1.448)	-7.558*** (1.710)	-10.513*** (2.957)	-3.725*** (1.302)	-5.542*** (1.399)	-7.120*** (1.680)	-9.931*** (2.970)
closed movie theaters	-2.607* (1.460)	-6.240*** (1.581)	-3.260** (1.515)	0.600 (2.906)	-1.648 (1.369)	-5.224*** (1.466)	-2.721* (1.436)	1.208 (2.845)
closed restaurants	-2.621* (1.389)	-4.746*** (1.612)	-2.487** (1.090)	-6.277* (3.278)	-2.206* (1.171)	-4.325*** (1.385)	-2.168** (0.957)	-5.996* (3.171)
closed businesses	-4.469*** (1.284)	-4.299*** (1.428)	-4.358*** (1.352)	-3.593 (2.298)	-2.512* (1.297)	-2.217 (1.577)	-2.570* (1.415)	-1.804 (2.558)
$\Delta \log T_{st}$	1.435*** (0.230)	1.420*** (0.340)	1.443*** (0.399)	1.547*** (0.422)	1.060*** (0.203)	1.193*** (0.322)	0.817** (0.370)	1.451*** (0.434)
lag(tests per 1000, 7)	0.088 (0.178)	0.042 (0.367)	0.025 (0.202)	-0.703* (0.371)	0.497*** (0.176)	0.563* (0.292)	0.242 (0.198)	-0.217 (0.333)
log(days since 2020-01-15)	-7.589 (25.758)	38.828 (32.010)	2.777 (27.302)	27.182 (26.552)	-14.697 (20.427)	26.449 (30.218)	6.197 (25.691)	15.213 (27.375)
lag( $\Delta \log \Delta C_{st}$ , 7)					-1.949*** (0.527)	-2.024* (1.035)	-0.315 (0.691)	-0.526 (1.481)
lag(log $\Delta C_{st}$ , 14)					-2.398*** (0.416)	-2.390*** (0.786)	-1.898*** (0.596)	-1.532 (1.127)
$\frac{\Delta D}{\Delta C} T_{st}$					-1.362 (2.074)	-4.006 (3.061)	1.046 (1.685)	-6.424* (3.793)
log t $\times$ state variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
state variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\sum_j \text{Policy}_j$	-26.98 (3.91)	-38.22 (5.58)	-31.90 (4.04)	-35.80 (5.92)	-21.35 (3.60)	-32.00 (5.42)	-27.92 (4.37)	-30.90 (6.77)
Observations	3,009	3,009	3,009	3,009	3,009	3,009	3,009	3,009
R <sup>2</sup>	0.750	0.678	0.676	0.717	0.798	0.710	0.704	0.728
Adjusted R <sup>2</sup>	0.749	0.676	0.674	0.715	0.796	0.708	0.702	0.726

Yeste:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Dependent variables are “Transit Intensity,” “Workplace Intensity,” “Retail Intensity,” and “Grocery Intensity” defined as 7 days moving averages of corresponding daily measures obtained from Google Mobility Reports. Columns (1)-(4) use specifications with the information structure (I1) while columns (5)-(8) use those with the information structure (I3). All specifications include state-level characteristics (population, area, unemployment rate, poverty rate, and a percentage of people subject to illness) as well as their interactions with the log of days since Jan 15, 2020. The row “ $\sum_j \text{Policy}_j$ ” reports the sum of six policy coefficients.

In columns (1)-(4), the estimated sum effect of all policies are substantial and can account for a large fraction of observed declines in behavior variables. For example, retail intensity was approximately -40% at its lowest point in mid April, and the estimated policy coefficients imply that imposing all six policies would lead to  $38.2/40 \approx 95\%$  of the observed decline.

Columns (5)-(8) reports the estimated coefficients for the model with lagged dependent variables. Except for transit, the estimated coefficients of lagged growth of new cases and lagged new cases are negative and often significant at conventional levels. This suggests that both the growth and the number of past cases reduce social interactions, perhaps because people are increasingly aware of prevalence of Covid-19 (Maloney and Taskin, 2020).

The estimated aggregate effects of policies in columns (5)-(8) are largely consistent with those reported in columns (1)-(4). The policy coefficients in columns (5)-(8) are generally 15-20% smaller in magnitude than in columns (1)-(4). It may be that the simple trend in columns (1)-(4) does not capture information as well as the lagged growth and cases used a information variables in columns (5)-(8).

**4.3. The Direct Effect of Policies and Behavior on Case Growth.** We now analyze how behavior and policies together influence case growth rates by estimating equation (BPI $\rightarrow$ Y).

$$Y_{it} = \alpha' B_{it} + \pi' P_{it} + \mu' I_{it} + \underbrace{\delta_Y' W_{it}}_{\delta_X' W_{X,it} + \delta_T \Delta \log(T)_{it} + \delta_D \frac{T_{it} \Delta D_{it}}{\Delta C_{it}}} + \varepsilon_{it}^y, \quad (12)$$

where  $B_{it} = (B_{it}^1, \dots, B_{it}^4)'$  is a vector of four behavior variables in state  $i$  at  $t - 14$ , where a lag length of 14 days is chosen to reflect the delay between infection and confirmation.<sup>15</sup>  $P_{it}$  includes the Covid related policies in state  $i$  at  $t - 14$  that directly affect the spread of Covid-19 after controlling for behavior variables (e.g., masks for employees). We include information variables,  $I_{it}$ , as covariates because some information variables such as the past confirmed cases may be correlated with (latent) government policies or people's behaviors that are not fully captured by our observed policy and behavior variables.  $W_{X,it}$  consists of state-level covariates. As discussed in section 2.3, equation (12) corresponds to (M) derived from the SIR model, and the terms  $\delta_T \Delta \log(T)_{it}$  and  $\delta_D \frac{T_{it} \Delta D_{it}}{\Delta C_{it}}$  capture the effect of changing test rates on confirmed cases.

Table 4 shows the results of estimating (12). In columns (1) and (3), we use “state of emergency” policy as a proxy for all other policies because a “state of emergency” order can be viewed as preparation for implementing a variety of policies subsequently. The results indicate that mandatory face masks reduce infections while holding behavior constant, suggesting that requiring masks may be an effective preventive measure. Except for mask requirements, policies appear to have little direct effect on confirmed case growth when behavior is held constant. This supports a directed causal model where causality flows from policies to behavior to infections.

<sup>15</sup>As we review in the Appendix A.6, a lag length of 14 days is broadly consistent with currently available evidence.

