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 adopted by US states on the growth rates of confirmed Covid-19 cases and deaths as well as social distancing behavior measured by Google Mobility Reports, where we take into consideration people's voluntarily behavioral response to new information of transmission risks. Our analysis finds that both policies and information on transmission risks are important determinants of Covid-19 cases and deaths and shows that a change in policies explains a large fraction of observed changes in social distancing behavior. Our counterfactual experiments suggest that nationally mandating face masks for employees on April 1st could have reduced the growth rate of cases and deaths by more than 10 percentage points in late April, and could have led to as much as 17 to 55 percent less deaths nationally by the end of May, which roughly translates into 17 to 55 thousand saved lives. Our estimates imply that removing non-essential business closures (while maintaining school closures, restrictions on movie theaters and restaurants) could have led to -20 to 60 percent more cases and deaths by the end of May. We also find that, without stay-at-home orders, cases would have been larger by 25 to 170 percent, which implies that 0.5 to 3.4 million more Americans could have been infected if stay-at-home orders had not been implemented. Finally, we find considerable uncertainty over the effects of removing all policies because the timing of school closures had little cross-sectional variation.

1. Introduction

Accumulating evidence suggests that various policies in the US have reduced social interactions and slowed down the growth of Covid-19 infections.[1] An important outstanding issue, however, is how much of the observed slow down in the spread is attributable to the effect of policies as opposed to a voluntarily change in people's behavior out of fear of being infected. This question is critical for evaluating 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.

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

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[1] See **?**, **?**, **?**, **?**, and **?**.

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

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 deaths, 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 and deaths into three components: (1) direct policy effect, (2) policy effect through behavior, and (3) direct behavior effect in response to new information.[2]

Guided by the causal model, our empirical analysis examines how the weekly growth rates of confirmed Covid-19 cases and deaths are determined by (the lags of) policies and behavior using 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 and death growths is explicitly guided by a SIR model although our causal approach does not hinge on the validity of a SIR model.

As policy variables, we consider mandatory face masks for employees in public businesses, stay-at-home orders (or shelter-in-place orders), closure of K-12 schools, closure of restaurants except take out, closure of movie theaters, and closure of non-essential businesses. 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 the lagged growth rate of cases and deaths and the log of lagged cases and deaths at both state-level and national-level as our measures of information on infection risks that affects people's behavior. We also consider the growth rate of tests, month dummies, and state-level characteristics (e.g., population size and total area) as confounders that have to be controlled for in order to identify the causal relationship between policy/behavior and the growth rate of cases and deaths.

Our key findings from regression analysis are as follows. We find that both policies and information on past cases and deaths are important determinants of people's social distancing behavior, where policy effects explain more than 50% of the observed decline in

[2] The causal model is framed using the language of structural equations models and causal diagrams of econometrics (**???** and genetics (**?**), with natural unfolding potential outcomes representation (**????**). See **?**, **?**, and **?** for modern developments, especially in computer science and epidemiology. The particular causal diagram has several "mediation" components, where variables affect outcomes directly and indirectly through other variables called mediators; these structures go back at least to (**?**, see Figure 6); see, e.g., **?** and **?** for modern treatments. The father and son, P. Wright and S. Wright closely collaborated to develop structural equation models and causal path diagrams; P.Wright's key work represented supply-demand system as a directed acyclical graph and established its identification using exclusion restrictions on instrumental variables.

the four behavior variables.[3] Our estimates suggest that there are both large policy effects and large behavioral effects on the growth of cases and deaths. Except for mandatory masks, the effect of policies on cases and deaths is indirectly materialized through their impact on behavior; the effect of mandatory mask policy is direct without affecting behavior.

Using the estimated model, we evaluate the dynamic impact of the following counterfactual policies on Covid-19 cases and deaths: mandating face masks, allowing non-essential businesses to open, not implementing a stay-at-home order, and removing all policies. The counterfactual experiments show a large impact of those policies on the number of cases and deaths. They also highlight the importance of voluntary behavioral response to infection risks for evaluating the dynamic policy effects.

Figure 1 shows that nationally implementing mandatory face masks for employees in public businesses on April 1st would have reduced the growth rate of cases (top panel) and that of deaths (bottom panel) by more than 10 percentage points in late April. This leads to reductions of 25% and 35% in reported cases and deaths, respectively, by the end of May with a 90 percent confidence interval of $[10, 45]\%$ and $[17, 55]\%$, which roughly implies that as many as 17 to 55 thousand lives could have been saved.[4] This finding is significant: given this potentially large benefit of reducing the spread of Covid-19, mandating masks is an attractive policy instrument especially because it involves relatively little economic disruption. These estimates contribute to the ongoing efforts towards designing approaches to minimize risks from reopening (**?**).

Figure 2 illustrates how allowing non-essential businesses to remain open could have affected the growth of cases. We estimate that non-essential business closures have a small impact on growth rates, with a 90% confidence interval that includes both negative and positive effects. When this effect on growth rates is converted to a change in levels, the point estimates indicate that keeping non-essential businesses open (other than movie theaters, gyms, and keeping restaurants in the "take-out" mode) could have increased cases and deaths by 15% (with a 90 percent confidence interval of -20% to 60%). These estimates contribute to the ongoing efforts of evaluating various reopening approaches.

In Figure 3, we find that, without stay-at-home orders, the case growth rate would have been nearly 10 percentage points higher in late April. No stay-at-home orders could have led to 80% more cases by the start of June with a 90 precent confidence interval given by 25% to 170%. This implies that 0.5 to 3.4 million more Americans would have been infected without stay-at-home orders, providing suggestive evidence that reopening via removal of stay-at-home orders could lead to a substantial increase in cases and deaths.

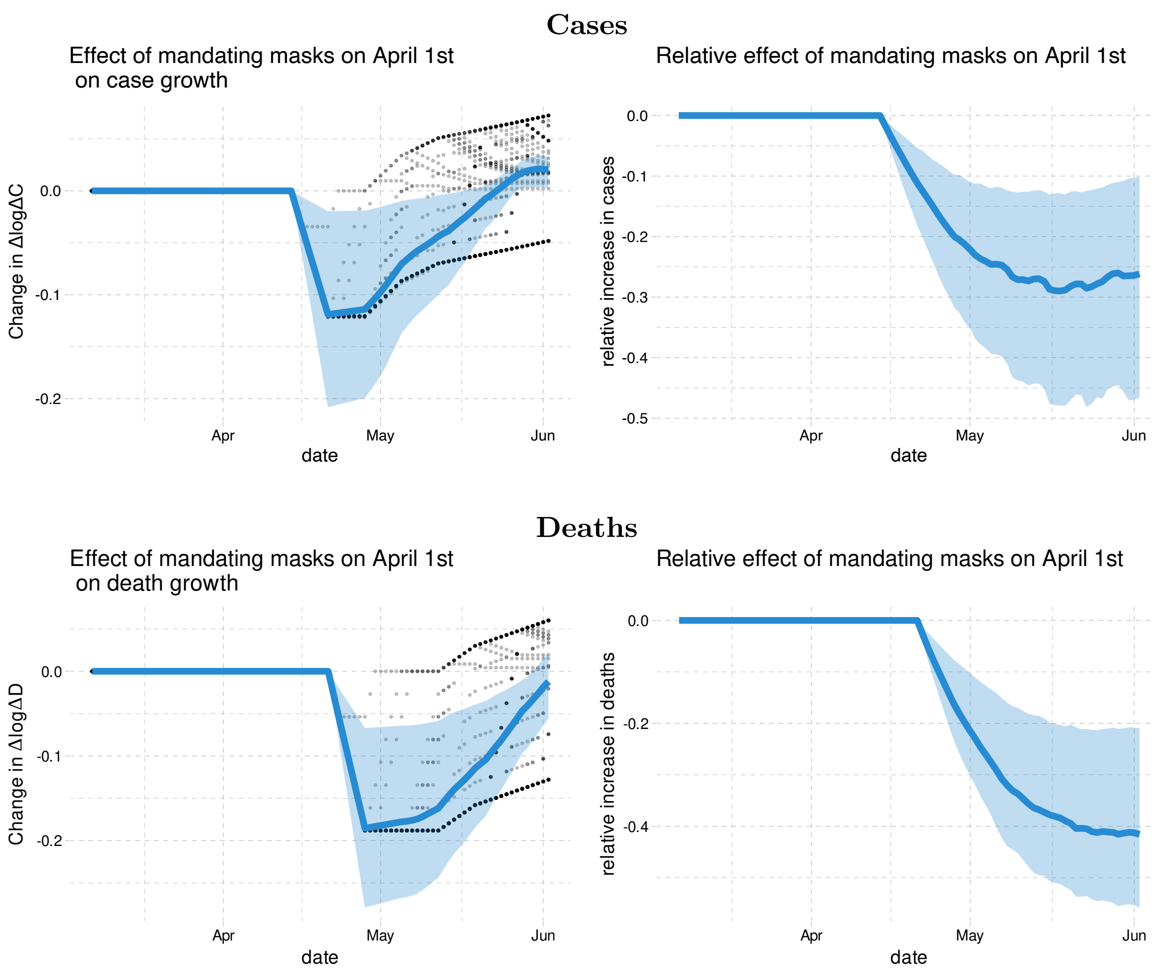
In our counterfactual experiment of removing all policies, we find that the results are sensitive to whether the number of past national cases/deaths is included in a specification

[3]The behavior accounts for the other half. This is in line with theoretical study by **?** that investigates the role of private behavior and negative external effects for individual decisions over policy compliance as well as information acquisition during pandemics.

[4]As of May 27, 2020, the US Centers for Disease Control and Prevention reports 99,031 deaths in the US.

or not. This sensitivity arises because there is little variation across states in the timing of school closures. This makes the effect of school closures difficult to identify. In Figure 15, we show that in a specification that excludes past national cases (which allow for greater attribution of effects to school closures), the number of cases by the end of May could have increased 7-fold or more with a very large upper bound. On the other hand, as shown in Figure 16, under a specification with past national cases, our counterfactual experiment implies a 0 to 10 fold increase in cases by the end of May. This highlights the uncertainty regarding the impact of all policies versus private behavioral responses to information. Evaluation of re-opening policies needs to be aware of this uncertainty.

FIGURE 1. Effect of nationally mandating masks for employees on April 1st in the US



A growing number of other papers have examined the link between non-pharmaceutical interventions and Covid-19 cases.[5] **?** estimate the effect of policies on the growth rate

[5]We refer the reader to **?** 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 2. Effect of leaving non-essential businesses open on cases in the US

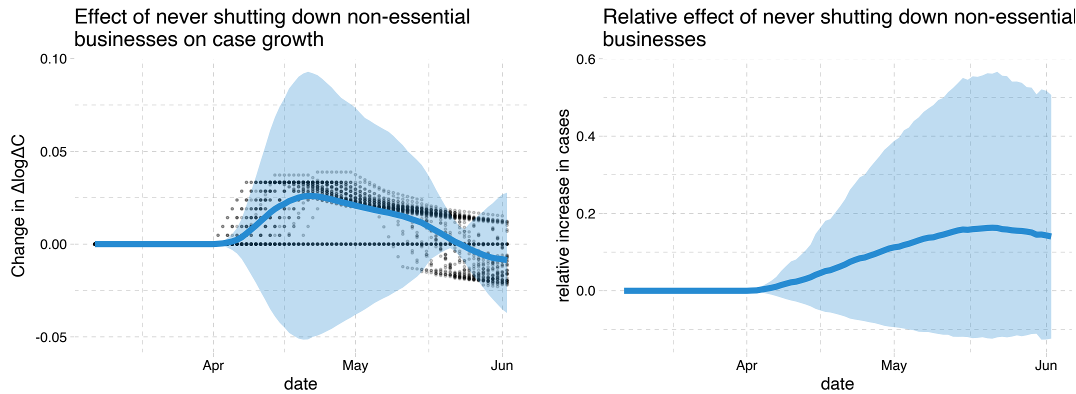
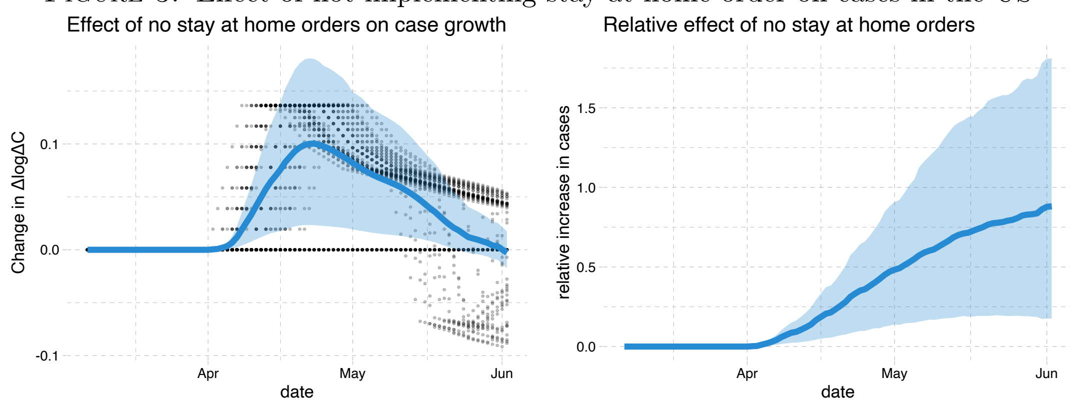


FIGURE 3. Effect of not implementing stay-at-home order on cases in the US



of cases using data from the United States, China, Iran, Italy, France, and South Korea. In the United States, they find that the combined effect of all policies they consider on the growth rate is -0.347 (0.061). **?** 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 are attributed to shelter in place orders. Both **?** and **?** adopted a reduced-form approach to estimate the total policy effect on case growth without using any social 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. **?** employ a difference-in-differences methodology to find that statewide stay-at-home orders have strong causal impacts on reducing social interactions. In contrast, using data from Google Mobility Reports, **?** find that the increase in social distancing is largely voluntary and driven by information.[6] Another study by **?** also found little evidence that stay-at-home mandates induced distancing by using mobility measures from PlaceIQ and SafeGraph. Using data from SafeGraph, **?** show that there has been substantial voluntary social distancing but also provide evidence that mandatory measures such as stay-at-home orders have been effective at reducing the frequency of visits outside of one's home.

? 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. 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 **?**, there exist substantial uncertainty about the values of key epidimiological parameters (see also **??**). Simulations are often done under strong assumptions about the impact of social distancing policies without connecting to the relevant data (e.g., **?**). Furthermore, simulated models do not take into account that people may limit their contact with other people in response to higher transmission risks.[7] When 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 with health authorities of different countries providing contradiction recommendations. Reviewing evidence, **?** recognize that there is no randomized controlled trial evidence for the effectiveness of face masks, but they state "indirect evidence exists to support the argument for the public wearing masks in the Covid-19 pandemic."[8] **?** 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." The laboratory findings in **?** suggest that the nasal cavity may be the initial site of infection followed by aspiration to the lung, supporting the argument "for the widespread use of masks to prevent aersol, large droplet, and/or mechanical exposure to the nasal passages."

Given the lack of experimental evidence on the effect of masks, 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

[6]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.

[7]See **?** and **?** for the implications of the SIR model for Covid-19 in the US. **?** estimate a SIRD model in which time-varying reproduction numbers depend on the daily deaths to capture feedback from daily deaths to future behavior and infections.

[8]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.

medical observational evidence in **?**. Analyzing mitigation measures in New York, Wuhan, and Italy, **?** conclude that mandatory face coverings substantially reduced infections. **?** find that the growth rates of cases and of deaths in countries with pre-existing norms that sick people should wear masks are lower by 8 to 10% than those rates in countries with no pre-existing mask norms. Our finding is also corroborated by a completely different causal methodology based on synthetic control using German data in **?**.[9]

Our empirical results contribute to informing the economic-epidemiological models that combine economic models with variants of SIR models to evaluate the efficiency of various economic policies aimed at gradual "reopening" of various sectors of economy.[10] For example, the estimated effects of masks, stay-home mandates, and various other policies on behavior, and of behavior on infection can serve as useful inputs and validation checks in the calibrated macro, sectoral, and micro models (see, e.g., **??????** and references therein). Furthermore, the causal framework developed in this paper could be applicable, with appropriate extensions, to the impact of policies on economic outcomes replacing health outcomes (see, e.g., **??**).