TABLE 4. The Direct Effect of Behavior and Policies on Case Growth ( $PBI \rightarrow Y$ )

	<i>Dependent variable:</i>			
	Trend Information		Lag Cases Information	
	(1)	(2)	(3)	(4)
lag(state of emergency, 14)	-0.502*** (0.141)		-0.342** (0.137)	
lag(masks for employees, 14)	-0.072 (0.050)	-0.039 (0.055)	-0.104** (0.045)	-0.092* (0.048)
lag(closed K-12 schools, 14)		-0.132 (0.116)		-0.130 (0.115)
lag(stay at home, 14)		-0.028 (0.068)		-0.054 (0.077)
lag(closed movie theaters, 14)		0.144** (0.056)		0.132** (0.061)
lag(closed restaurants, 14)		-0.035 (0.060)		-0.077 (0.079)
lag(closed businesses, 14)		-0.022 (0.049)		0.008 (0.057)
lag(workplaces, 14)	0.011* (0.006)	0.010 (0.007)	0.004 (0.008)	0.001 (0.009)
lag(retail, 14)	0.006 (0.004)	0.014*** (0.005)	0.002 (0.005)	0.006 (0.006)
lag(grocery, 14)	0.002 (0.003)	-0.007** (0.003)	0.007** (0.003)	0.002 (0.003)
lag(transit, 14)	0.002 (0.003)	0.002 (0.003)	0.004 (0.004)	0.005 (0.004)
$\Delta \log T_{st}$	0.106*** (0.020)	0.115*** (0.022)	0.120*** (0.019)	0.121*** (0.019)
lag(tests per 1000, 7)	-0.007 (0.006)	-0.004 (0.006)	0.025*** (0.009)	0.029*** (0.009)
log(days since 2020-01-15)	4.691*** (1.562)	3.779** (1.504)	3.170** (1.268)	2.519* (1.379)
lag( $\Delta \log \Delta C_{st}$ , 7)			-0.139*** (0.049)	-0.140*** (0.049)
lag(log $\Delta C_{st}$ , 14)			-0.132*** (0.043)	-0.149*** (0.042)
$\frac{\Delta D}{\Delta C} T_{st}$			-0.267*** (0.103)	-0.247*** (0.094)
log t $\times$ state variables	Yes	Yes	Yes	Yes
state variables	Yes	Yes	Yes	Yes
$\sum$ policies except masks		-0.07 (0.17)		-0.12 (0.18)
$\sum w_k \text{behavior}_k$		-1.05 (0.15)		-0.54 (0.19)
Observations	3,403	3,403	3,403	3,403
R <sup>2</sup>	0.771	0.765	0.793	0.791
Adjusted R <sup>2</sup>	0.769	0.763	0.791	0.790

Yeste:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Dependent variable is the weekly growth rate of confirmed cases as defined in equation (3). The covariates include 14 days lagged policy and behavior variables, which are constructed as 7 days moving averages between  $t - 14$  to  $t - 21$  of corresponding daily measures. Columns (1)-(2) use specifications with the information structure (I1) while columns (3)-(4) use those with the information structure (I3). All specifications include state-level characteristics (population, area, unemployment rate, poverty rate, and a percentage of people subject to illness) and their interactions with the log of days since Jan 15, 2020. The row " $\sum$  policies except for masks" reports the sum of five policy coefficients except for "masks for employees" while the row " $\sum_k w_k \text{behavior}_k$ " reports the sum of four coefficients of behavior variables weighted by the average of each behavioral variable from April 1st-10th.

TABLE 5. Immediate Effects

	Trend Information	Lag Cases Information
masks	-0.04 (0.06)	-0.09 (0.05)
$\sum$ policies except masks	-0.07 (0.17)	-0.12 (0.18)
$\sum w_k \text{behavior}_k$	-1.05 (0.15)	-0.54 (0.19)

The reported numbers are from columns (2) and (4) of Table 4. The row “masks” reports the estimated coefficients of “masks for employees” on weekly case growth. The row “ $\sum$  policies except for masks” reports the sum of five policy coefficients except for “masks for employees” while the row “ $\sum_k w_k \text{behavior}_k$ ” reports the sum of four coefficients of behavior variables weighted by the average of each behavioral variable from April 1st-10th.

A useful practical implication of these results are that Google Mobility Reports and similar data might be useful as a leading indicator of potential case growth. This should be done cautiously, however, because other changes in the environment might alter the relationship between behavior and infections. Preventative measures, including mandatory face masks, and changes in habit that are not captured in our data might alter the future relationship between Google Mobility Reports and case growth.

Table 5 reports the sum of short run policy and behavior effects. Policy effects are simply the sum of coefficients. The behavior effect is the sum of coefficients weighted by the average of the behavioral variables from April 1st-10th.

In the trend information model, the short run and long run effects coincide, abstracting from any feedback mechanism. On the other hand, if policies are enacted and behavior changes, then future cases and information will change. The lag cases information model based on information structure (I3) can capture such feedback effects. However, since the lag cases information model includes lags of both case growth and log cases, computing a long-run effect is not completely straightforward. We investigate dynamic effects that incorporate feedback mechanism through a change in information in section 5.

In this section, we focus our analysis of policy effects when we hold information constant. The estimates of the effect of policy on behavior in table 4 and of the effect of policies and behavior and case growth in table 3 can be combined to calculate the total effect of policy as well as its decomposition into the direct and the indirect effects.

Table 7 show the direct (holding behavior constant) and indirect (through behavior changes) effects of policy on case growth for the lag cases information model, where the standard errors are computed by bootstrap and clustered on state. The estimates imply that all policies combined would reduce the growth rate of cases by 0.451, out of which 0.21 is attributable to direct effect while 0.20 is attributable to indirect effect through their impact on behavior, although we need to interpret these numbers carefully given that information is held constant. The estimate also indicates that the effect of “masks for employees” policy is mostly direct.

TABLE 6. The Total Effect of Policies on Case Growth ( $PI \rightarrow Y$ )

	<i>Dependent variable:</i>			
	Trend Information		Lag Cases Information	
	(1)	(2)	(3)	(4)
lag(state of emergency, 14)	-0.998*** (0.145)		-0.395*** (0.150)	
lag(masks for employees, 14)	-0.076 (0.095)	-0.118* (0.067)	-0.065 (0.063)	-0.174** (0.071)
lag(closed K-12 schools, 14)		-0.842*** (0.141)		-0.516*** (0.123)
lag(stay at home, 14)		-0.164** (0.067)		-0.196** (0.076)
lag(closed movie theaters, 14)		0.042 (0.074)		0.060 (0.071)
lag(closed restaurants, 14)		-0.190** (0.082)		-0.155** (0.077)
lag(closed businesses, 14)		-0.090* (0.049)		-0.028 (0.058)
$\Delta \log T_{st}$	0.218*** (0.029)	0.189*** (0.024)	0.191*** (0.023)	0.166*** (0.022)
lag(tests per 1000, 7)	-0.016 (0.011)	-0.004 (0.007)	0.028*** (0.009)	0.029*** (0.008)
log(days since 2020-01-15)	3.975* (2.283)	3.277 (2.149)	1.973 (1.594)	2.020 (1.652)
lag( $\Delta \log \Delta C_{st}$ , 7)			-0.012 (0.061)	-0.085* (0.048)
lag(log $\Delta C_{st}$ , 14)			-0.146*** (0.042)	-0.154*** (0.036)
$\frac{\Delta D}{\Delta C} T_{st}$			-0.448*** (0.112)	-0.344*** (0.087)
log t $\times$ state variables	Yes	Yes	Yes	Yes
state variables	Yes	Yes	Yes	Yes
$\sum_j \text{Policy}_j$		-1.36 (0.18)		-1.01 (0.20)
Observations	3,433	3,433	3,427	3,427
R <sup>2</sup>	0.666	0.707	0.730	0.757
Adjusted R <sup>2</sup>	0.665	0.705	0.729	0.755

Yeste:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Dependent variable is the weekly growth rate of confirmed cases as defined in equation (3). The covariates include 14 days lagged policy variables, which are constructed as 7 days moving averages between  $t - 14$  to  $t - 21$  of corresponding daily measures. Columns (1)-(2) use specifications with the information structure (I1) while columns (3)-(4) use those with the information structure (I3). All specifications include state-level characteristics (population, area, unemployment rate, poverty rate, and a percentage of people subject to illness) and their interactions with the log of days. The row " $\sum_j \text{Policy}_j$ " reports the sum of six policy coefficients.

**4.4. The Total Effect of Policies on Case Growth.** We can also examine the total effect of policies and information on case growth, by estimating ( $PI \rightarrow Y$ ). The coefficients on policy in this regression combine both the direct and indirect effects. As show in the final two columns of table 7, the policy effects from estimating ( $PI \rightarrow Y$ ) are about twice as large as the policy effect from combining ( $BPI \rightarrow Y$ ) and ( $PI \rightarrow B$ ).

TABLE 7. Direct and Indirect Policy Effects: Lag Cases Information Model

	Direct	Via-behavior	Total	PI→Y Coefficient	Difference
masks for employees	-0.09 (0.06)	-0.00 (0.03)	-0.09 (0.06)	-0.17 (0.09)	0.08 (0.07)
closed K-12 schools	-0.13 (0.13)	-0.19 (0.09)	-0.32 (0.14)	-0.52 (0.14)	0.19 (0.07)
stay at home	-0.05 (0.09)	-0.10 (0.05)	-0.15 (0.09)	-0.20 (0.09)	0.04 (0.05)
closed movie theaters	0.13 (0.07)	-0.03 (0.04)	0.10 (0.08)	0.06 (0.08)	0.04 (0.04)
closed restaurants	-0.08 (0.10)	-0.06 (0.04)	-0.14 (0.09)	-0.15 (0.09)	0.02 (0.04)
closed businesses	0.01 (0.07)	-0.03 (0.03)	-0.02 (0.07)	-0.03 (0.07)	0.01 (0.02)
all	-0.21 (0.22)	-0.42 (0.18)	-0.63 (0.20)	-1.01 (0.23)	0.38 (0.18)

Direct effects capture the effect of policy on case growth holding behavior, information, and confounders constant. Direct effects are given by  $\pi$  in equation (BPI→Y). Indirect effects capture how policy changes behavior and behavior shift case growth. They are given by  $\alpha$  from (BPI→Y) times  $\beta$  from (PI→B). The total effect is  $\pi + \beta\alpha$ . Column “PI→Y Coefficients” shows the coefficient estimates from PI→Y. Column “Difference” are the differences between the estimates from (PI→Y) and the combination of (BPI→Y) and (PI→B). Standard errors are computed by bootstrap and clustered on state.

Table 6 shows the full set of coefficient estimates for (PI→Y). The results are broadly consistent with what we found above. As in tables 3 and 7, school closures appear to have the largest effect on growth rates, followed by restaurant closures. However, as mentioned previously, the policies are highly correlated, so it is difficult to separately identify their impacts except mask mandates. The coefficient of mandatory face masks is estimated at -0.174 and significant at 5 percent level.

As reported in column “PI→Y Coefficient” of Table 7, the estimates imply that all policies combined would reduce  $\Delta \log \Delta C$  by 0.101 for the lag information model. For comparison, the daily average of  $\Delta \log \Delta C$  reached its peak in mid-March of about three. Since then it has declined to near 0. This peak of 3 is arguably somewhat overstated because there was also a rapid increase in testing at that time. If we adjust  $\Delta \log \Delta C$  for increasing in testing by subtracting  $0.166\Delta \log T$ , its peak is around 2. Thus, the estimate of -0.101 roughly imply that policy changes can account for one half of the observed decrease in case growth. The remainder of the decline is likely due to changes in behavior from information.



## 5. EMPIRICAL EVALUATION OF COUNTERFACTUAL POLICIES

We now turn our focus to the specification with information as lagged dependent information. This allows dynamic feedback effects. Policy and behavior changes that reduce case growth today can lead to a more optimistic outlook in the future, attenuating longer run effects. To simplify and focus on dynamics, in this section we work with the estimates of the total policy effects (equation PI $\rightarrow$ Y and table 6), rather than decomposing into direct and via-behavior effects.

**5.1. Removing Policies.** We first consider the impact of changing from the observed policies to none. For illustrative purpose, we begin by focusing on Washington. Figure 6 shows the observed, estimated average, and counterfactual without policies average of  $\Delta \log \Delta C$  in Washington. To compute the estimated and counterfactual paths we use the estimates from column 2 of table 6. We set initial  $\Delta \log \Delta C$  and  $\log \Delta C$  to their values first observed in the state we are simulating. We hold all other regressors at their observed values. Error terms are drawn with replacement from the residuals. We do this many times and report the average over draws of the residuals. To calculate confidence intervals, we repeat the above with coefficients drawn randomly from their asymptotic distribution. The shaded region is a point-wise 90% confidence interval. We can see that fit of the estimated and observed  $\Delta \log \Delta C$  is quite good.

Figure 6 shows the change in case growth from removing policies. Since there is a two week lag between policy implementation and their effect on recorded cases, the counterfactual without policy average begins differing from the average with policies two weeks after each policy was implemented. The effect of removing policies on case growth peaks at about 0.75 and then slowly declines. This decline is due to a feedback effect of information. Without policies, cases grow more rapidly. With more dire case numbers, people adjust their behavior to reduce infection. This somewhat offsets the increase in infection from removing policies. Given the delay between infection and reported case numbers, this offsetting effect takes some time to appear.

Even small differences in case growth can lead to very large differences in case numbers. Removing policies in Washington increases case growth from around 0 to above 0.5 throughout most of April. Figure 7 shows that this increase in growth implies a tremendous increase in cases.

The effect of removing cases in other states is broadly similar to that in Washington. Figures 8 and 9 show the changes in growth rate and cases from removing policy interventions in Illinois and Massachusetts.

Figure 10 shows the average across states of the change in case growth. Similar to what we saw in Washington, removing policies leads to an increase of about 0.6 in case growth throughout April. This increase in growth implies a very large increase in cases by

FIGURE 6. Case growth with and without policies in Washington

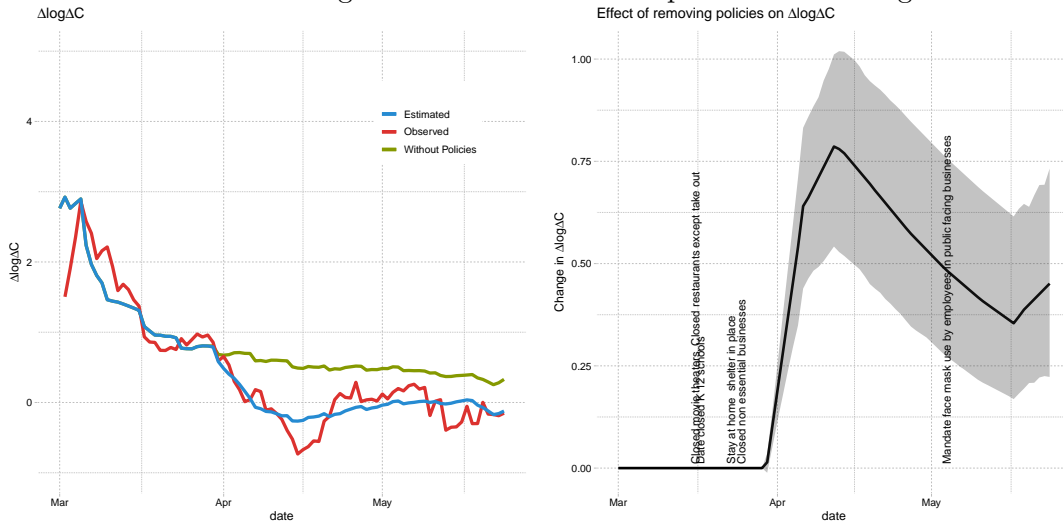
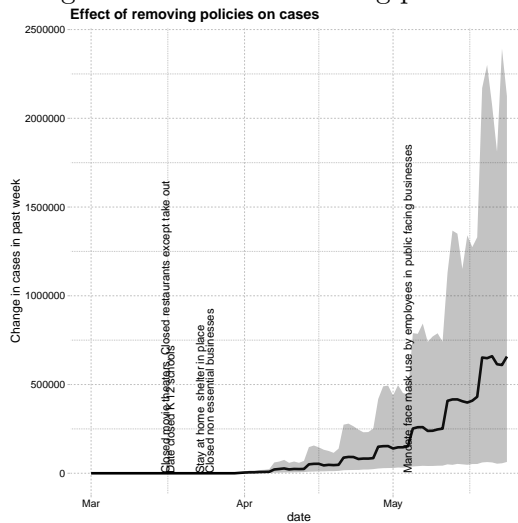