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, $Y_{i,t+\ell}$, is determined last, after all other variables have been determined;
- The adopted policies, P_{it}, affect health outcome $Y_{i,t+\ell}$ either directly, or indirectly by altering human behavior B_{it};
- Information variables, I_{it}, such as lagged values of outcomes can affect human behavior and policies, as well as outcomes;
- The confounding factors W_{it}, which vary across states and time, affect all other variables.

The index i denotes observational unit, the state, and t and $t+\ell$ denotes the time, where ℓ represents the time lag between infection and case confirmation or death.

Our main outcomes of interest are the growth rates in Covid-19 cases and deaths, behavioral variables include proportion of time spent in transit or shopping and others, policy

[9]Our study was first released in ArXiv on May 28, 2020 whereas **?** was released at SSRN on June 8, 2020.

[10]**?** analyzes the effect of policies reducing interpersonal contacts such as school closures or the closure of public transportation networks on the spread of influenza, gastroenteritis, and chickenpox using high frequency data from France.

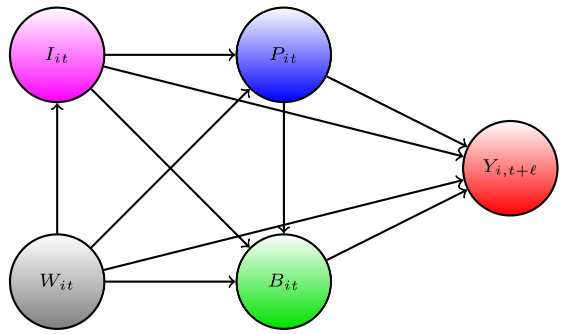


FIGURE 4. S. & P. Wright type causal path diagram for our model.

variables include stay-at-home orders and school and business closures, and the information variables include lagged values of outcome. We provide a detailed description of these variables and their timing in the next section.

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 also 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. Policies such as closures of schools, non-essential business, and 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:

(1) information and confounders get determined at t,
(2) policies are set in place, given information and confounders at t;
(3) behavior is realized, given policies, information, and confounders at t;
(4) outcomes get realized at $t+\ell$ given policies, behavior, information, and confounders.

The model also allows for direct dynamic effects of information variables on the outcome through autoregressive structures that capture persistence in growth patterns. As 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:

$$\begin{aligned} Y_{i,t+\ell}(b,p,\iota) &:= \alpha' b + \pi' p + \mu' \iota + \delta_Y' W_{it} + \varepsilon_{it}^{y}, \\ B_{it}(p,\iota) &:= \beta' p + \gamma' \iota + \delta_B' W_{it} + \varepsilon_{it}^{b}, \end{aligned} \tag{SEM}$$

which is a collection of functional relations with stochastic shocks, decomposed into observable part $\delta' W$ and unobservable part ε. The terms ε^y_{it} and ε^b_{it} are the centered stochastic shocks that obey the orthogonality restrictions posed below.

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

$$P_{it}(\iota) := \eta'\iota + \delta_P' W_{it} + \varepsilon^p_{it}, \tag{P}$$

although linearity is not critical.[11]

The orthogonality restrictions on the stochastic components are as follows:

$$\begin{aligned} \varepsilon^y_{it} &\perp (\varepsilon^b_{it}, \varepsilon^p_{it}, W_{it}, I_{it}),\\ \varepsilon^b_{it} &\perp (\varepsilon^p_{it}, W_{it}, I_{it}),\\ \varepsilon^p_{it} &\perp (W_{it}, I_{it}), \end{aligned} \tag{O}$$

where we say that $V \perp U$ if $\mathrm{E}VU = 0$. This is a standard way of representing restrictions on errors in structural equation modeling.[12][13]

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

$$\begin{aligned} Y_{i,t+\ell} &:= Y_{i,t+\ell}(B_{it}, P_{it}, I_{it}),\\ B_{it} &:= B_{it}(P_{it}, I_{it}),\\ P_{it} &:= P_{it}(I_{it}). \end{aligned}$$

The system above together with orthogonality restrictions (O) implies the following collection of stochastic equations for realized variables:

$$Y_{i,t+\ell} = \alpha' B_{it} + \pi' P_{it} + \mu' I_{it} + \delta_Y' W_{it} + \varepsilon^y_{it}, \qquad \varepsilon^y_{it} \perp B_{it}, P_{it}, I_{it}, W_{it} \tag{BPI→Y}$$

$$B_{it} = \beta' P_{it} + \gamma' I_{it} + \delta_B' W_{it} + \varepsilon^b_{it}, \qquad \varepsilon^b_{it} \perp P_{it}, I_{it}, W_{it} \tag{PI→B}$$

$$P_{it} = \eta' I_{it} + \delta_P' W_{it} + \varepsilon^p_{it}, \qquad \varepsilon^p_{it} \perp I_{it}, W_{it} \tag{I→P}$$

and

$$Y_{i,t+\ell} = (\alpha'\beta' + \pi') P_{it} + (\alpha'\gamma' + \mu') I_{it} + \bar{\delta}' W_{it} + \bar{\varepsilon}_{it}, \quad \bar{\varepsilon}_{it} \perp P_{it}, I_{it}, W_{it}. \tag{PI→Y}$$

These equations form the basis of our empirical analysis.

As discussed below, the information variable includes case growth. Therefore, an orthogonality restriction $\varepsilon^y_{it} \perp P_{it}$ holds if the government does not have knowledge on future

[11]Under some additional independence conditions, this can be replaced by an arbitrary non-additive function $P_{it}(\iota) = p(\iota, W_{it}, \varepsilon^p_{it})$, such that the unconfoundedness condition stated in the next footnote holds.

[12] An alternative useful starting point is to impose the Rubin-Rosenbaum type unconfoudedness condition:

$$Y_{i,t+\ell}(\cdot,\cdot,\cdot) \perp\!\!\!\perp (P_{it}, B_{it}, I_{it}) \mid W_{it},\ B_{it}(\cdot,\cdot) \perp\!\!\!\perp (P_{it}, I_{it}) \mid W_{it},\ P_{it}(\cdot) \perp\!\!\!\perp I_{it} \mid W_{it},$$

which imply, with treating stochastic errors as independent additive components, the orthogonal conditions stated above.

[13]The structural equations of this form are connected to triangular structural equation models, appearing in microeconometrics and macroeconometrics (SVARs), going back to the work of **?**. .

case growth beyond what is predicted by today's case growth, policies, behavior, and confounders; even when the government has some knowledge on ε_{it}^y, the orthogonality restriction may hold if there is a time lag for the government to implement its policies based on ε_{it}^y.

The orthogonality condition in (PI→Y) is weaker than the orthogonality conditions in (BPI→Y)-(PI→B) in that the former is implied by the latter but not vice versa. The system over-identifies the regression coefficients because $(\alpha'\beta' + \pi')$ and $(\alpha'\gamma' + \mu')$ in (PI→Y) can be also identified from α', π', μ', β', and γ' in (BPI→Y)-(PI→B). Comparing the estimates of $(\alpha'\beta' + \pi')$ and $(\alpha'\gamma' + \mu')$ from (PI→Y) with those implied by the estimates of α', π', μ', β', and γ' from (BPI→Y)-(PI→B) provides a useful specification test.

Identification and Parameter Estimation. The orthogonality equations imply that these are all projection equations, and the parameters of the 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:

$$\begin{aligned}
\tilde{Y}_{i,t+\ell} &= \alpha'\tilde{B}_{it} + \pi'\tilde{P}_{it} + \mu'\tilde{I}_{it} + \varepsilon_{it}^y, &\quad& \varepsilon_{it}^y \perp \tilde{B}_{it}, \tilde{P}_{it}, \tilde{I}_{it}, \\
\tilde{B}_{it} &= \beta'\tilde{P}_{it} + \gamma'\tilde{I}_{it} + \varepsilon_{it}^b, && \varepsilon_{it}^b \perp \tilde{P}_{it}, \tilde{I}_{it}, \\
\tilde{P}_{it} &= \eta'\tilde{I}_{it} + \varepsilon_{it}^p, && \varepsilon_{it}^p \perp \tilde{I}_{it}
\end{aligned} \tag{1}$$

where $\tilde{V}_{it} = V_{it} - W_{it}'\mathrm{E}[W_{it}W_{it}']^{-}\mathrm{E}[W_{it}V_{it}]$ 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 the 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

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

Our main estimation method is the standard correlated random effects estimator, where the random effects are parameterized as functions of observable characteristic, W_{it}, which include both state-level and time random effects. The state-level random effects are modeled as a function of state level characteristics, and the time random effects are modeled by including month dummies and their interactions 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 of 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 changes the estimates substantially, often changing the sign of coefficients.[14] 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 it is a more standard and familiar method, and report the former estimates in the supplementary materials for this paper.[15]

2.2. **Information Structures and Induced Dynamics.** We consider three examples of information structures: Information variable is a function of time:

$$I_{it} = g(t);$$

Information variable is lagged value of outcome:

$$I_{it} = Y_{it};$$

and finally:

(I) Information variables include time, lagged and integrated values of outcome:

$$I_{it} = \left(g(t), Y_{it}, \sum_{m=0}^{t/\ell} Y_{i,t-\ell m} \right)',$$

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

The first information structure captures the basic idea that, as individuals discover more information about covid over time, they adapt to 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 from considering autoregressive components and captures people's behavioral response to information on cases in the state they reside. Specifically, we model persistence in growth rates, $Y_{i,t+\ell}$, through an AR(1) model, which leads to $I_{it} = Y_{it}$. 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 the behavior equation. The third information structure is the combination of the first two structures plus an additional term representing the log of the 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 a function of time such as month dummies, 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 a local stochastic trend in cases.

[14]This is a pre-cautionary message that may be useful for other researchers using fixed effects estimators in the context of Covid-19 analysis. We recommend using debiased fixed effects estimators, see e.g., **?** for expository treatment.

[15]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.

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

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

with the initialization $I_{i0} = 0$ and $Y_{i0} = 0$.[16]

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.

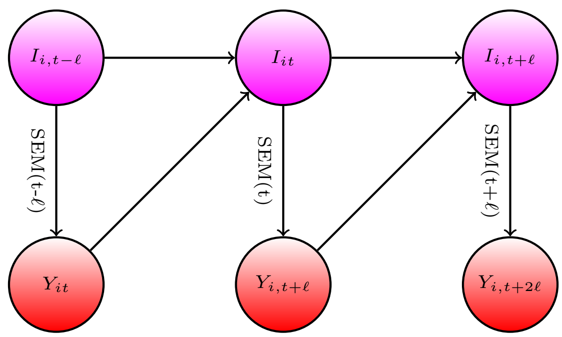


FIGURE 5. Dynamic System Induced by Information Structure and SEM

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

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

approximates the weekly growth rate in new cases from $t-7$ to t.[17] Here Δ 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" (**?**). 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.

[16] This initialization is appropriate in our context for analyzing pandemics from the very beginning, but other initializations could be appropriate in other contexts. The lagged values of behavior variable may be also included in the information set.

[17] 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.

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

$$\Delta \log(\Delta C_{it}) = X'_{i,t-14}\theta - \gamma + \delta_T \Delta \log(T_{it}) + \epsilon_{it}, \tag{M-C}$$

where i is state, t is day, C_{it} is cumulative confirmed cases, T_{it} is the number of tests over 7 days, Δ is a 7-days differencing operator, ϵ_{it} is an unobserved error term. $X_{i,t-14}$ collects other behavioral, policy, and confounding variables, depending on whether we estimate (BPI→Y) or (PI→Y), where the lag of 14 days captures the time lag between infection and confirmed case (see the Appendix A.6). Here

$$\Delta \log(T_{it}) := \log(T_{it}) - \log(T_{i,t-7})$$

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

Our main estimating equation (M-C) is motivated by a variant of SIR model, where we add confirmed cases and infection detection via testing. Let S, $\mathcal{I}$, R, and D denote the number of susceptible, infected, recovered, and dead individuals in a given state. Each of these variables are a function of time. We model them as evolving as

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

$$\dot{\mathcal{I}}(t) = \frac{S(t)}{N}\beta(t)\mathcal{I}(t) - \gamma\mathcal{I}(t) \tag{5}$$

$$\dot{R}(t) = (1-\kappa)\gamma\mathcal{I}(t) \tag{6}$$

$$\dot{D}(t) = \kappa\gamma\mathcal{I}(t) \tag{7}$$

where N is the population, $\beta(t)$ is the rate of infection spread, γ is the rate of recovery or death, and κ is the probability of death conditional on infection.

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

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

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

$$\frac{\ddot{C}(t)}{\dot{C}(t)} = \frac{S(t)}{N}\beta(t) - \gamma + \frac{\dot{\tau}(t)}{\tau(t)}. \tag{9}$$

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 $X_{i,t-14}$. This results in

$$\underbrace{\Delta \log(\Delta C_{it})}_{\frac{\ddot{C}(t)}{\dot{C}(t)}} = \underbrace{X'_{i,t-14}\theta + \epsilon_{it}}_{\frac{S(t)}{N}\beta(t)-\gamma} + \underbrace{\delta_T \Delta \log(T)_{it}}_{\frac{\dot{\tau}(t)}{\tau(t)}}$$

which is equation (M-C), where $X_{i,t-14}$ captures a vector of variables related to $\beta(t)$.

> Structural Interpretation. Early in the pandemic, when the number of susceptibles is approximately the same as the entire population, i.e. $S_{it}/N_{it} \approx 1$, the component $X_{i,t-14}'\theta$ is the projection of infection rate $\beta_i(t)$ on $X_{i,t-14}$ (policy, behavioral, information, and confounders other than testing rate), provided the stochastic component ϵ_{it} is orthogonal to $X_{i,t-14}$ and the testing variables:
>
> $$\beta_i(t)S_{it}/N_{it} - \gamma = X_{i,t-14}'\theta + \epsilon_{it}, \quad \epsilon_{it} \perp X_{i,t-14}.$$

2.4. **Growth Rate in Deaths as Outcome.** By differentiating (7) and (8) with respect to t and using (9), we obtain

$$\frac{\ddot{D}(t)}{\dot{D}(t)} = \frac{\ddot{C}(t)}{\dot{C}(t)} - \frac{\dot{\tau}(t)}{\tau(t)} = \frac{S(t)}{N}\beta(t) - \gamma. \tag{10}$$

Our measurement equation for the growth rate of deaths is based on equation (10) but account for a 21 day lag between infection and death as

$$\Delta \log(\Delta D_{it}) = X_{i,t-21}'\theta + \epsilon_{it}, \tag{M-D}$$

where

$$\Delta \log(\Delta D_{it}) := \log(\Delta D_{it}) - \log(\Delta D_{i,t-7}) \tag{11}$$

approximates the weekly growth rate in deaths from $t-7$ to t in state i.

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 $\mathrm{E}\tilde{Y}_{i,t+\ell} - \mathrm{E}\tilde{Y}_{io}$ in the expected outcome, measured at two different time points $t+\ell$ and o into the sum of three components:

$$\begin{aligned}
\underbrace{\mathrm{E}\tilde{Y}_{i,t+\ell} - \mathrm{E}\tilde{Y}_{io}}_{\text{Total Change}} = \; & \underbrace{\alpha'\beta'\left(\mathrm{E}\tilde{P}_{it} - \mathrm{E}\tilde{P}_{io}\right)}_{\text{Policy Effect via Behavior}} \\
& + \underbrace{\pi'\left(\mathrm{E}\tilde{P}_{it} - \mathrm{E}\tilde{P}_{io}\right)}_{\text{Direct Policy Effect}} \\
& + \underbrace{\alpha'\gamma'\left(\mathrm{E}\tilde{I}_{it} - \mathrm{E}\tilde{I}_{io}\right) + \mu'\left(\mathrm{E}\tilde{I}_{it} - \mathrm{E}\tilde{I}_{io}\right)}_{\text{Dynamic Effect}} \\
& =: \mathrm{PEB}_t + \mathrm{PED}_t + \mathrm{DynE}_t,
\end{aligned} \tag{12}$$

where the first two components capture the immediate effect and the third represents the delayed or dynamic effect.