FIGURE 7. Change in cases from removing policies in Washington



late May.<sup>16</sup> Figure 11 displays the national increase in aggregate cases without any policy intervention. The estimates imply 10 to 100 million additional cases by late-May, or a 30-200 fold increase.

<sup>16</sup>This estimate should be interpreted somewhat cautiously because it involves some extrapolation. The information variables, in particular  $\log C$ , soon reach levels not seen in the data.

FIGURE 8. Effect of removing policies in Illinois

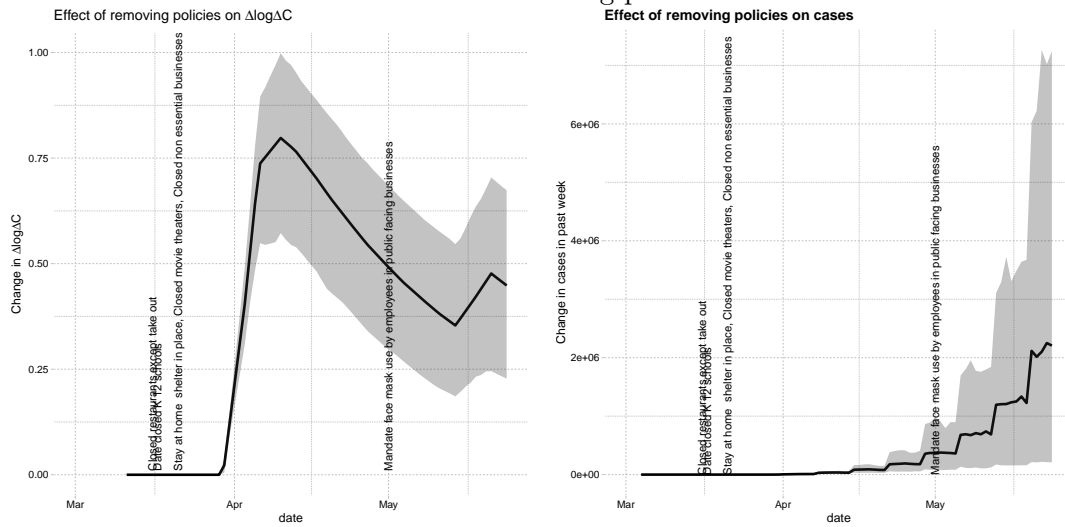


FIGURE 9. Effect of removing policies in Massachusetts

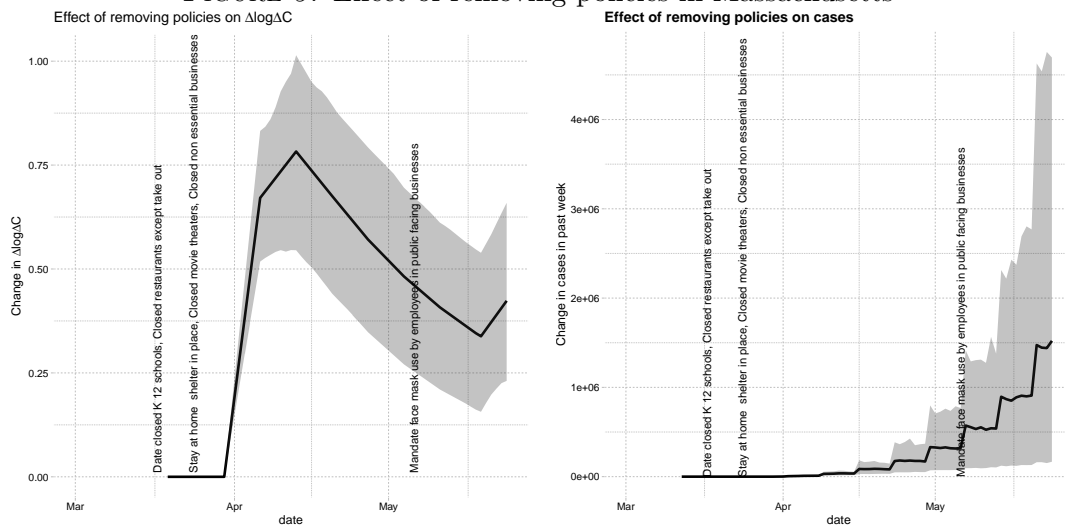


FIGURE 10. Average change in case growth from removing policies

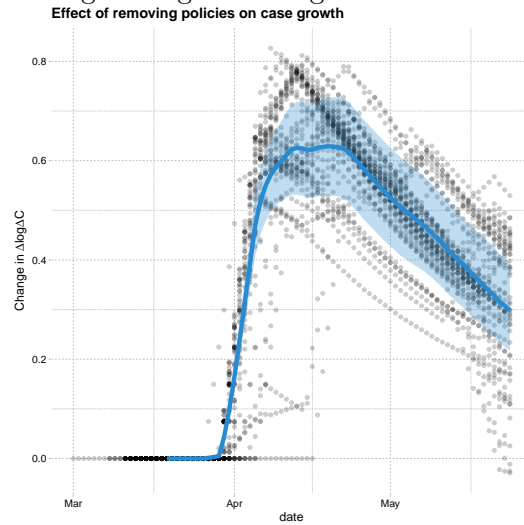
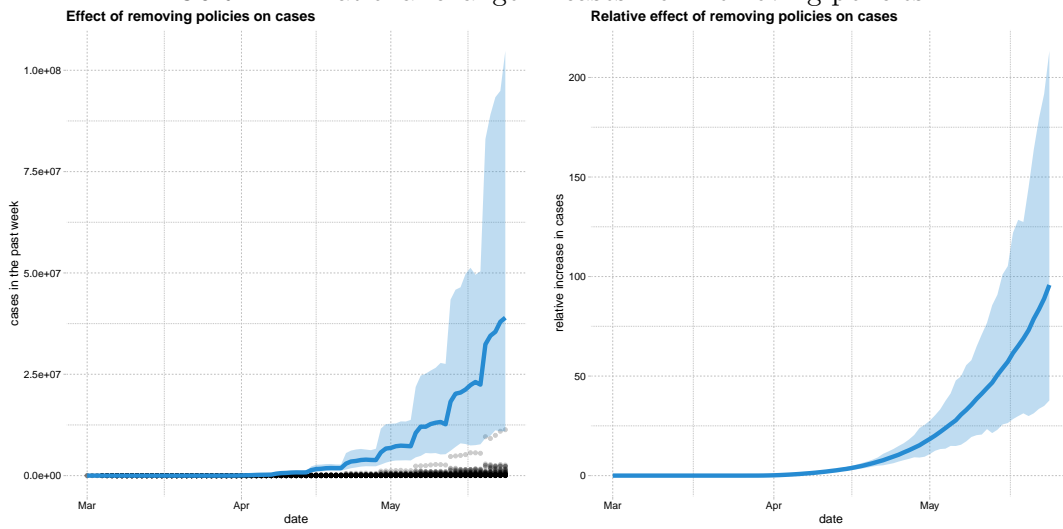
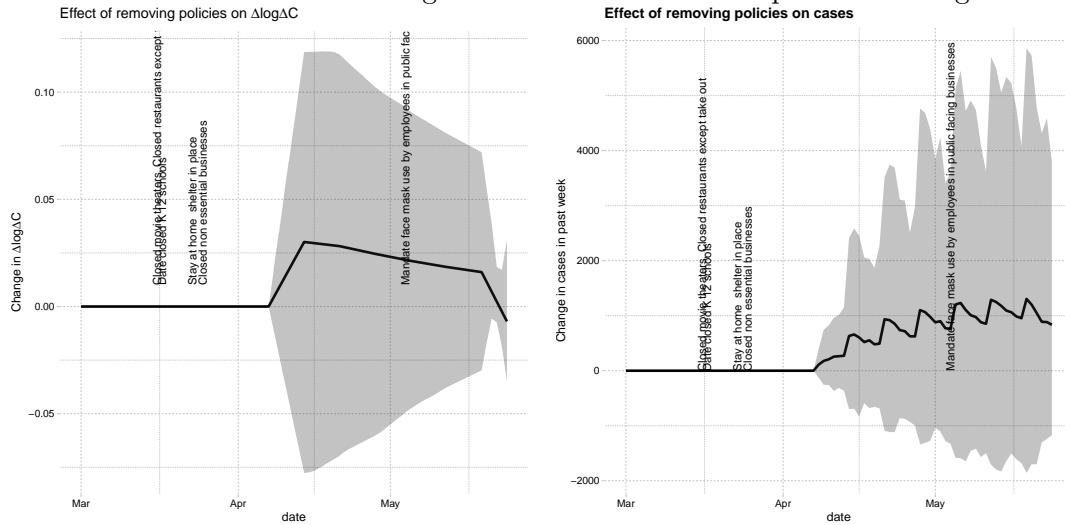