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

$$\mathrm{DynE}_t = (\gamma\alpha + \mu)\Delta g_t, \quad \Delta g_t = (g(t) - g(t-\ell))$$

and for the lag model,

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

interpreting t/ℓ as $\lfloor t/\ell \rfloor$. For the general model we use, the dynamic effect is

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

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, (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:

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

We assume that the SEM remains invariant, except of course for the policy equation.[18] Given the policies, we propagate the dynamic equations:

$$\begin{aligned} Y^\star_{i,t+\ell} &:= Y_{i,t+\ell}(B^\star_{it}, P^\star_{it}, I^\star_{it}), \\ B^\star_{it} &:= B_{it}(P^\star_{it}, I^\star_{it}), \\ I^\star_{it} &:= I_{it}(I^\star_{i,t-\ell}, Y^*_{it}, t), \end{aligned} \qquad \text{(CEF-SEM)}$$

with the initialization $I^\star_{i0} = 0$, $Y^\star_{i0} = 0$, $B^\star_{i0} = 0$, $P^\star_{i0} = 0$. 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 $\{P^\star_{it}\}$, parameters and stochastic shocks in (SEM) and (I) remain the same as under the original policy intervention $\{P_{it}\}$.

Let $\mathcal{P}Y^\star_{i,t+\ell}$ and $\mathcal{P}Y_{i,t+\ell}$ denote the predicted values produced by working with the counterfactual system (CEF-SEM) and the factual system (SEM):

$$\begin{aligned} \mathcal{P}Y^\star_{i,t+\ell} &= (\alpha'\beta' + \pi')P^\star_{it} + (\alpha'\gamma' + \mu')I^\star_{it} + \bar\delta' W_{it}, \\ \mathcal{P}Y_{i,t+\ell} &= (\alpha'\beta' + \pi')P_{it} + (\alpha'\gamma' + \mu')I_{it} + \bar\delta' W_{it}. \end{aligned}$$

[18] 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.

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

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

$$\begin{aligned}\underbrace{\mathcal{P}Y^\star_{i,t+\ell} - \mathcal{P}Y_{i,t+\ell}}_{\text{Predicted CF Change}} = & \underbrace{\alpha'\beta'(P^\star_{it} - P_{it})}_{\text{CF Policy Effect via Behavior}} + \underbrace{\pi'\,(P^\star_{it} - P_{it})}_{\text{CF Direct Effect}} \\ & + \underbrace{\alpha'\gamma'\,(I^\star_{it} - I_{it}) + \mu'\,(I^\star_{it} - I_{it})}_{\text{CF Dynamic Effect}} \\ =:\ & \mathrm{PEB}^\star_{it} + \mathrm{PED}^\star_{it} + \mathrm{DynE}^\star_{it}. \end{aligned} \tag{13}$$

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

$$\begin{aligned}\text{(I)}\quad \mathrm{DynE}^\star_{it} &= \textstyle\sum_{m=1}^{t/\ell}\left((\gamma\alpha)_2 + \mu_2 + (\gamma\alpha)_3 + \mu_3\right)^m \left(\mathrm{PEB}^\star_{i,t-m\ell} + \mathrm{DPE}^\star_{i,t-m\ell}\right) \\ &+ \textstyle\sum_{m=1}^{t/\ell-1}\left((\gamma\alpha)_3 + \mu_3\right)^m \left(\mathrm{PEB}^\star_{i,t-(m+1)\ell} + \mathrm{DPE}^\star_{i,t-(m+1)\ell}\right),\end{aligned}$$

interpreting t/ℓ as $\lfloor t/\ell \rfloor$. 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, (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 21 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.

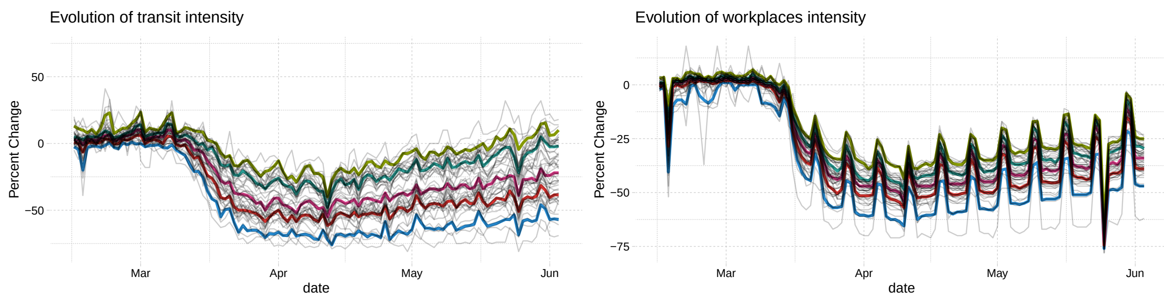
We use the database on US state policies created by **?**. In our analysis, we focus on 6 policies: stay-at-home, closed nonessential businesses, closed K-12 schools, closed restaurants except takeout, closed movie theaters, and mandate face mask by employees in public facing businesses. We believe that the first four 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 (**???**). 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 **?**, which include population size, total area, unemployment rate, poverty rate, and a percentage of people who are subject to illness.These confounders are motivated by **?** who finds that case growth is associated with residential density and per capita income.

We obtain social distancing behavior measures from"Google COVID-19 Community Mobility Reports" (**?**). 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

	N	Min	Median	Max
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	44	2020-04-03	2020-05-01	2020-08-03

TABLE 1. State Policies

FIGURE 6. The Evolution of Google Mobility Measures: Transit stations and Workplaces



This figure shows the evolution of "Transit stations" and "Workplaces" of Google Mobility Reports. Thin gray lines are the value in each state and date. Thicker colored lines are quantiles of the variables conditional on date.

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."[19]

Figure 6 shows the evolution of "Transit stations" and "Workplaces," where thin lines are the value in each state and date while thicker colored lines are quantiles conditional on date. The figures illustrate a sharp decline in people's movements starting from mid-March as well as differences in their evolutions across states. They also reveal periodic fluctuations associated with days of the week, which motivates our use of weekly measures.

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 and deaths because daily new cases and deaths are affected by the timing of reporting and testing, and are quite volatile as shown in Figure 17 in the appendix. 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 $t-21$ for case growth, where the delay reflects the time lag between infection and case confirmation. The four weekly behavior

[19]The other two measures are "Residential" and "Parks." We drop "Residential" because it is highly correlated with both "Workplaces" and "Retail & recreation" at correlation coefficients of -0.98. We also drop "Parks" because it does not have clear implication on the spread of Covid-19.

Table 2. Correlations among Policies and Behavior

	workplaces	retail	grocery	transit	masks for employees	closed K-12 schools	stay at home	closed movie theaters	closed restaurants	closed non-essent bus	business closure policies
workplaces	1.00										
retail	0.93	1.00									
grocery	0.75	0.83	1.00								
transit	0.89	0.92	0.83	1.00							
masks for employees	-0.32	-0.17	-0.15	-0.29	1.00						
closed K-12 schools	-0.91	-0.79	-0.55	-0.72	0.43	1.00					
stay at home	-0.69	-0.69	-0.70	-0.71	0.28	0.62	1.00				
closed movie theaters	-0.81	-0.76	-0.64	-0.71	0.34	0.82	0.72	1.00			
closed restaurants	-0.77	-0.82	-0.68	-0.76	0.21	0.74	0.72	0.82	1.00		
closed non-essent bus	-0.65	-0.68	-0.68	-0.64	0.08	0.56	0.76	0.68	0.71	1.00	
business closure policies	-0.84	-0.84	-0.75	-0.79	0.24	0.78	0.81	0.92	0.93	0.87	1.00

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

variables are referred as "Transit Intensity," "Workplace Intensity," "Retail Intensity," and "Grocery Intensity." Consequently, our empirical analysis uses 7 day moving averages of all variables recorded at daily frequencies. Our sample period is from March 7, 2020 to June 3, 2020.

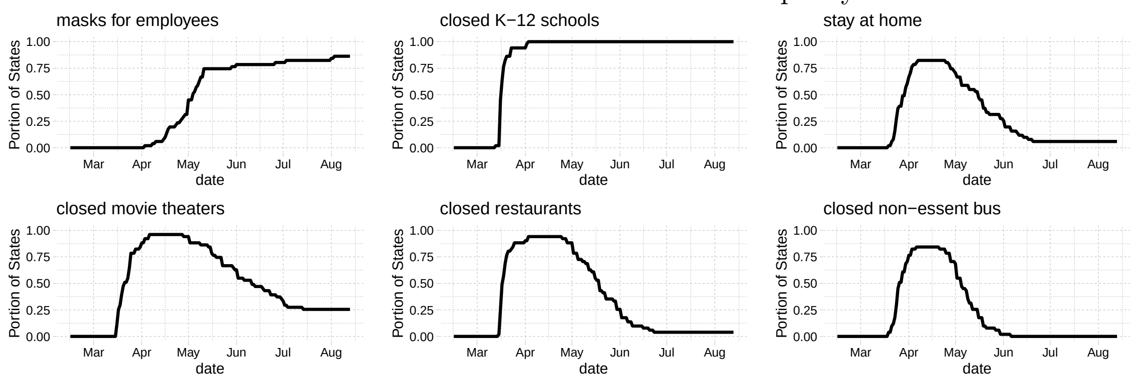
Table 2 reports that weekly policy and behavior variables are highly correlated with each other, except for the"masks for employees" policy. High correlations may cause multicolinearity problems and could limit our ability to separately identify the effect of each policy or behavior variable on case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

Figure 7 shows the portion of states that have each policy in place at each date. For most policies, there is considerable variation across states in the time in which the policies are active. The one exception is K-12 school closures. About 80% of states closed schools within a day or two of March 15th, and all states closed schools by early April. This makes the effect of school closings difficult to separate from aggregate time series variation.

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):

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

FIGURE 7. Portion of states with each policy



where B_{it}^j represents behavior variable j in state i at time t. P_{it} collects the Covid related policies in state i at t. Confounders, W_{it}, include state-level covariates, month indicators, and their interactions. I_{it} is a set of information variables that affect people's behaviors at t. As information, we include each state's growth of cases (in panel 3a) or deaths (in panel 3b), and log cases or deaths. Additionally, in columns (5)-(8) of each panel, we include national growth and log of cases or deaths.

Table 3 reports the estimates with standard errors clustered at the state level. Across different specifications, our results imply that policies have large effects on behavior. Comparing columns (1)-(4) with columns (5)-(8), the magnitude of policy effects are sensitive to whether national cases or deaths are included as information. The coefficient on school closures is particularly sensitive to the inclusion of national information variables. As shown in Figure 7, there is little variation across states in the timing of school closures. Consequently, it is difficult to separate the effect of school closures from a behavioral response to the national trend in cases and deaths.

The other policy coefficients are less sensitive to the inclusion of national case/death variables. After school closures, stay-at-home orders and restaurant closures have the next largest effect. Somewhat surprisingly, closure of nonessential businesses appears to have a modest effect on behavior. Closing movie theaters has a similar, small effect on behavior. The effect of masks for employees is also small. The comparison of effects across policies should be interpreted with caution. Differences between policy effects are often statistically insignificant; except for masks for employees, the policies are highly correlated and it is difficult to separate their effects.

The row "$\sum_j \text{Policy}_j$" reports the sum of the estimated effect of all policies, which is substantial and can account for a large fraction of the observed declines in behavior variables. For example, in Figure 6, transit intensity for a median state was approximately -50% at its lowest point in early April. The estimated policy coefficients in columns imply that imposing all six policies would lead to roughly 85% (in columns 1-4) or roughly 50% (in columns 5-8) of the observed decline. The large impact of policies on transit intensity

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

(a) Cases as Information

	Dependent variable:							
	workplaces	retail	grocery	transit	workplaces	retail	grocery	transit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
masks for employees	0.023^{*}	0.033^{*}	0.012	0.015	0.005	0.0005	0.003	-0.010
	(0.012)	(0.020)	(0.012)	(0.025)	(0.008)	(0.015)	(0.011)	(0.023)
closed K-12 schools	-0.196^{***}	-0.253^{***}	-0.143^{***}	-0.243^{***}	-0.044^{***}	-0.025	-0.069^{**}	-0.047
	(0.030)	(0.048)	(0.027)	(0.050)	(0.013)	(0.018)	(0.027)	(0.041)
stay at home	-0.028^{**}	-0.024	-0.068^{***}	-0.062^{**}	-0.034^{***}	-0.047^{***}	-0.071^{***}	-0.074^{***}
	(0.013)	(0.017)	(0.015)	(0.028)	(0.011)	(0.013)	(0.015)	(0.028)
business closure policies	-0.081^{***}	-0.136^{***}	-0.088^{***}	-0.080^{**}	-0.049^{***}	-0.094^{***}	-0.073^{***}	-0.042
	(0.017)	(0.028)	(0.017)	(0.038)	(0.012)	(0.020)	(0.018)	(0.036)
$\Delta \log \Delta C_{it}$	0.015^{***}	-0.002	0.016^{***}	0.014^{***}	0.017^{***}	0.014^{***}	0.018^{***}	0.020^{***}
	(0.003)	(0.005)	(0.004)	(0.005)	(0.002)	(0.004)	(0.004)	(0.005)
$\log \Delta C_{it}$	-0.024^{***}	-0.022^{***}	-0.0002	-0.018^{*}	-0.005	-0.001	0.009	0.004
	(0.005)	(0.008)	(0.005)	(0.010)	(0.004)	(0.007)	(0.006)	(0.011)
$\Delta \log \Delta C_{it}$.national					-0.033^{***}	-0.086^{***}	-0.018^{**}	-0.053^{***}
					(0.005)	(0.008)	(0.008)	(0.012)
$\log \Delta C_{it}$.national					-0.072^{***}	-0.103^{***}	-0.035^{***}	-0.091^{***}
					(0.004)	(0.008)	(0.008)	(0.012)
state variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month $\times$ state variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\sum_j \text{Policy}_j$	-0.282^{***}	-0.380^{***}	-0.287^{***}	-0.371^{***}	-0.122^{***}	-0.166^{***}	-0.211^{***}	-0.172^{***}
	(0.041)	(0.066)	(0.040)	(0.078)	(0.022)	(0.035)	(0.037)	(0.060)
Observations	3,825	3,825	3,825	3,825	3,825	3,825	3,825	3,825
R^2	0.913	0.829	0.749	0.818	0.953	0.906	0.765	0.856
Adjusted R^2	0.912	0.829	0.748	0.817	0.952	0.905	0.764	0.855

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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. 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. Standard errors are clustered at the state level.