FIGURE 11. National change in cases from removing policies



**5.2. Non essential Business Closures.** A particularly controversial policy is the closure of non essential businesses. We now examine a counterfactual where non essential businesses are never closed. Figure 12 shows the effect of leaving non essential businesses open in Washington. Non essential businesses have a modest impact on cases, with an average increase of 1000 by late May, with a 90% confidence interval from roughly -1000 to 4000.

**FIGURE 12. Effect of leaving non essential businesses open in Washington**



**FIGURE 13. Effect of leaving businesses open in Illinois**

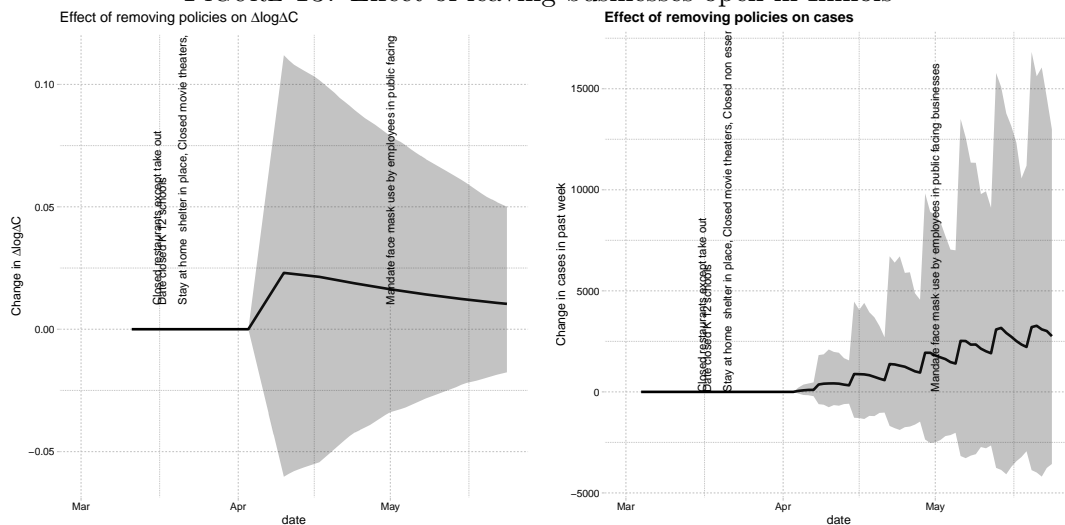
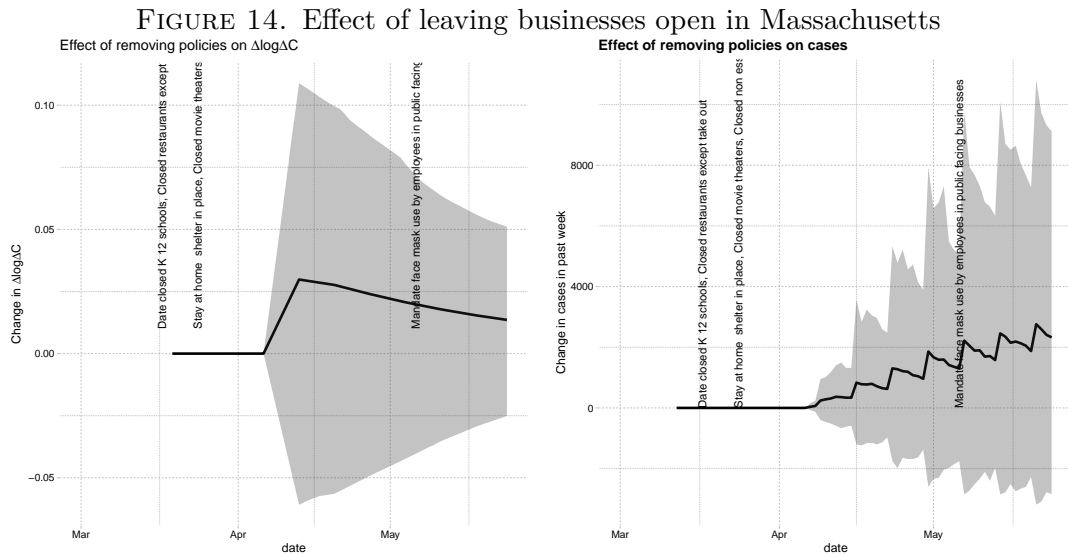
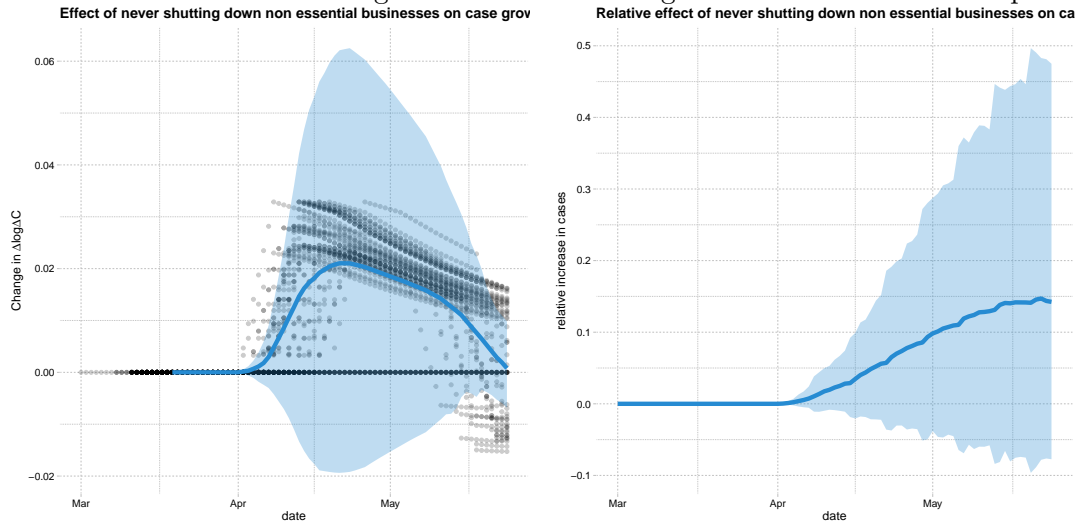


Figure 15 shows the national aggregate effect of leaving non essential businesses open. The estimates imply that with non essential businesses open, cases would be about -10 to 50% higher in late May.