(B) Deaths as Information

	Dependent variable:							
	workplaces	retail	grocery	transit	workplaces	retail	grocery	transit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
masks for employees	0.018	0.027	0.006	0.006	0.007	0.012	0.002	−0.005
	(0.011)	(0.017)	(0.014)	(0.026)	(0.009)	(0.016)	(0.012)	(0.025)
closed K-12 schools	-0.226^{***}	-0.261^{***}	-0.114^{***}	-0.240^{***}	-0.045^{***}	-0.033^{*}	−0.024	−0.050
	(0.024)	(0.033)	(0.018)	(0.035)	(0.014)	(0.019)	(0.020)	(0.039)
stay at home	-0.031^{**}	-0.035^{**}	-0.082^{***}	-0.072^{**}	-0.024^{*}	-0.032^{**}	-0.073^{***}	-0.066^{**}
	(0.012)	(0.017)	(0.016)	(0.031)	(0.012)	(0.015)	(0.017)	(0.032)
business closure policies	-0.101^{***}	-0.156^{***}	-0.101^{***}	-0.111^{***}	-0.044^{***}	-0.091^{***}	-0.067^{***}	−0.054
	(0.022)	(0.033)	(0.020)	(0.041)	(0.012)	(0.021)	(0.020)	(0.039)
$\Delta \log \Delta D_{it}$	-0.012^{***}	-0.031^{***}	−0.001	-0.021^{***}	−0.003	-0.012^{***}	−0.002	-0.009^{*}
	(0.005)	(0.006)	(0.004)	(0.006)	(0.002)	(0.004)	(0.004)	(0.005)
$\log \Delta D_{it}$	-0.013^{***}	−0.001	−0.005	−0.006	−0.007	0.003	0.002	−0.0003
	(0.004)	(0.006)	(0.005)	(0.009)	(0.004)	(0.007)	(0.005)	(0.010)
$\Delta \log \Delta D_{it}$.national					-0.058^{***}	-0.095^{***}	−0.008	-0.067^{***}
					(0.005)	(0.008)	(0.006)	(0.010)
$\log \Delta D_{it}$.national					-0.056^{***}	-0.065^{***}	-0.033^{***}	-0.057^{***}
					(0.004)	(0.007)	(0.006)	(0.010)
state variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month × state variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\sum_j \text{Policy}_j$	-0.340^{***}	-0.425^{***}	-0.292^{***}	-0.417^{***}	-0.105^{***}	-0.144^{***}	-0.162^{***}	-0.176^{***}
	(0.026)	(0.036)	(0.033)	(0.060)	(0.024)	(0.039)	(0.034)	(0.068)
Observations	3,468	3,468	3,468	3,468	3,468	3,468	3,468	3,468
R^2	0.908	0.836	0.760	0.826	0.953	0.899	0.783	0.856
Adjusted R^2	0.907	0.835	0.759	0.825	0.953	0.898	0.782	0.855

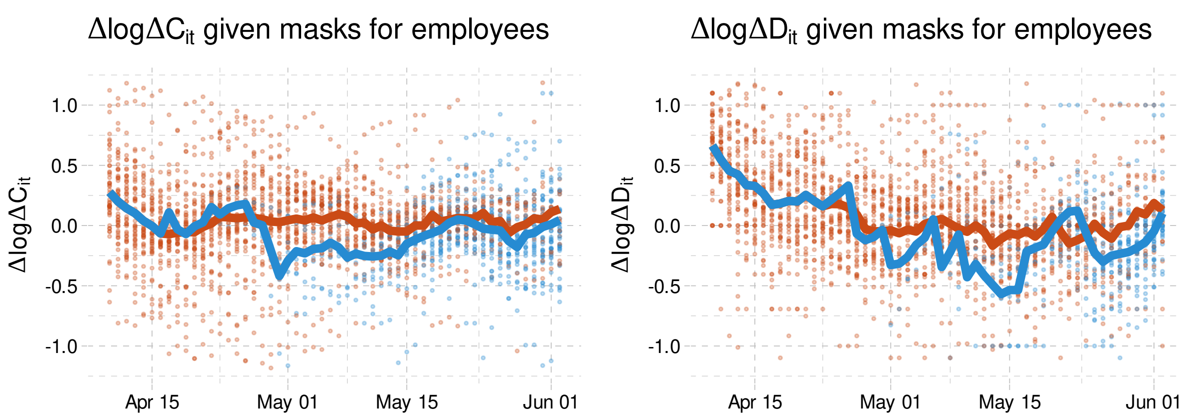
Note: *p<0.1; **p<0.05; ***p<0.01

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. 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. Standard errors are clustered at the state level.

suggests that the policies may have reduced the Covid-19 infection by reducing people's use of public transportation.[20]

In panel 3b, estimated coefficients of deaths and death growth are generally negative. This suggests that the higher number of deaths reduces social interactions measured by Google Mobility Reports perhaps because people are increasingly aware of prevalence of Covid-19 (**?**). The coefficients on log cases and case growth in panel 3a are more mixed. In columns (5)-(8) of both panels, we see that national case/death variables have large, negative coefficients. This suggests that behavior responded to national conditions although it is also likely that national case/death variables capture unobserved aggregate time effects beyond information (e.g., latent policy variables and time-varying confounders that are common across states) which are not fully controlled by month dummies.

FIGURE 8. Case and death growth conditional on mask mandates



In these figures, red points are the case or death growth rate in states without a mask mandate. Blue points are states with a mask mandate 14 (21 for deaths) days prior. The red line is the average across states without a mask mandate 14 (21 for deaths) days earlier. The blue line is the average across states with a mask mandate 14 (21 for deaths) earlier.

4.3. **The Direct Effect of Policies and Behavior on Case and Death Growth.** We now analyze how behavior and policies together influence case and death growth rates. We begin with some simple graphical evidence of the effect of policies on case and death growth. Figure 8 shows average case and death growth conditional on date and whether masks are mandatory for employees.[21] The left panel of the figure shows that states with a mask mandate consistently have 0-0.2 lower case growth than states without. The right panel

[20]Analyzing the New York City's subway ridership, **?** finds a strong link between public transit and spread of infection.

[21]We take 14 and 21 day lags of mask policies for case and death growths, respectively, to identify the states with a mask mandate because policies affect cases and deaths with time lags. See our discussion in the Appendix A.6.

Table 4. The Direct Effect of Behavior and Policies on Case and Death Growth ($BPI \to Y$)

	Dependent variable: $\Delta \log \Delta C_{it}$			
	(1)	(2)	(3)	(4)
lag(masks for employees, 14)	-0.090^{***}	-0.091^{***}	-0.100^{***}	-0.100^{***}
	(0.031)	(0.032)	(0.029)	(0.030)
lag(closed K-12 schools, 14)	-0.074	-0.083	0.043	0.031
	(0.080)	(0.090)	(0.096)	(0.103)
lag(stay at home, 14)	-0.063	-0.058	-0.079	-0.071
	(0.050)	(0.048)	(0.052)	(0.050)
lag(business closure policies, 14)	0.051		0.045	
	(0.062)		(0.060)	
lag(closed movie theaters, 14)		0.032		0.045
		(0.050)		(0.049)
lag(closed restaurants, 14)		0.023		0.022
		(0.044)		(0.043)
lag(closed non-essent bus, 14)		-0.001		-0.016
		(0.040)		(0.040)
lag(workplaces, 14)	1.055^{*}	1.042^{*}	0.391	0.355
	(0.543)	(0.556)	(0.610)	(0.618)
lag(retail, 14)	0.594^{*}	0.611^{**}	0.316	0.342
	(0.303)	(0.309)	(0.316)	(0.317)
lag(grocery, 14)	-0.471^{*}	-0.478^{*}	-0.259	-0.266
	(0.284)	(0.288)	(0.282)	(0.284)
lag(transit, 14)	0.347	0.339	0.355	0.339
	(0.258)	(0.268)	(0.247)	(0.253)
lag($\Delta \log \Delta C_{it}$, 14)	0.015	0.015	0.024	0.024
	(0.026)	(0.025)	(0.028)	(0.028)
lag($\log \Delta C_{it}$, 14)	-0.105^{***}	-0.105^{***}	-0.088^{***}	-0.087^{***}
	(0.019)	(0.019)	(0.021)	(0.021)
lag($\Delta \log \Delta C_{it}$.national, 14)			-0.095^{**}	-0.095^{**}
			(0.042)	(0.043)
lag($\log \Delta C_{it}$.national, 14)			-0.177^{***}	-0.180^{***}
			(0.049)	(0.050)
$\Delta \log T_{it}$	0.152^{***}	0.153^{***}	0.155^{***}	0.156^{***}
	(0.043)	(0.043)	(0.042)	(0.041)
state variables	Yes	Yes	Yes	Yes
Month $\times$ state variables	Yes	Yes	Yes	Yes
$\sum_j$ Policy$_j$	-0.176	-0.178	-0.091	-0.090
	(0.128)	(0.133)	(0.153)	(0.158)
$\sum_k w_k$Behavior$_k$	-0.804^{***}	-0.801^{***}	-0.425^{***}	-0.413^{***}
	(0.140)	(0.140)	(0.157)	(0.160)
Observations	3,825	3,825	3,825	3,825
R^2	0.761	0.761	0.766	0.766
Adjusted R^2	0.759	0.759	0.763	0.764
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

	Dependent variable: $\Delta \log \Delta D_{it}$			
	(1)	(2)	(3)	(4)
lag(masks for employees, 21)	-0.146^{***}	-0.150^{***}	-0.147^{***}	-0.150^{***}
	(0.050)	(0.050)	(0.049)	(0.049)
lag(closed K-12 schools, 21)	-0.232^{**}	-0.250^{**}	-0.178^{*}	-0.198^{**}
	(0.102)	(0.098)	(0.103)	(0.100)
lag(stay at home, 21)	-0.066	-0.050	-0.065	-0.050
	(0.067)	(0.065)	(0.067)	(0.064)
lag(business closure policies, 21)	0.098		0.107	
	(0.087)		(0.092)	
lag(closed movie theaters, 21)		0.006		0.021
		(0.090)		(0.088)
lag(closed restaurants, 21)		0.087		0.083
		(0.072)		(0.070)
lag(closed non-essent bus, 21)		-0.001		-0.001
		(0.058)		(0.059)
lag(workplaces, 21)	1.297^{**}	1.279^{**}	0.896	0.889
	(0.515)	(0.510)	(0.554)	(0.558)
lag(retail, 21)	0.572	0.598	0.523	0.546
	(0.441)	(0.460)	(0.438)	(0.455)
lag(grocery, 21)	-0.935^{**}	-0.966^{**}	-0.887^{**}	-0.912^{**}
	(0.388)	(0.397)	(0.368)	(0.377)
lag(transit, 21)	0.348	0.368	0.384	0.396
	(0.284)	(0.273)	(0.283)	(0.272)
lag($\Delta \log \Delta D_{it}$, 21)	0.016	0.015	0.016	0.015
	(0.035)	(0.035)	(0.037)	(0.037)
lag($\log \Delta D_{it}$, 21)	-0.055^{**}	-0.052^{**}	-0.053^{**}	-0.050^{**}
	(0.024)	(0.025)	(0.024)	(0.024)
lag($\Delta \log \Delta D_{it}$.national, 21)			-0.034	-0.036
			(0.044)	(0.046)
lag($\log \Delta D_{it}$.national, 21)			-0.047	-0.046
			(0.039)	(0.038)
state variables	Yes	Yes	Yes	Yes
Month $\times$ state variables	Yes	Yes	Yes	Yes
$\sum_j$ Policy$_j$	-0.346^{**}	-0.358^{**}	-0.283^{*}	-0.296^{*}
	(0.162)	(0.164)	(0.172)	(0.175)
$\sum_k w_k$Behavior$_k$	-0.837^{***}	-0.845^{***}	-0.661^{***}	-0.670^{***}
	(0.164)	(0.170)	(0.176)	(0.179)
Observations	3,468	3,468	3,468	3,468
R^2	0.518	0.518	0.518	0.519
Adjusted R^2	0.512	0.512	0.513	0.513
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Dependent variable is the weekly growth rate of confirmed cases (in the left panel) or deaths (in the right panel) as defined in equation (3). The covariates include lagged policy and behavior variables, which are constructed as 7 day moving averages between t to $t-7$ of corresponding daily measures. The row "$\sum_j$ Policies$_j$" reports the sum of six policy coefficients. The row "$\sum_k w_k$Behavior$_k$" reports the sum of four coefficients of behavior variables weighted by the average of each behavioral variable from April 1st-10th. Standard errors are clustered at the state level.

also illustrates that states with a mask mandate tend to have lower average death growth than states without a mask mandate.

Similar plots are shown for other policies in Figures 23 and 24 in the appendix. The figures for stay-at-home orders and closure of nonessential businesses are qualitatively similar to that for masks. States with these two policies appear to have about 0.1 percentage point lower case growth than states without. The effects of school closures, movie theater closures, and restaurant closures are not clearly visible in these figures. These figures are merely suggestive; the patterns observed in them may be driven by confounders.

We more formally analyze the effect of policies by estimating regressions. We first look at the direct effect of policies on case and death growth conditional on behavior by estimating equation (BPI→Y):

$$Y_{i,t+\ell} = \alpha' B_{it} + \pi' P_{it} + \mu' I_{it} + \delta_Y' W_{it} + \varepsilon_{it}^{y}, \tag{14}$$

where the outcome variable, $Y_{i,t+\ell}$, is either case growth or death growth.

For case growth as the outcome, we choose a lag length of $\ell = 14$ days for behavior, policy, and information variables to reflect the delay between infection and confirmation of case.[22] $B_{it} = (B_{it}^1, ..., B_{it}^4)'$ is a vector of four behavior variables in state i. P_{it} includes the Covid-related policies in state i that directly affect the spread of Covid-19 after controlling for behavior variables (e.g., masks for employees). We include information variables, I_{it}, that include the past cases and case growths because the past cases may be correlated with (latent) government policies or people's behaviors that are not fully captured by our observed policy and behavior variables. We also consider a specification that includes the past cases and case growth at the national level as additional information variables. W_{it} is a set of confounders that include month dummies, state-level covariates, and the interaction terms between month dummies and state-level covariates.[23] For case growth, W_{it} also includes the test rate growth $\Delta \log(T)_{it}$ to capture the effect of changing test rates on confirmed cases. Equation (14) corresponds to (M-C) derived from the SIR model.

For death growth as the outcome, we take a lag length of $\ell = 21$ days. The information variables I_{it} include past deaths and death growth rates; W_{it} is the same as that of the case growth equation except that the growth rate of test rates is excluded from W_{it} as implied by equation (M-D).

Table 4 shows the results of estimating (14) for case and death growth rates. Column (1) represents our baseline specification while column (2) allows the effect of masks to be different before and after May 1st. Columns (3) and (4) include past cases/deaths and growth rates at national level as additional regressors.

[22]As we review in the Appendix A.6, a lag length of 14 days between exposure and case reporting, as well as a lag length of 21 days between exposure and deaths, is broadly consistent with currently available evidence.

[23]Month dummies also represent the latent information that is not fully captured by the past cases and growths.

The estimates indicate that mandatory face masks for employees reduce the growth rate of infections and deaths by 8-15 percent, while holding behavior constant. This suggests that requiring masks for employees in public-facing businesses may be an effective preventive measure.[24] The estimated effect of masks on death growth is larger than the effect on case growth, but this difference between the two estimated effects is not statistically significant.

Except for mask requirements, policies appear to have little direct effect on case or death growth when behavior is held constant. The one exception is that closing schools has a large and statistically significant coefficient in the death growth regressions. As discussed above, there is little cross-state variation in the timing of school closures, making estimates of its effect less reliable.

The row "$\sum_k w_k \text{Behavior}_k$" reports the sum of estimated coefficients weighted by the average of the behavioral variables from April 1st-10th. The estimates of -0.76 and -0.87 for "$\sum_k w_k \text{Behavior}_k$" in column (1) imply that a reduction in mobility measures relative to the baseline in January and February have induced a decrease in case and death growth rates by 76 and 83 percent, respectively, suggesting an importance of social distancing for reducing the spread of Covid-19. When including national cases and deaths in information, as shown in columns (3) and (4), the estimated aggregate impact of behavior is substantially smaller, but remains large and statistically significant.

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 or death growth. This should be done with caution, 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/death growth.

The negative coefficients of past cases or deaths in Table 4 is consistent with a hypothesis that higher reported cases and deaths change people's behavior to reduce transmission risks. Such behavioral changes in response to new information are partly captured by Google mobility measures, but the negative estimated coefficient of past cases or deaths imply that other latent behavioral changes that are not fully captured by Google mobility measures (e.g., frequent hand-washing, wearing masks, and keeping 6ft/2m distancing) are also important for reducing future cases and deaths.

If policies are enacted and behavior changes, then future cases/deaths and information will change, which will induce further behavior changes. However, since the model includes

[24]Note that we are *not* evaluating the effect of *universal* mask-wearing for the public but that of mask-wearing for employees. The effect of *universal* mask-wearing for the public could be larger if people comply with such a policy measure. **?** considered a model in which mask wearing reduces the reproduction number by a factor $(1 - e \cdot pm)^2$, where e is the efficacy of trapping viral particles inside the mask and pm is the percentage of mask-wearing population. Given an estimate of $R_0 = 2.4$, **?** argue that 50% mask usage and a 50% mask efficacy level would reduce the reproduction number from 2.4 to 1.35, an order of magnitude impact.

Table 5. The Total Effect of Policies on Case and Death Growth ($PI \to Y$)

	Dependent variable: $\Delta \log \Delta C_{it}$			
	(1)	(2)	(3)	(4)
lag(masks for employees, 14)	-0.083^{**}	-0.081^{**}	-0.103^{***}	-0.102^{***}
	(0.038)	(0.040)	(0.033)	(0.035)
lag(closed K-12 schools, 14)	-0.226^{**}	-0.236^{**}	0.029	0.017
	(0.089)	(0.097)	(0.102)	(0.107)
lag(stay at home, 14)	-0.127^{**}	-0.121^{**}	-0.115^{**}	-0.103^{**}
	(0.057)	(0.054)	(0.054)	(0.052)
lag(business closure policies, 14)	-0.076		-0.001	
	(0.068)		(0.061)	
lag(closed movie theaters, 14)		0.027		0.062
		(0.051)		(0.046)
lag(closed restaurants, 14)		-0.041		-0.011
		(0.049)		(0.045)
lag(closed non-essent bus, 14)		-0.051		-0.038
		(0.050)		(0.043)
lag($\Delta \log \Delta C_{it}$, 14)	0.040	0.041^{*}	0.036	0.035
	(0.024)	(0.025)	(0.028)	(0.028)
lag($\log \Delta C_{it}$, 14)	-0.137^{***}	-0.137^{***}	-0.091^{***}	-0.090^{***}
	(0.022)	(0.022)	(0.026)	(0.026)
lag($\Delta \log \Delta C_{it}$.national, 14)			-0.128^{***}	-0.123^{***}
			(0.039)	(0.041)
lag($\log \Delta C_{it}$.national, 14)			-0.243^{***}	-0.245^{***}
			(0.045)	(0.045)
$\Delta \log T_{it}$	0.156^{***}	0.157^{***}	0.158^{***}	0.160^{***}
	(0.044)	(0.044)	(0.042)	(0.041)
state variables	Yes	Yes	Yes	Yes
Month $\times$ state variables	Yes	Yes	Yes	Yes
$\sum_j \text{Policy}_j$	-0.512^{***}	-0.504^{***}	-0.190	-0.175
	(0.150)	(0.154)	(0.156)	(0.159)
Observations	3,825	3,825	3,825	3,825
R^2	0.749	0.750	0.763	0.763
Adjusted R^2	0.747	0.747	0.760	0.761
Note:				*p<0.1; **p<0.05; ***p<0.01

	Dependent variable: $\Delta \log \Delta D_{it}$			
	(1)	(2)	(3)	(4)
lag(masks for employees, 21)	-0.134^{***}	-0.133^{**}	-0.156^{***}	-0.155^{***}
	(0.051)	(0.053)	(0.050)	(0.052)
lag(closed K-12 schools, 21)	-0.610^{***}	-0.621^{***}	-0.234^{**}	-0.248^{**}
	(0.115)	(0.121)	(0.111)	(0.109)
lag(stay at home, 21)	-0.082	-0.075	-0.068	-0.057
	(0.066)	(0.064)	(0.066)	(0.062)
lag(business closure policies, 21)	-0.059		0.059	
	(0.086)		(0.086)	
lag(closed movie theaters, 21)		-0.006		0.050
		(0.089)		(0.082)
lag(closed restaurants, 21)		-0.012		0.030
		(0.061)		(0.055)
lag(closed non-essent bus, 21)		-0.040		-0.016
		(0.066)		(0.063)
lag($\Delta \log \Delta D_{it}$, 21)	-0.001	-0.001	0.017	0.016
	(0.033)	(0.033)	(0.036)	(0.037)
lag($\log \Delta D_{it}$, 21)	-0.078^{***}	-0.078^{***}	-0.064^{**}	-0.063^{**}
	(0.026)	(0.027)	(0.027)	(0.027)
lag($\Delta \log \Delta D_{it}$.national, 21)			-0.147^{***}	-0.148^{**}
			(0.056)	(0.057)
lag($\log \Delta D_{it}$.national, 21)			-0.116^{***}	-0.117^{***}
			(0.032)	(0.032)
state variables	Yes	Yes	Yes	Yes
Month $\times$ state variables	Yes	Yes	Yes	Yes
$\sum_j \text{Policy}_j$	-0.885^{***}	-0.887^{***}	-0.399^{**}	-0.396^{**}
	(0.159)	(0.166)	(0.183)	(0.188)
Observations	3,468	3,468	3,468	3,468
R^2	0.502	0.502	0.512	0.512
Adjusted R^2	0.497	0.497	0.507	0.507
Note:				*p<0.1; **p<0.05; ***p<0.01

Dependent variable is the weekly growth rate of confirmed cases (in the left panel) or deaths (in the right panel) as defined in equation (3). The covariates include lagged policy variables, which are constructed as 7 day moving averages between t to $t-7$ of corresponding daily measures. The row "$\sum_j \text{Policies}_j$" reports the sum of six policy coefficients. Standard errors are clustered at the state level.

TABLE 6. Direct and Indirect Policy Effects without national case/death variables

Cases

	Direct	Indirect	Total	PI→Y Coef.	Average	Difference
masks for employees	-0.090***	0.043	-0.047	-0.083**	-0.065	0.036**
	(0.031)	(0.028)	(0.043)	(0.038)	(0.040)	(0.015)
closed K-12 schools	-0.074	-0.374***	-0.448***	-0.226***	-0.337***	-0.223***
	(0.078)	(0.094)	(0.116)	(0.086)	(0.099)	(0.054)
stay at home	-0.063	-0.034	-0.096*	-0.127**	-0.112**	0.031**
	(0.049)	(0.027)	(0.054)	(0.056)	(0.055)	(0.014)
business closure policies	0.051	-0.153***	-0.101	-0.076	-0.089	-0.025
	(0.062)	(0.045)	(0.069)	(0.067)	(0.067)	(0.020)
$\sum_j \text{Policy}_j$	-0.176	-0.517***	-0.693***	-0.512***	-0.603***	-0.181***
	(0.123)	(0.145)	(0.181)	(0.144)	(0.161)	(0.060)
$\Delta \log \Delta C_{it}$	0.015	0.012	0.027	0.040*	0.033	-0.013*
	(0.025)	(0.010)	(0.024)	(0.024)	(0.023)	(0.007)
$\log \Delta C_{it}$	-0.105***	-0.045***	-0.150***	-0.137***	-0.144***	-0.013*
	(0.018)	(0.015)	(0.025)	(0.021)	(0.023)	(0.008)

Deaths

	Direct	Indirect	Total	PI→Y Coef.	Average	Difference
masks for employees	-0.146***	0.035***	-0.111**	-0.134***	-0.122**	0.022
	(0.048)	(0.000)	(0.048)	(0.050)	(0.048)	(0.020)
closed K-12 schools	-0.232**	-0.420***	-0.653***	-0.610***	-0.632***	-0.042*
	(0.101)	(0.090)	(0.115)	(0.114)	(0.114)	(0.025)
stay at home	-0.066	-0.008	-0.073	-0.082	-0.078	0.008
	(0.066)	(0.032)	(0.065)	(0.064)	(0.064)	(0.016)
business closure policies	0.098***	-0.163**	-0.065	-0.059	-0.062	-0.006
	(0.000)	(0.069)	(0.069)	(0.083)	(0.061)	(0.093)
$\sum_j \text{Policy}_j$	-0.346***	-0.557***	-0.902***	-0.885***	-0.894***	-0.018
	(0.121)	(0.148)	(0.161)	(0.158)	(0.150)	(0.110)
$\Delta \log \Delta D_{it}$	0.016	-0.040***	-0.024	-0.001	-0.012	-0.023***
	(0.034)	(0.012)	(0.031)	(0.032)	(0.032)	(0.005)
$\log \Delta D_{it}$	-0.055**	-0.015	-0.070***	-0.078***	-0.074***	0.009
	(0.024)	(0.009)	(0.027)	(0.025)	(0.026)	(0.005)

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

Table 7. Direct and Indirect Policy Effects with national case/death variables

Cases

	Direct	Indirect	Total	PI→Y Coef.	Average	Difference
masks for employees	-0.100***	-0.002	-0.102***	-0.103***	-0.103***	0.001
	(0.027)	(0.018)	(0.034)	(0.031)	(0.032)	(0.011)
closed K-12 schools	0.043	-0.024	0.019	0.029	0.024	-0.011
	(0.091)	(0.035)	(0.098)	(0.096)	(0.097)	(0.014)
stay at home	-0.079	-0.036*	-0.115**	-0.115**	-0.115**	0.000
	(0.051)	(0.019)	(0.054)	(0.055)	(0.054)	(0.010)
business closure policies	0.045	-0.045*	0.000	-0.001	-0.000	0.001
	(0.058)	(0.026)	(0.060)	(0.059)	(0.059)	(0.013)
$\sum_j \text{Policy}_j$	-0.091	-0.107*	-0.198	-0.190	-0.194	-0.008
	(0.149)	(0.060)	(0.154)	(0.151)	(0.153)	(0.021)
$\Delta \log \Delta C_{it}$	0.024	0.014**	0.038	0.036	0.037	0.002
	(0.028)	(0.007)	(0.027)	(0.027)	(0.027)	(0.003)
$\log \Delta C_{it}$	-0.088***	-0.003	-0.091***	-0.091***	-0.091***	-0.000
	(0.020)	(0.010)	(0.026)	(0.025)	(0.026)	(0.004)
$\Delta \log \Delta C_{it}$.national	-0.095**	-0.054***	-0.149***	-0.128***	-0.138***	-0.022
	(0.040)	(0.015)	(0.040)	(0.037)	(0.038)	(0.013)
$\log \Delta C_{it}$.national	-0.177***	-0.084***	-0.261***	-0.243***	-0.252***	-0.018*
	(0.050)	(0.023)	(0.045)	(0.045)	(0.045)	(0.009)

Deaths

	Direct	Indirect	Total	PI→Y Coef.	Average	Difference
masks for employees	-0.147***	0.009***	-0.138***	-0.156***	-0.147***	0.018
	(0.049)	(0.000)	(0.049)	(0.051)	(0.049)	(0.018)
closed K-12 schools	-0.178*	-0.055	-0.234**	-0.234**	-0.234**	0.000
	(0.103)	(0.036)	(0.112)	(0.110)	(0.111)	(0.020)
stay at home	-0.065	0.001	-0.063	-0.068	-0.066	0.005
	(0.066)	(0.028)	(0.064)	(0.065)	(0.064)	(0.015)
business closure policies	0.107***	-0.048	0.059*	0.059	0.059	-0.001
	(0.000)	(0.035)	(0.035)	(0.086)	(0.045)	(0.095)
$\sum_j \text{Policy}_j$	-0.283**	-0.094	-0.377***	-0.399**	-0.388**	0.023
	(0.125)	(0.066)	(0.143)	(0.184)	(0.158)	(0.094)
$\Delta \log \Delta D_{it}$	0.016	-0.010**	0.006	0.017	0.012	-0.010***
	(0.037)	(0.005)	(0.035)	(0.036)	(0.036)	(0.004)
$\log \Delta D_{it}$	-0.053**	-0.006	-0.059**	-0.064**	-0.062**	0.005
	(0.024)	(0.009)	(0.027)	(0.027)	(0.027)	(0.006)
$\Delta \log \Delta D_{it}$.national	-0.034	-0.120***	-0.154***	-0.147***	-0.151***	-0.007
	(0.044)	(0.022)	(0.049)	(0.056)	(0.052)	(0.013)
$\log \Delta D_{it}$.national	-0.047	-0.077**	-0.124***	-0.116***	-0.120***	-0.008
	(0.039)	(0.030)	(0.035)	(0.032)	(0.033)	(0.013)

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

lags of cases/deaths as well as their growth rates, computing a long-run effect is not completely straightforward. We investigate dynamic effects that incorporate feedback through information in section 5.

4.4. **The Total Effect of Policies on Case Growth.** In this section, we focus our analysis on policy effects when we hold information constant. The estimated effect of policy on behavior in Table 3 and those of policies and behavior on case/death growth in Table 4 can be combined to calculate the total effect of policy as well as its decomposition into direct and indirect effects.

The first three columns of Table 6 show the direct (holding behavior constant) and indirect (through behavior changes) effects of policy under a specification that excludes national information variables. These are computed from the specification with national cases or deaths included as information (columns (1)-(4) of Table 3 and column (1) of Table 4). The estimates imply that all policies combined would reduce the growth rate of cases and deaths by 0.70 and 0.98, respectively, out of which about two-third to three-fourth is attributable to the indirect effect through their impact on behavior. The estimate also indicates that the effect of mandatory masks for employees is mostly direct.

We can also examine the total effect of policies and information on case or death growth, by estimating (PI→Y). The coefficients on policy in this regression combine both the direct and indirect effects.

Table 5 shows the full set of coefficient estimates for (PI→Y). The results are broadly consistent with what we found above. As in Table 3, the effect of school closures is sensitive to the inclusion of national information variables. Also as above, mask mandates have a significant negative effect on growth rates.

In columns (2) and (4) of Table 5, we find that the estimated effect of mask mandates in April is larger than that in May for both case and death regressions. This may reflect a wider *voluntary* adoption of masks in May than in April — if more people wear masks even without mandatory mask policy, the policy effect of mandating masks for employees becomes weaker.

Table 7 presents the estimates for the specification with past national case/death variables. The effects of school closures and the sum of policies are estimated substantially smaller in Table 7 when national case/death variables are included than in Table 6. This sensitivity reflects the difficulty in identifying the aggregate time effect—which is largely captured by national cases/deaths—given little cross-sectional variation in the timing of school closures across states. On the other hand, the estimated effects of policies other than school closures are similar between Table 6 and Table 7; the effect of other policies are well-identified from cross-sectional variations.

Column "Difference" in Tables 6 and 7 show the difference between the estimate of (PI→Y) in column "PI→Y Coefficient" and the implied estimate from (BPI→Y)-(PI→B) in column "Total." Differences are generally small and statistically insignificant, broadly supporting the validity of extra orthogonality condition in (BPI→Y). The difference for school closures as well as the sum of all policies in Table 6 is significantly different from zero, which may be due to the aforementioned difficulty in identifying the effect of school closures. There is substantial external epidemiological evidence that suggests that schooling closures may have substantial effects on the spread of the virus: studies like **?** and **?** establish that children carry substantial amounts of viral loads and can contribute to the transmission (due to higher contact rate than other age groups).[25] The US data does not allow us to pint down the effect of closing schools reliably due to their approximate collinearity with trends in national cases.

Column "Average" of Tables 6 and 7 reports the average of "Total" and "PI→Y Coefficient" columns. The average is an appealing and simple way to combine the two estimates of the total effect: one relying on the causal structure and another inferred from a direct estimation of equation (PI → Y).[26] We shall be using the average estimate in generating the counterfactuals in the next section. Turning to the results, the estimates of Tables 6 and 7 imply that all policies combined would reduce $\Delta \log \Delta D$ by 0.97 and 0.40, respectively. For comparison, the median of $\Delta \log \Delta D_{it}$ reached its peak in mid-March of about 1.3 (see Figure 20 in the appendix). Since then it has declined to near 0. Therefore, -0.97 and -0.40 imply that policy changes can account for roughly one-third to two-third of the observed decrease in death growth. The remainder of the decline is likely due to changes in behavior from information.

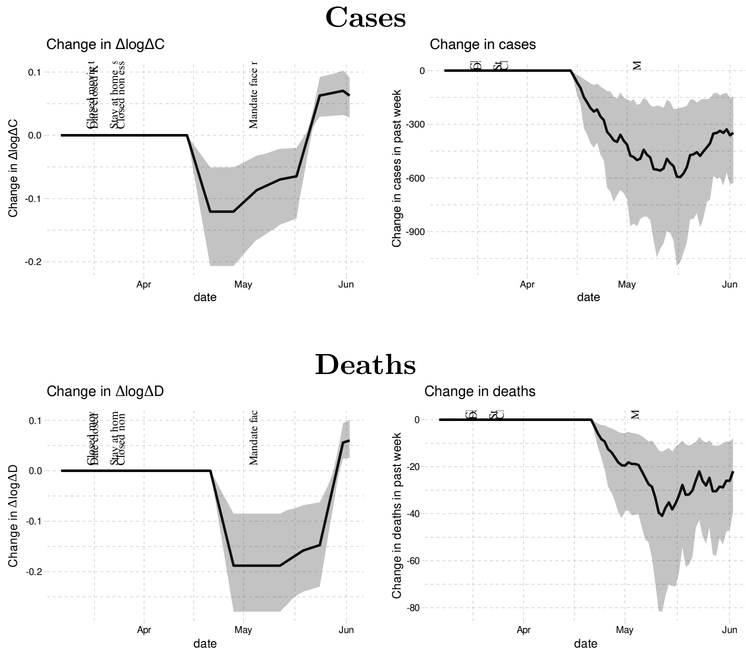
5. Empirical Evaluation of Counterfactual Policies

We now turn our focus to dynamic feedback effects. Policy and behavior changes that reduce case and death growth today can lead to a more optimistic, riskier behavior in the future, attenuating longer run effects. We perform the main counterfactual experiments using the average of two estimated coefficients as reported in column "Average" of Table 6 under a specification that excludes the number of past national cases and deaths from information variables. In the appendix, we also report additional counterfactual experiment results with the specification that includes the national information variables, and find that they are very similar. The results on mask policies, business closures, stay-at-home orders are robust with respect to this variation (see Figures 10-13 in the appendix). On the other hand, the results on removing all policies, particularly closure of schools, reported in the next section, are sensitive to the inclusion of national information variables, highlighting the large uncertainty regarding the size of the effect. In Figures 9-13 below, the top panel presents the result on cases while the bottom panel presents the result on deaths.