**FIGURE 15. National change in cases from leaving non essential businesses open**



**5.3. Mask Mandate.** As discussed earlier, we find that mask mandates reduce case growth even holding behavior constant. In other words, mask mandates may reduce infections with relatively little economic disruption. This makes mask mandates a particularly attractive policy instrument. In this section we examine what would have happened to cases if all states had imposed a mask mandate on April 1st. Figure 16 shows the changes in case growth and cases in Washington. In Figures 17 and 18, implementing mandatory mask policy on April 1st would have reduced the total number of confirmed cases by 2,500-12,500 in Illinois and 2,000-11,000 in Massachusetts by late-May. Figure 19 shows the national

FIGURE 16. Effect of mandating masks on April 1st in Washington

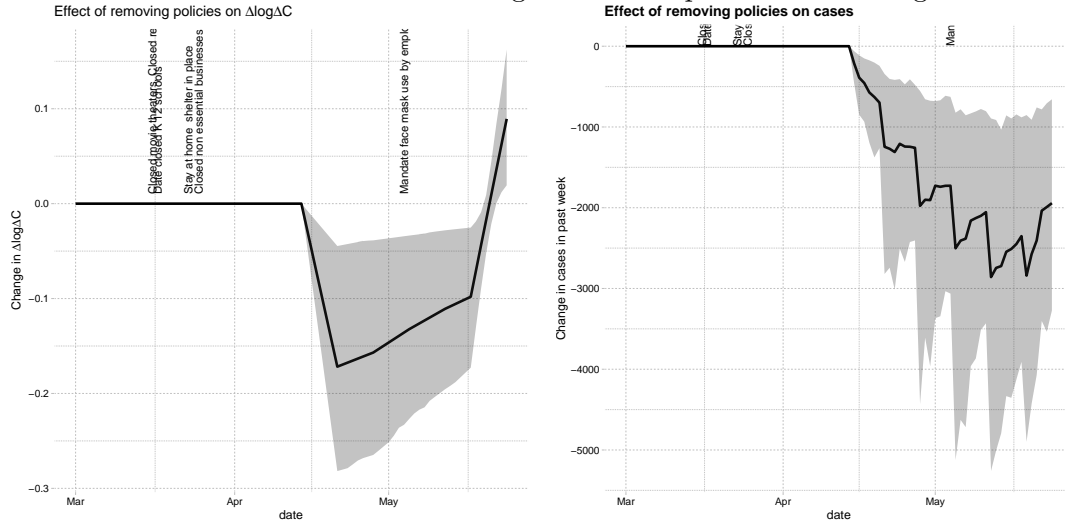
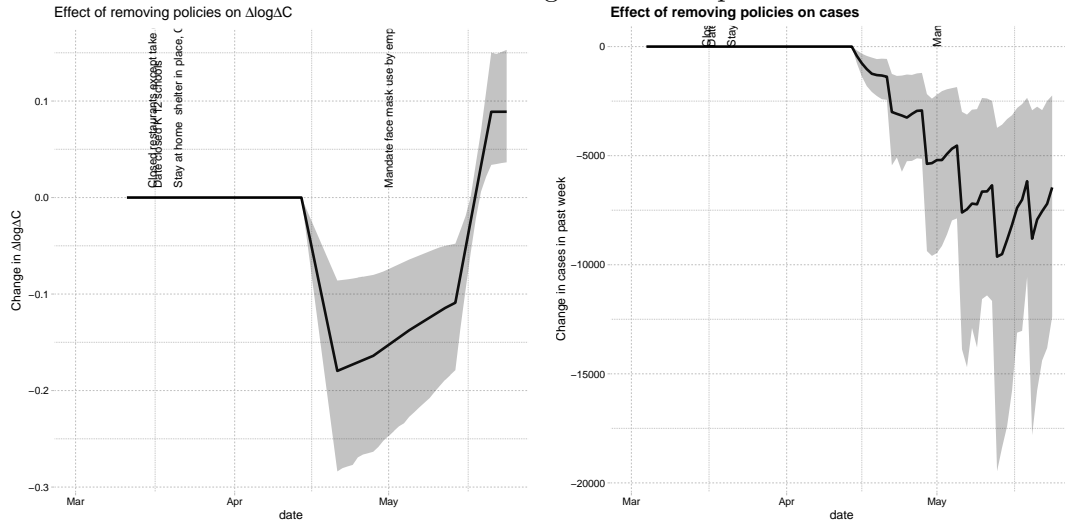
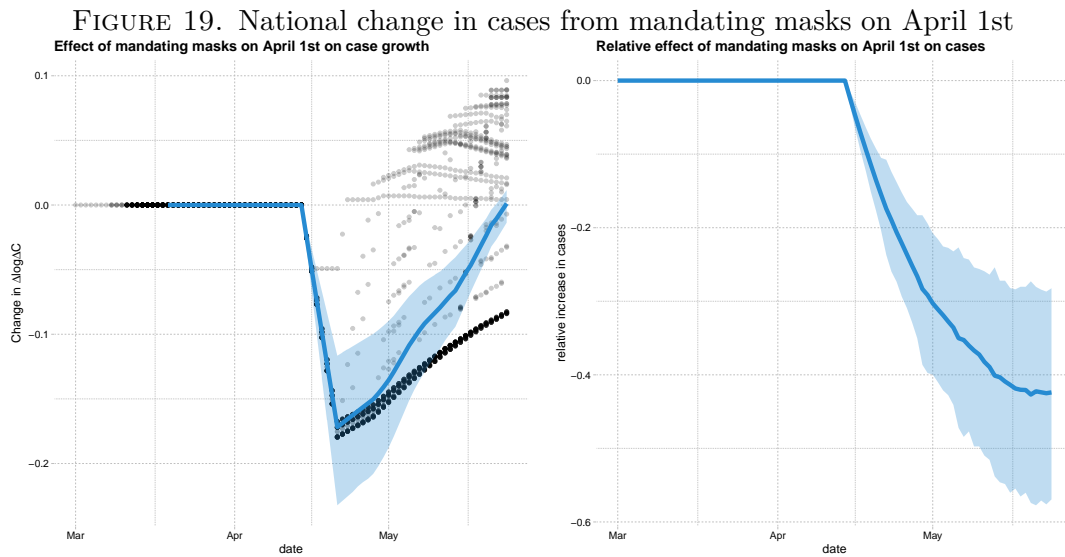
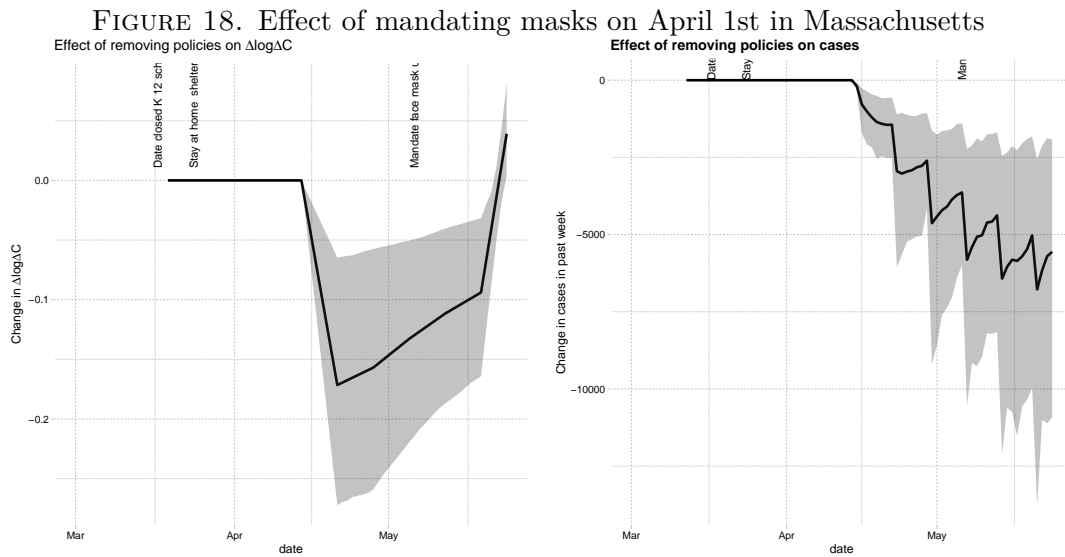