[25]The evidence presented in **?** has lead German to make the decision to close schools early.

[26]Averaging the two estimates theoretically reduces noise, albeit in our case the reductions are small. Another approach would be to use precision averaging, which would give similar result. Finally, another approach would be to use generalized method of moments to estimate all of the equations jointly. We don't pursue this approach since it is likely to be non-robust under local deviations from correct specification; simple model averaging is more appealing in this case.

FIGURE 9. Effect of mandating masks on April 1st in Washington State



To compute the estimated and counterfactual paths we use the average of two estimated coefficients as reported in column "Average" 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. The shaded region is a point-wise 90% confidence interval.

5.1. **Business Mask Mandate.** We first consider the impact of a nationwide mask mandate for employees beginning on April 1st. As discussed earlier, we find that mask mandates reduce case and death growth even when 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 the number of cases if all states had imposed a mask mandate on April 1st.[27]

For illustrative purpose, we begin by focusing on Washington State. The left column of Figure 9 shows the observed, estimated average, and counterfactual average of $\Delta \log \Delta C$ (top panel) and $\Delta \log \Delta D$ (bottom panel). To compute the estimated and counterfactual paths, we use the estimate in column "Average" 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. The

[27]We feel this is a very plausible counterfactual policy. In a paper made publicly available on April 1st, **?** argued for mask usage based on comparisons between countries with and without pre-existing norms of widespread mask usage.

shaded region is a point-wise 90% confidence interval. The left column shows that the fit of the estimated and observed growth rate is quite good.

The middle column of Figure 9 shows the change in growth rate from mandating masks on April 1st. The shaded region is a 90% pointwise confidence interval. As shown, mandating masks on April 1st lowers the growth of cases or deaths 14 or 21 days later by 0.1 to 0.15. This effect then gradually declines due to information feedback. Mandatory masks reduce past cases or deaths, which leads to less cautious behavior, attenuating the impact of the policy. The reversal of the decrease in growth in late April is due to our comparison of a mask mandate on April 1st with Washington's actual mask mandate in early May. By late April, the counterfactual mask effect has decayed through information feedback, and we are comparing it the undecayed impact of Washington's actual, later mask mandate.

The right column of Figure 9 shows how the changes in case and death growth translate into changes in cases and deaths. The estimates imply that mandating masks on April 1st would have led to 500 fewer cases and 250 fewer deaths in Washington by the start of June.

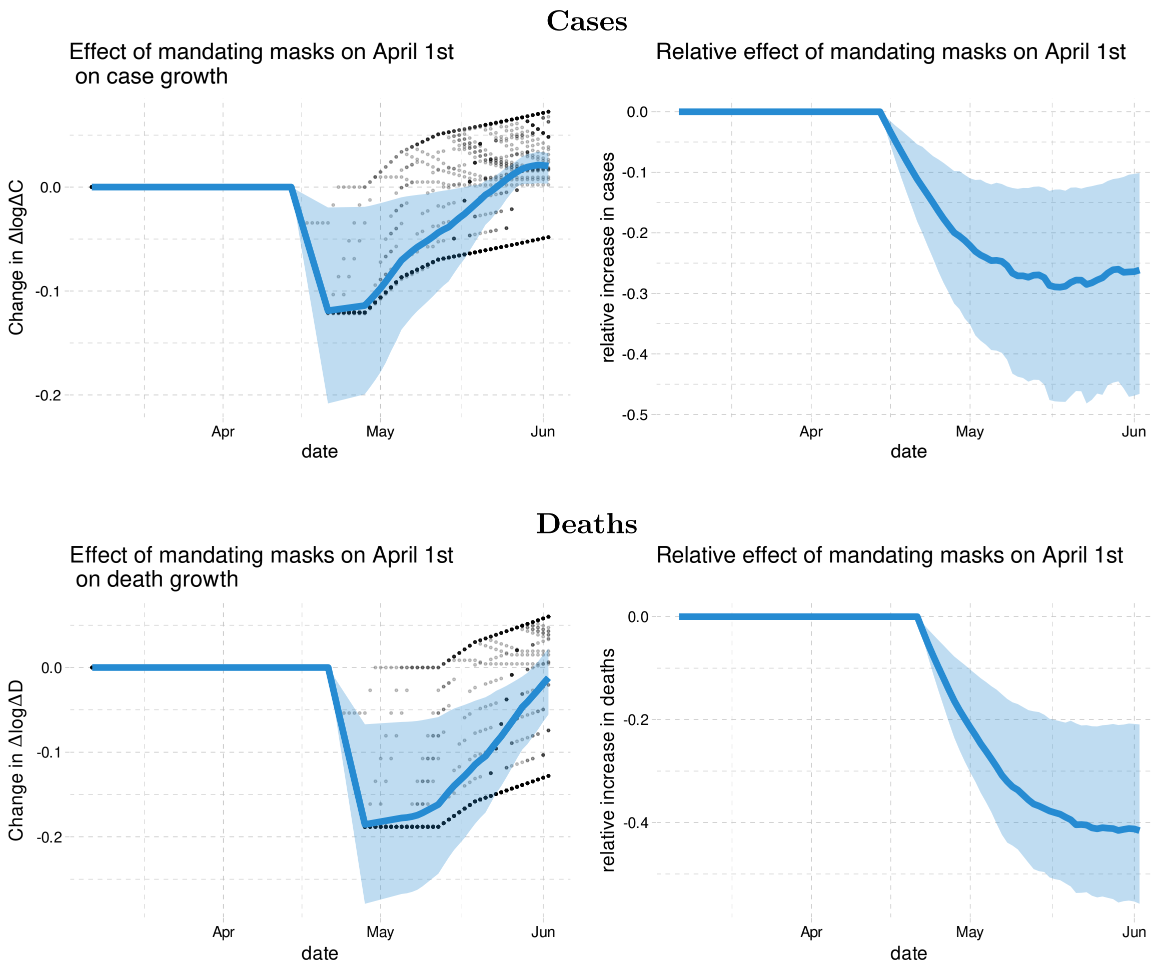
The results for other states are similar to those for Washington. In the appendix, Figures 25 and 26 display similar results for Massachusetts and Illinois. Figure 10 shows the average change in cases and deaths across states, where the top panel shows the effect on cases and the bottom panel shows the effect on deaths. The point estimates indicate that mandating masks on April 1st could have led to 25% fewer cumulative cases and 37% fewer cumulative deaths by the end of May with their 90 percent intervals given by $[10, 47]$% and $[18, 55]$%, respectively. The result roughly translates into 18 to 55 thousand saved lives.

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 11 shows the effect of leaving non-essential businesses open in Washington. The point estimate implies that the closure of non-essential businesses reduced cases and deaths by a small amount. However, this estimate is relatively imprecise; 90% confidence intervals for the change in cases and deaths from leaving non-essential businesses open by the end of May are [-250,700] and [-100,1200], respectively.

Figure 12 shows the national effect of leaving non essential businesses open on cases and deaths. For cases, the estimates imply that with non-essential businesses open, cases would be about -15 to 60% higher in late May. The results for deaths are similar but less precise.

5.3. **Stay-at-home orders.** We next examine a counterfactual where stay-at-home orders had been never issued. Figure 13 shows the average effect of no stay-at-home orders. On average, without stay-at-home orders, case growth rate would have been nearly 0.1 higher in late April. This translates to 80% [25%,170%] more cases by the start of June. The results for deaths are similar, but slightly less precise, with no increase included in a 90 percent confidence interval.

FIGURE 10. Effect of nationally mandating masks for employees on April 1st in the US



In the left column, the dots are the average change in growth in each state. The blue line is the average across states of the change in growth. The shaded region is a point-wise 90% confidence interval. The right column shows the change in cases or deaths relative to the baseline of actual policies.

FIGURE 11. Effect of leaving non-essential businesses open in Washington

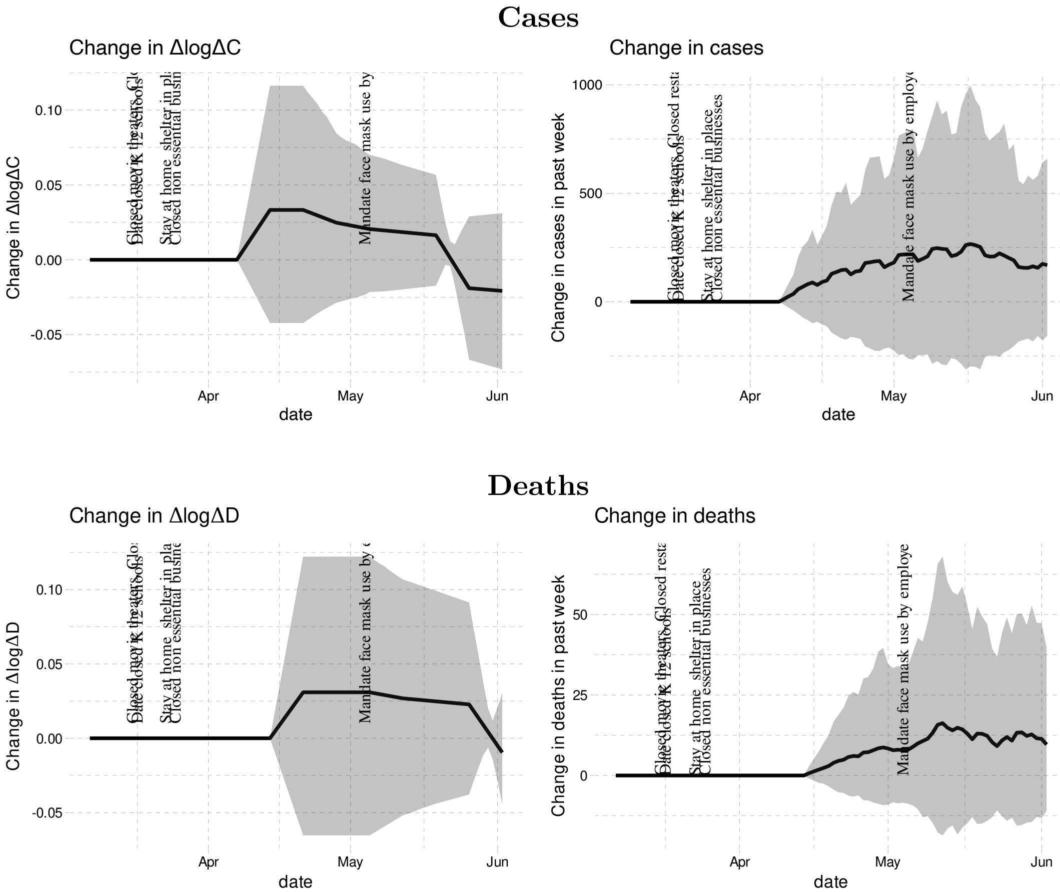


FIGURE 12. Effect of leaving non-essential businesses open in the US

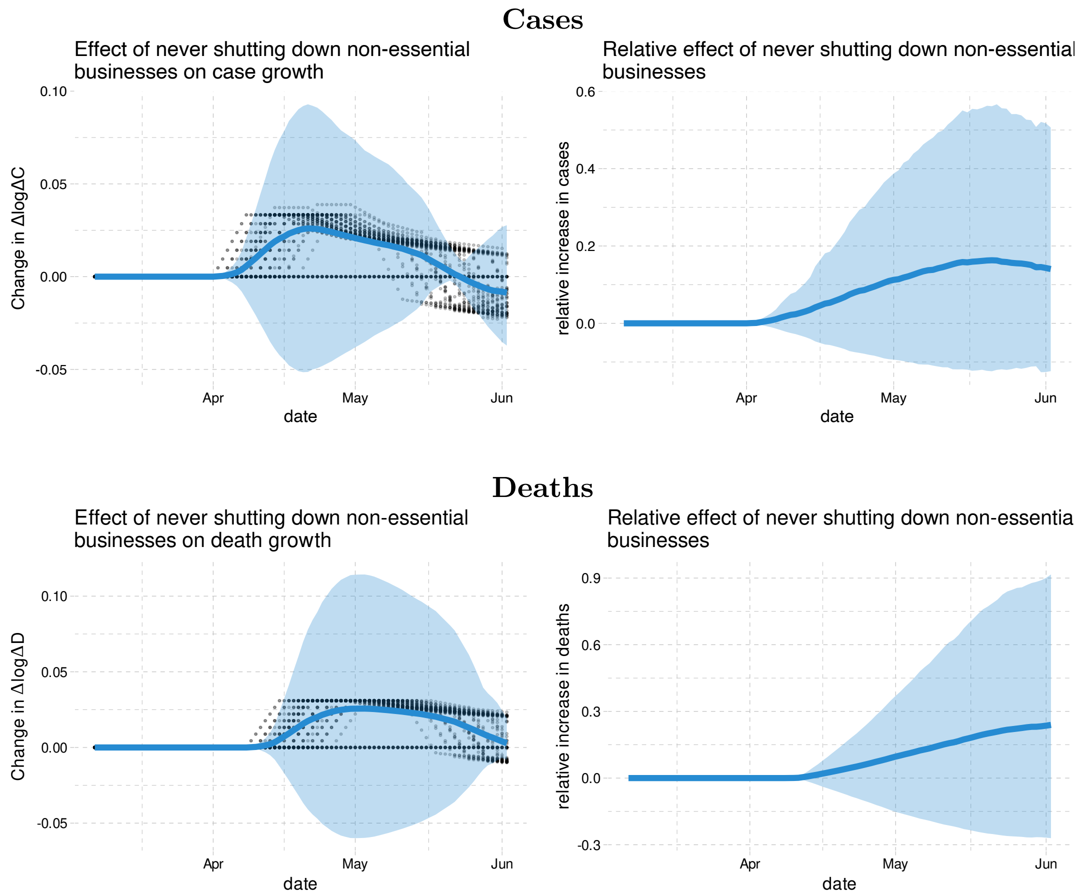
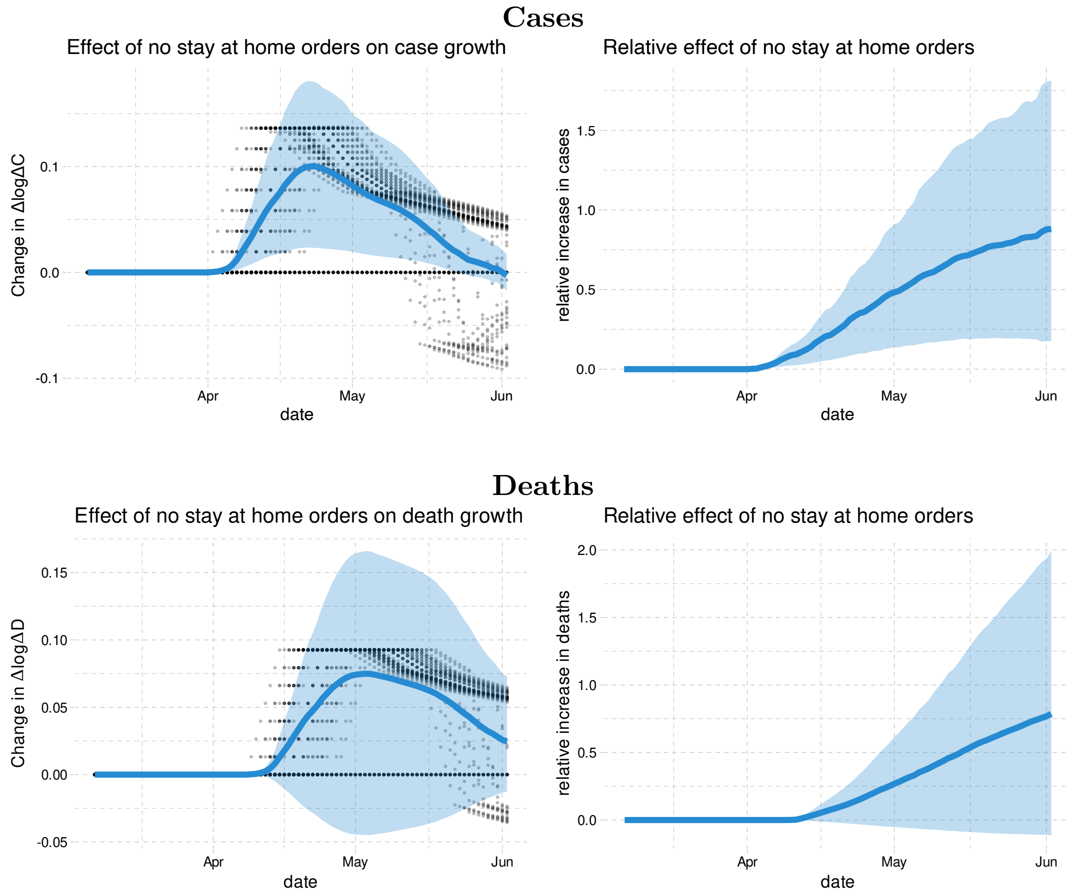


FIGURE 13. Effect of having no stay-at-home orders in the US



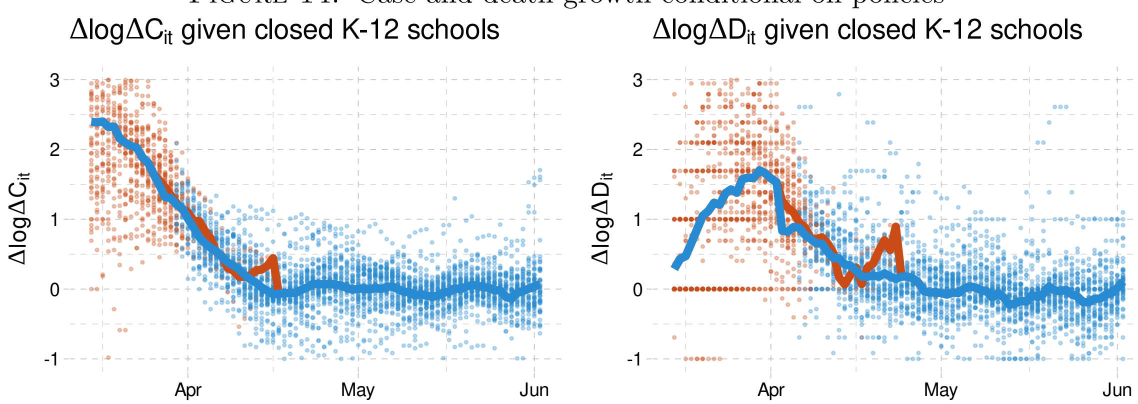
6. Counterfactual Effect of Removing All Policies and its Sensitivity

We now consider the impact of changing from the observed policies to none. Figure 15 shows the average across states of the change in case growth and relative increase in cases under a specification without past national case variables. Removing policies leads to an increase of above 0.2 in case growth throughout April and May. The confidence interval is fairly wide, and its upper bound includes a very large increase in cases by the end of May. The right panel displays the national increase in aggregate cases without any policy intervention. The estimates imply at least a 7 fold increase in cases with a large upper bound by the end of May, or at least 14 million additional cases. The estimated impact on deaths is larger than cases, and even more imprecise.

The effect of removing all policies includes the effect of school closures. The visual evidence on growth rates for states with and without school closures, presented blow, suggest that there may be a potentially large effect, though the history is very short. The main results presented in Section 3 also support the hypothesis that the school closures were important at lowering the growth rates. This evidence is consistent with the emerging evidence of prevalence of Covid-19 among children aged 10-17. **?** find that although children's transmission and susceptibility rates are half that of ages 20-30, children's contact rates are much higher. This type of evidence, as well as, evidence that children carry viral loads similar to older people (**?**), led Germany to make the early decision of closing schools.

As discussed above, there is little variation across states in the timing of school closures. Consequently, the effect of school closures is difficult to identify statistically, because it is hard to separate it from aggregate time effect, and its estimate is sensitive to an inclusion of some aggregate variables such as national cases. To support this point, Figure 16 shows the

Figure 14. Case and death growth conditional on policies



In these figures, red points are the case or death growth rate in states without each policy 14 (or 21 for deaths) days earlier. Blue points are states with each policy 14 (or 21 for deaths) days earlier. The red line is the average across states without each policy. The blue line is the average across states with each policy.

effect of removing all policies on cases based on the estimates with national cases included as information. When national case variables are included in the specification, the estimated effect of school closures, and hence that of removing all policies, is much smaller with a 90% confidence interval of [0,10] fold increases.

Given this sensitivity, we conclude that there still exists a lot of uncertainty as to the effect of removing all policies, especially schooling. The impact of not implementing any policies on cases and deaths can be quite large, but the effect of school closures, hence that of removing all policies, is not well identified statistically from the US state-level data alone, because of the lack of cross-sectional variations. Any analyses of re-opening plans need to be aware of this uncertainty. An important research question is how to resolve this uncertainty using additional data sources.

FIGURE 15. Effect of removing policies on cases in the US under a specification with only state-level cases/deaths as information

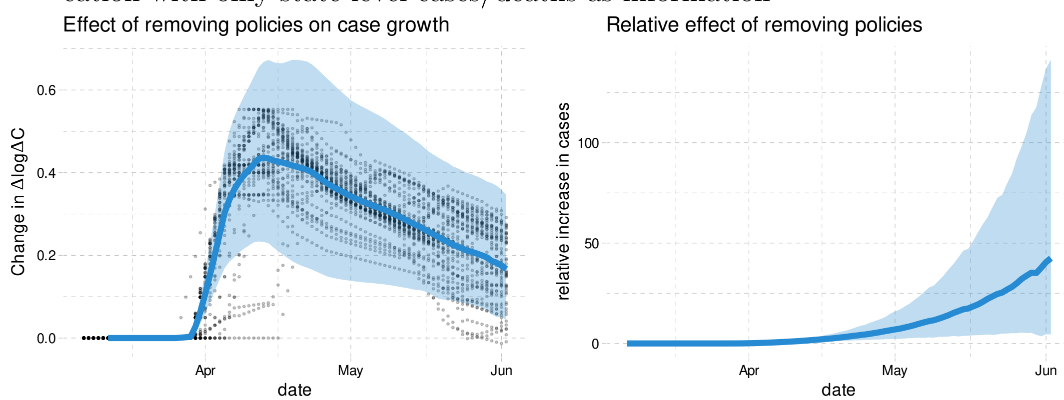
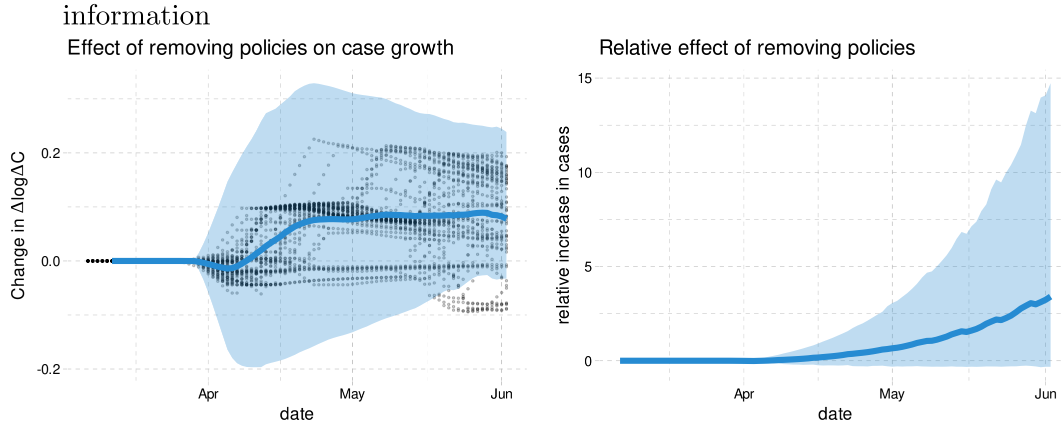


FIGURE 16. Effect of removing policies on cases in the US under a specification with both state-level cases/deaths and national-level cases/deaths as information



7. Conclusion

This paper assesses the effects of policies on the spread of Covid-19 in the US using 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 has 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 suggests that if all states had have adopted mandatory face mask policies on April 1st of 2020, then the number of deaths by the end of May would have been smaller by as much as 17 to 55%, which roughly translates to 17 to 55 thousand saved lives.

Second, we find that keeping non-essential businesses open would have led to -20 to 60% more cases while not implementing stay-at-home orders would have increased cases by 25 to 170 % by the start of June.

Third, we find considerable uncertainty over the impact of all policies combined on case or death growth because it is difficult to identify the effect of school closures from the US state-level data due to the lack of variation in the timing of school closures across states.

Fourth, our analysis shows that people voluntarily reduce their visits to workplace, retails, grocery stores, and limit their use of public transit when they receive information on a higher number of new cases and deaths. 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 that affects future cases and deaths. Model simulations that ignore this voluntary behavioral response to information on transmission risks would over-predict the future number of cases and deaths.

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. More broadly, our causal framework can be useful for quantitatively analyzing not only health outcomes but also various economic outcomes (**??**).

Appendix A. Data Construction

A.1. **Measuring ΔC 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	0.99985	0.99970
JHU	0.99985	1.00000	0.99985
CTP	0.99970	0.99985	1.00000

Table 8. Correlation of cumulative cases

	1	2	3
NYT	1.00	0.38	0.32
JHU	0.38	1.00	0.51
CTP	0.32	0.51	1.00

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

Figure 17 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. The NYT new case numbers have the lowest variance.[28] In our subsequent results, we will primarily use the case numbers from The New York Times.

	NYT	JHU	CTP
NYT	1.00	0.93	0.86
JHU	0.93	1.00	0.82
CTP	0.86	0.82	1.00
Variance	5.05	5.81	6.11

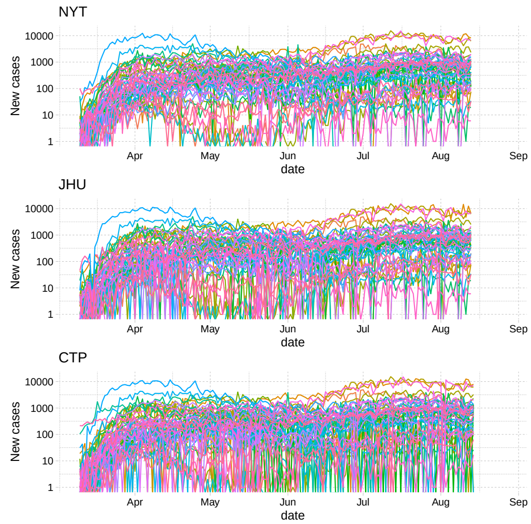
Table 10. Correlation and variance of log daily new cases

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 18 shows the evolution of weekly new cases in each state over time.

[28]This comparison is somewhat sensitive to how you handle negative and zero cases when taking logs. Here, we replaced log(0) with -1. In our main results, we work with weekly new cases, which are very rarely zero.

FIGURE 17. Daily cases



Each line shows daily new cases in a state.

	NYT	JHU	CTP
NYT	1.00	1.00	0.98
JHU	1.00	1.00	0.98
CTP	0.98	0.98	1.00
Variance	3.68	3.76	3.47

TABLE 11. Correlation and variance of log weekly new cases

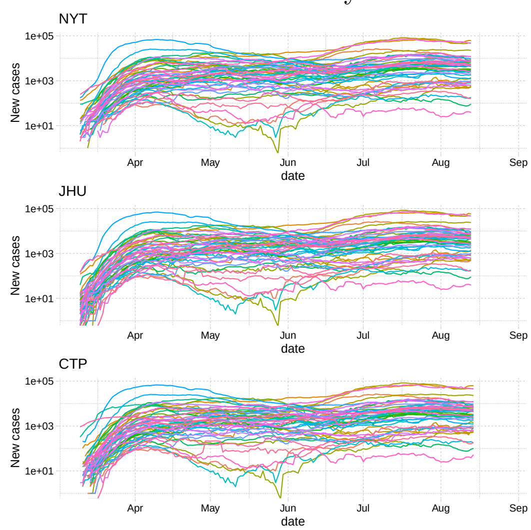
A.2. **Deaths.** Table 12 reports the correlation and variance of weekly deaths in the three data sets. Figure 19 shows the evolution of weekly deaths in each state. As with cases, we use death data from The New York Times in our main results.

	NYT	JHU	CTP
NYT	1.00	0.98	0.97
JHU	0.98	1.00	0.98
CTP	0.97	0.98	1.00
Variance	172292.15	174310.07	126952.94

TABLE 12. Correlation and variance of weekly deaths

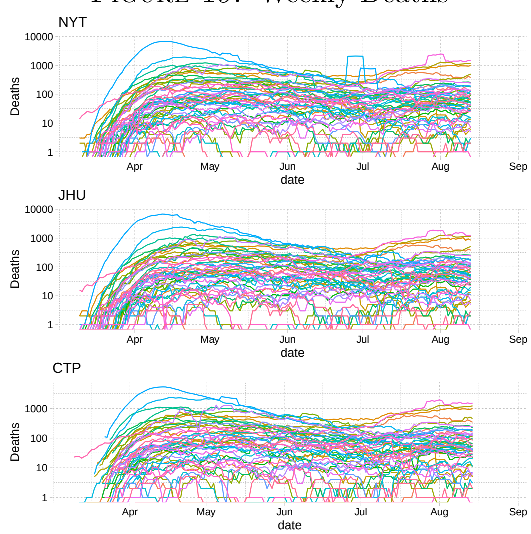
A.3. **Tests.** Our test data comes from The Covid Tracking Project. Figure 21 shows the evolution of tests over time.

Figure 18. Weekly Cases



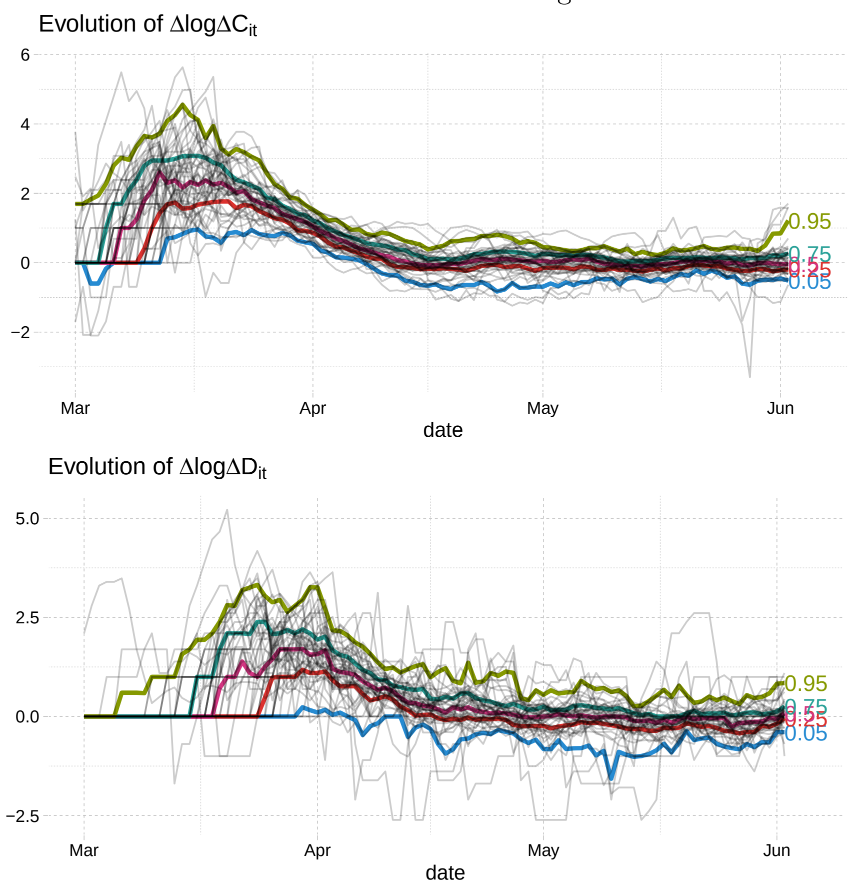
Each line shows weekly new cases in a state.