FIGURE 17. Effect of mandating masks on April 1st in Illinois







change in case growth and cases. Mandating masks on April 1st leads to 30 to 57% fewer cases nationally in late May.

## 6. CONCLUSION

This paper assesses the effects of policies on the spread of Covid-19 in the US using the US state-level data on cases, tests, policies, and social distancing behavior measures from Google Mobility Reports. Our findings are summarized as follows.

First, our empirical analysis indicates that mandating face masks have reduced the spread of Covid-19 without affecting people’s social distancing behavior measured by Google Mobility Reports. Our counterfactual experiment based on the estimated model indicates that, if all states had have adopted mandatory face mask policy on April 1st of 2020, then the number of cases in late-May would have been smaller by 30 to 57 percent, potentially saving tens of thousands of lives.

Second, we find that the impact of all policies combined on case growth is quite large, reducing the growth rate of cases by 60 percent. Except for mandatory face mask policy, the effect of all other policies on case growth is realized through their impact on social distancing behavior. Our counterfactual experiment shows that, had all policies have been removed from all states, there would have been 10 to 100 million additional cases by late-May, suggesting that policy makers should be careful about removing all policies together.

Third, we find that people voluntarily reduce their visits to workplace, transit, grocery, and transits when they receive information on a higher number of new cases. This suggests that individuals make decisions to voluntarily limit their contact with others in response to greater transmission risks, leading to an important feedback mechanism to future cases. As our counterfactual experiments illustrate, model simulations that ignore this people’s voluntary behavioral response to information on transmission risks would over-predict the future number of cases.

Beyond these findings, our paper presents a useful conceptual framework to investigate the relative roles of policies and information on determining the spread of Covid-19 through their impact on people’s behavior. Our causal model allows us to explicitly define counterfactual scenarios to properly evaluate the effect of alternative policies on the spread of Covid-19, and can be used to quantitatively examine various Covid-19 related issues for future research.

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## APPENDIX A. DATA CONSTRUCTION

A.1. **Measuring  $\Delta C$  and  $\Delta \log \Delta C$ .** We have three data sets with information on daily cumulative confirmed cases in each state. As shown in table 8, these cumulative case numbers are very highly correlated. However, table 9 shows that the numbers are different more often than not.

	NYT	JHU	CTP
NYT	1.00000	0.99995	0.99990
JHU	0.99995	1.00000	0.99986
CTP	0.99990	0.99986	1.00000

TABLE 8. Correlation of cumulative cases

	1	2	3
NYT	1.00	0.29	0.38
JHU	0.29	1.00	0.33
CTP	0.38	0.33	1.00

TABLE 9. Portion of cumulative cases that are equal between data sets

Figure 20 shows the evolution of new cases in each of these three datasets. In all cases, daily changes in cumulative cases displays some excessive volatility. This is likely due to delays and bunching in testing and reporting of results. Table 10 shows the variance of log new cases in each data set, as well as their correlations. As shown, the correlations are approximately 0.9. Also of note, log of The New York Times new case numbers has the lowest variance.<sup>17</sup> In our subsequent results, we will primarily use the case numbers from The New York Times.

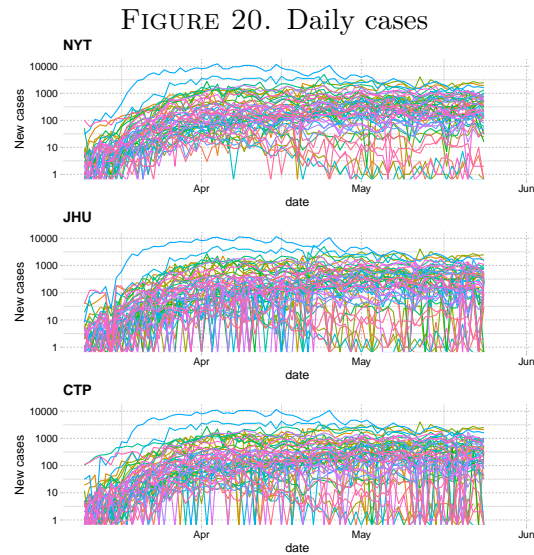
	NYT	JHU	CTP
NYT	1.00	0.88	0.87
JHU	0.88	1.00	0.81
CTP	0.87	0.81	1.00
Variance	5.84	7.17	6.78

TABLE 10. Correlation and variance of log daily new cases

For most of our results, we focus on new cases in a week instead of in a day. We do this for two reasons as discussed in the main text. First, a decline of new cases over two weeks has become a key metric for decision makers. Secondly, aggregating to weekly new cases smooths out the noise associated with the timing of reporting and testing.

Table 11 reports the correlation and variance of weekly log new cases across the three data sets. Figure 21 shows the evolution of weekly new cases in each state over time.

<sup>17</sup>This comparison is somewhat sensitive to how you handle negative and zero cases when taking logs. Here, we replaced  $\log(0)$  with  $\log(0.1)$ . In our main results, we work with weekly new cases, which are very rarely zero.



Each line shows daily new cases in a state.

	NYT	JHU	CTP
NYT	1.00	0.99	0.99
JHU	0.99	1.00	0.99
CTP	0.99	0.99	1.00
Variance	4.26	4.46	4.31

TABLE 11. Correlation and variance of log weekly new cases

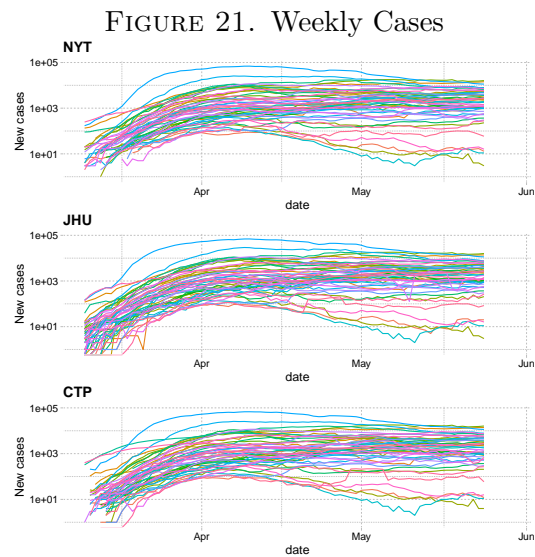
**A.2. Deaths.** Table 12 reports the correlation and variance of weekly deaths in the three data sets. Figure 22 shows the evolution of weekly deaths in each state. As with cases, we use death data from The New York Times in our main results.

	NYT	JHU	CTP
NYT	1.00		
JHU		1.00	
CTP			1.00
Variance	335619.76	330310.42	232303.30

TABLE 12. Correlation and variance of weekly deaths

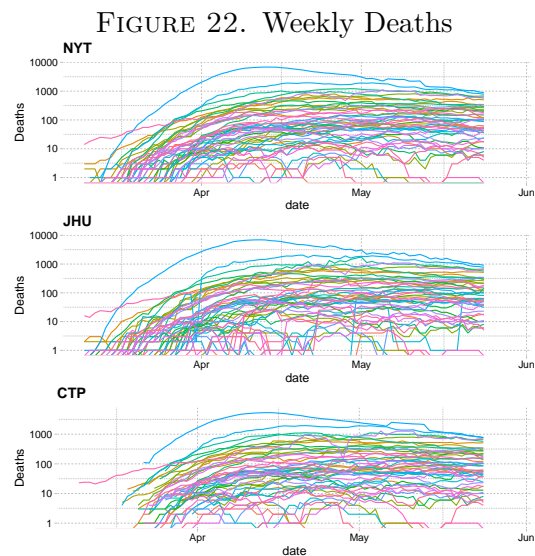
**A.3. Tests.** Our test data comes from The Covid Tracking Project. Figure 23 show the evolution of tests over time.

**A.4. Social Distancing Measures.** In measuring social distancing, we focus on Google Mobility Reports. This data has international coverage and is publicly available. We also




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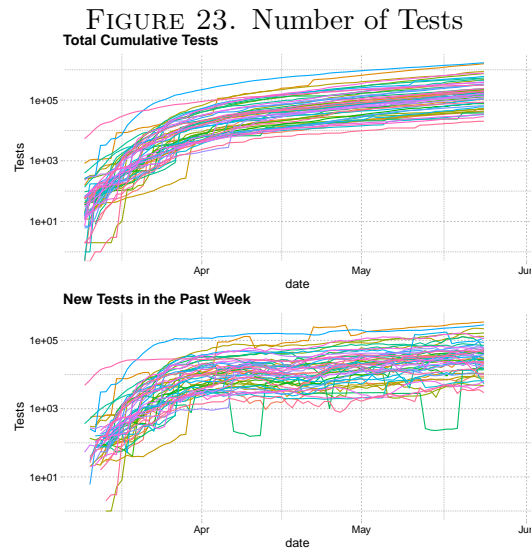
Each line shows weekly new cases in a state.




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Each line shows weekly deaths in a state.

compare Google Mobility Reports to other social distancing measures from SafeGraph, Unacast, and PlaceIQ. Each of these other data sources are limited to the United States. SafeGraph and Unacast data is not publicly available (both companies make the data available to researchers at no cost).



These figures use the “total test results” reported by The Covid Tracking Project. This is meant to reflect the number of people tested (as opposed to the number of specimens tested).

**A.5. Policy Variables.** We use the database on US state policies created by Raifman et al. (2020). As discussed in the main text, our analysis focuses on seven policies. For stay at home, closed nonessential businesses, closed K-12 schools, closed restaurants except takeout, and close movie theaters, we double-checked any state for which Raifman et al. (2020) does not record a date. We filled in a few missing dates. Our modified data is available here. Our modifications fill in 1 value for school closures, 2 for stay at home, 3 for movie theater closure, and 4 for non-essential business closures. Table 13 displays all 25 dated policy variables in Raifman et al. (2020)’s database with our modifications described above.

**A.6. Timing.** There is a delay between infection and when a person is tested and appears in our case data. MIDAS (2020) maintain a list of estimates of the duration of various stages of Covid-19 infections. The incubation period, the time from infection to symptom onset, is widely believed to be 5 days. For example, using data from Wuhan, Li et al. (2020) estimate a mean incubation period of 5.2 days. Siordia (2020) reviews the literature and concludes the mean incubation period is 3-9 days.

Estimates of the time between symptom onset and case reporting are less common. Using Italian data, Cereda et al. (2020) estimate an average of 7.3 days between symptom onset and reporting. Zhang et al. (2020) find an average of 7.4 days using Chinese data from December to early February, but they find this period declined from 8.9 days in January to 5.4 days in the first week of February. Both of these papers on time from symptom onset to reporting have large confidence intervals covering approximately 1 to 20 days.

Based on the above, we expect a delay of roughly two weeks between changes in behavior or policies, and changes in reported cases.



	N	Min	Median	Max
State of emergency	51	2020-02-29	2020-03-11	2020-03-16
Date closed K 12 schools	51	2020-03-13	2020-03-17	2020-04-03
Closed day cares	15	2020-03-16	2020-03-23	2020-04-06
Date banned visitors to nursing homes	30	2020-03-09	2020-03-16	2020-04-06
Stay at home shelter in place	42	2020-03-19	2020-03-28	2020-04-07
End relax stay at home shelter in place	22	2020-04-26	2020-05-06	2020-05-22
Closed non essential businesses	43	2020-03-19	2020-03-25	2020-04-06
Began to reopen businesses statewide	43	2020-04-20	2020-05-04	2020-05-20
Mandate face mask use by all individuals in public spaces	16	2020-04-08	2020-04-19	2020-05-16
Mandate face mask use by employees in public facing businesses	36	2020-04-03	2020-05-01	2020-05-11
Closed restaurants except take out	48	2020-03-15	2020-03-17	2020-04-03
Reopen restaurants	30	2020-04-24	2020-05-10	2020-05-22
Closed gyms	46	2020-03-16	2020-03-20	2020-04-03
Reopened gyms	21	2020-04-24	2020-05-13	2020-05-20
Closed movie theaters	49	2020-03-16	2020-03-21	2020-04-06
Reopened movie theaters	11	2020-04-27	2020-05-08	2020-05-16
Stop Initiation of Evictions overall or due to COVID related issues	24	2020-03-16	2020-03-24	2020-04-20
Stop enforcement of evictions overall or due to COVID related issues	26	2020-03-15	2020-03-23	2020-04-20
Renter grace period or use of security deposit to pay rent	2	2020-04-10	2020-04-17	2020-04-24
Order freezing utility shut offs	34	2020-03-12	2020-03-19	2020-04-13
Froze mortgage payments	1	2020-03-21	2020-03-21	2020-03-21
Modify Medicaid requirements with 1135 waivers date of CMS approval	51	2020-03-16	2020-03-26	2020-04-22
Suspended elective medical dental procedures	33	2020-03-16	2020-03-21	2020-04-16
Resumed elective medical procedures	34	2020-04-20	2020-04-29	2020-05-29
Waived one week waiting period for unemployment insurance	36	2020-03-08	2020-03-18	2020-04-06

TABLE 13. State Policies

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