Figure 19. Weekly Deaths



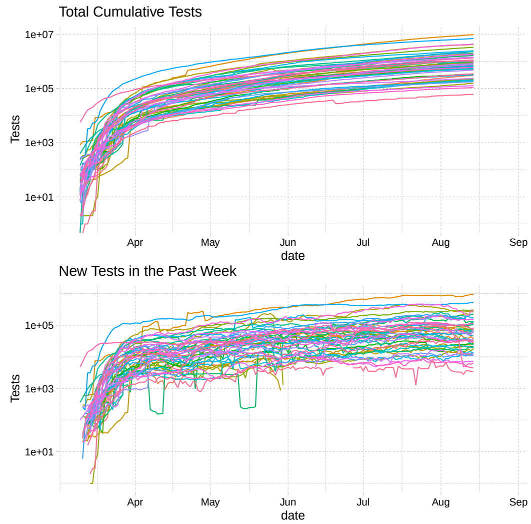
Each line shows weekly deaths in a state.

FIGURE 20. Case and death growth



Thin gray lines are case or death growth in each state and date. Thicker colored lines are quantiles of case or death growth conditional on date.

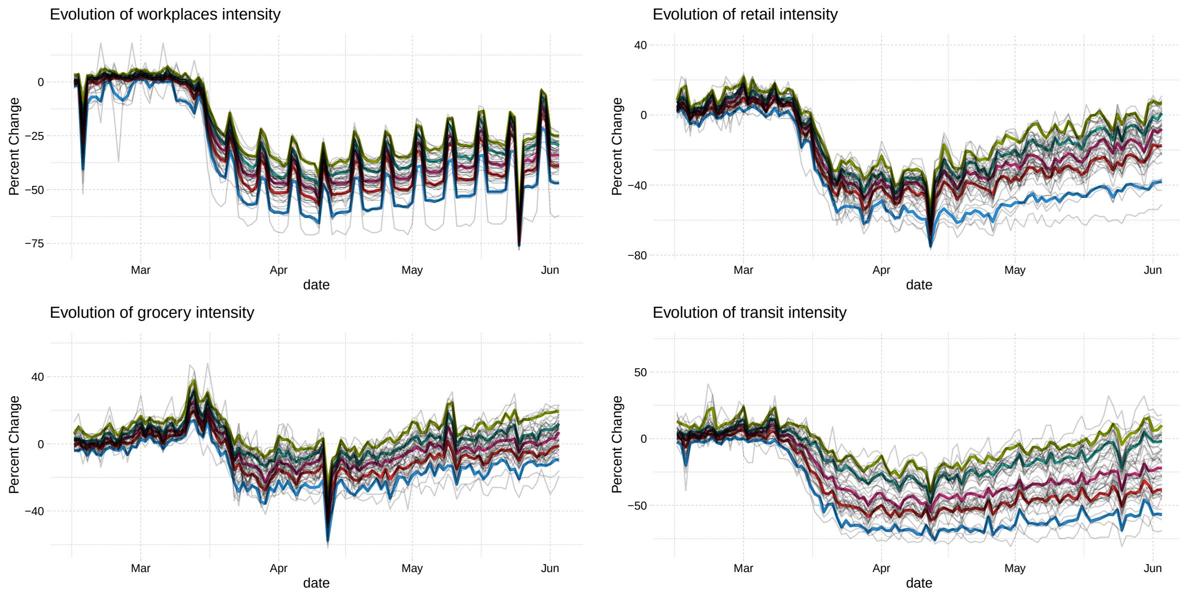
FIGURE 21. Number of Tests



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.4. **Social Distancing Measures.** In measuring social distancing, we focus on Google Mobility Reports. This data has international coverage and is publicly available. Figure 22 shows the evolution of the four Google Mobility Reports variables that we use in our analysis.

FIGURE 22. Evolution of Google Mobility Reports



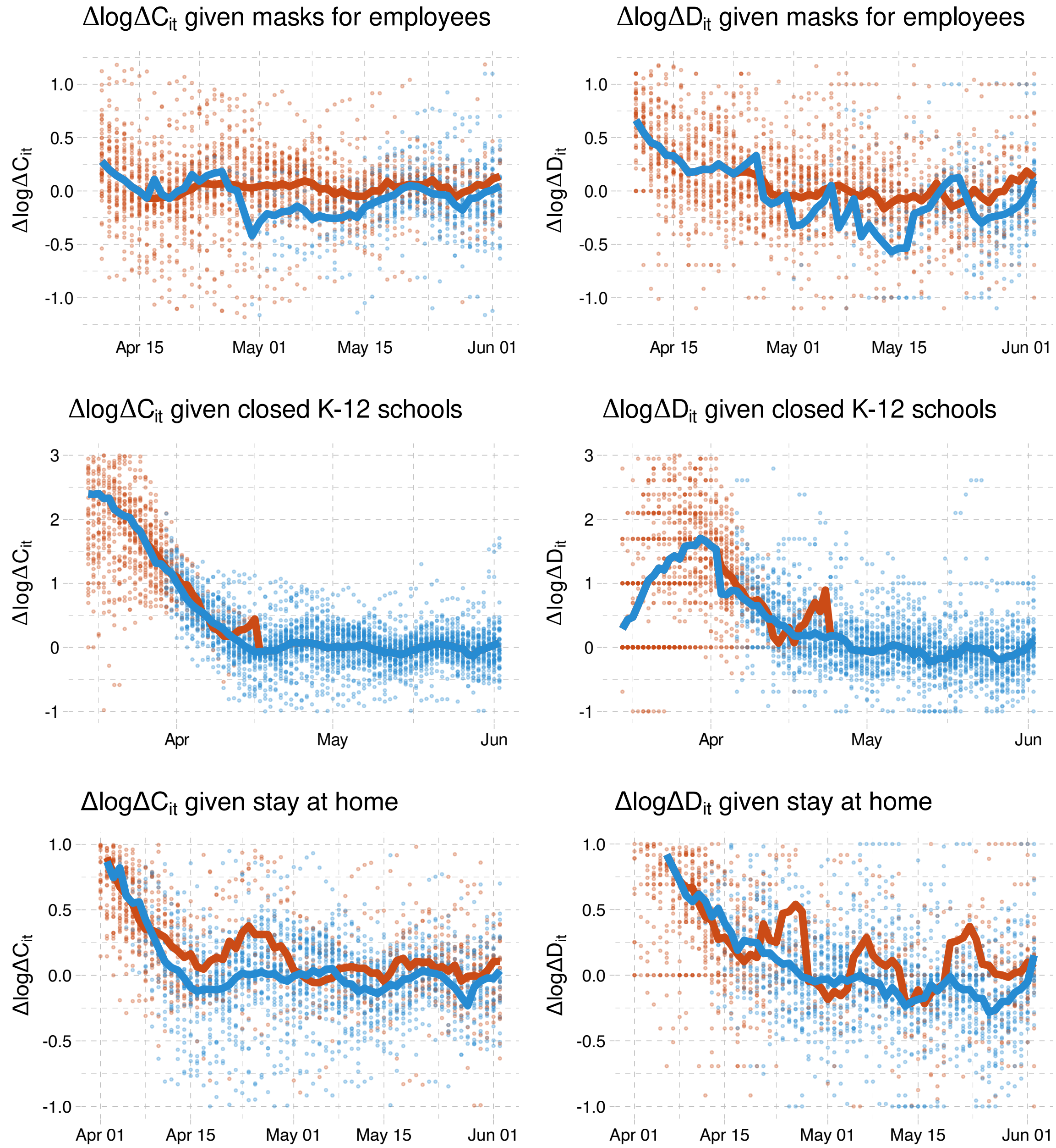
This figure shows the evolution of Google Mobility Reports over time. Thin gray lines are the value of the variables in each state and date. Thicker colored lines are quantiles of the variables conditional on date.

A.5. **Policy Variables.** We use the database on US state policies created by **?**. As discussed in the main text, our analysis focuses on seven policies. For stay-at-home orders, closed nonessential businesses, closed K-12 schools, closed restaurants except takeout, and closed movie theaters, we double-checked any state for which **?** 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 orders, 3 for movie theater closure, and 4 for non-essential business closures. Table 13 displays all 25 dated policy variables in **?**'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. **?** 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, **?** estimate a mean incubation period of 5.2 days. **?** reviews the literature and concludes the mean incubation period is 3-9 days.

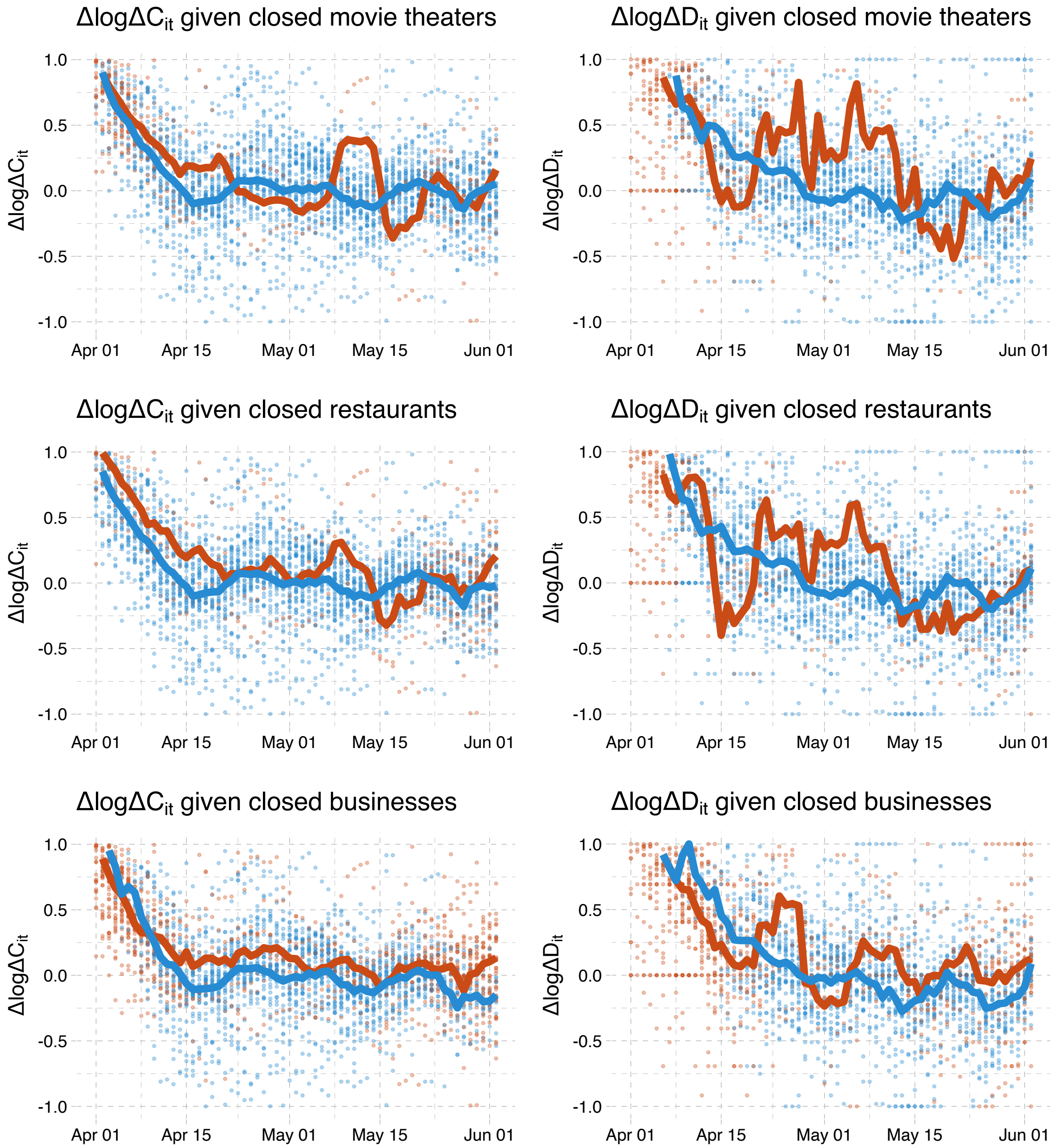
Estimates of the time between symptom onset and case reporting or death are less common. Using Italian data, **?** estimate an average of 7.3 days between symptom onset and

FIGURE 23. Case and death growth conditional on policies



In these figures, red points are the case or death growth rate in states without each policy 14 (or 21 for deaths) days earlier. Blue points are states with each policy 14 (or 21 for deaths) days earlier. The red line is the average across states without each policy. The blue line is the average across states with each policy.

FIGURE 24. Case and death growth conditional on policies



In these figures, red points are the case or death growth rate in states without each policy 14 (or 21 for deaths) days earlier. Blue points are states with each policy14 (or 21 for deaths) days earlier. The red line is the average across states without each policy. The blue line is the average across states with each policy.

	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
Closed non essential businesses	43	2020-03-19	2020-03-25	2020-04-06
Closed restaurants except take out	48	2020-03-15	2020-03-17	2020-04-03
Closed gyms	49	2020-03-16	2020-03-20	2020-04-03
Closed movie theaters	49	2020-03-16	2020-03-21	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	39	2020-04-24	2020-05-18	2020-06-19
Began to reopen businesses statewide	50	2020-04-20	2020-05-07	2020-06-05
Reopen restaurants	48	2020-04-24	2020-05-18	2020-06-22
Reopened gyms	44	2020-04-24	2020-05-18	2020-07-13
Reopened movie theaters	37	2020-04-27	2020-06-01	2020-07-13
Resumed elective medical procedures	35	2020-04-20	2020-04-30	2020-05-29
Mandate face mask use by all individuals in public spaces	35	2020-04-08	2020-06-26	2020-08-05
Mandate face mask use by employees in public facing businesses	44	2020-04-03	2020-05-01	2020-08-03
Stop Initiation of Evictions overall or due to COVID related issues	30	2020-03-16	2020-03-24	2020-05-30
Stop enforcement of evictions overall or due to COVID related issues	29	2020-03-15	2020-03-24	2020-06-08
Renter grace period or use of security deposit to pay rent	3	2020-04-10	2020-04-24	2020-05-20
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
Waived one week waiting period for unemployment insurance	36	2020-03-08	2020-03-18	2020-04-06

Table 13. State Policies

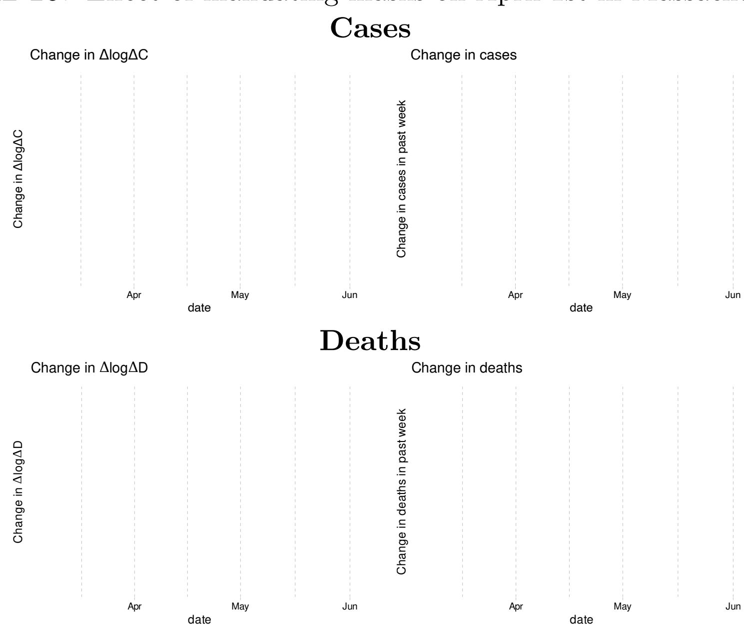
reporting. **?** find an average of 7.4 days using Chinese data from December to early February, but they find this period declined from 8.9 days in January to 5.4 days in the first week of February. Both of these papers on time from symptom onset to reporting have large confidence intervals covering approximately 1 to 20 days.

Studying publicly available data on infected persons diagnosed outside of Wuhan, **?** estimate an average of 15 days from onset to death. Similarly, using publicly available reports of 140 confirmed Covid-19 cases in China, mostly outside Hubei Province, **?** estimate the time from onset to death to be 16.1 days.

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

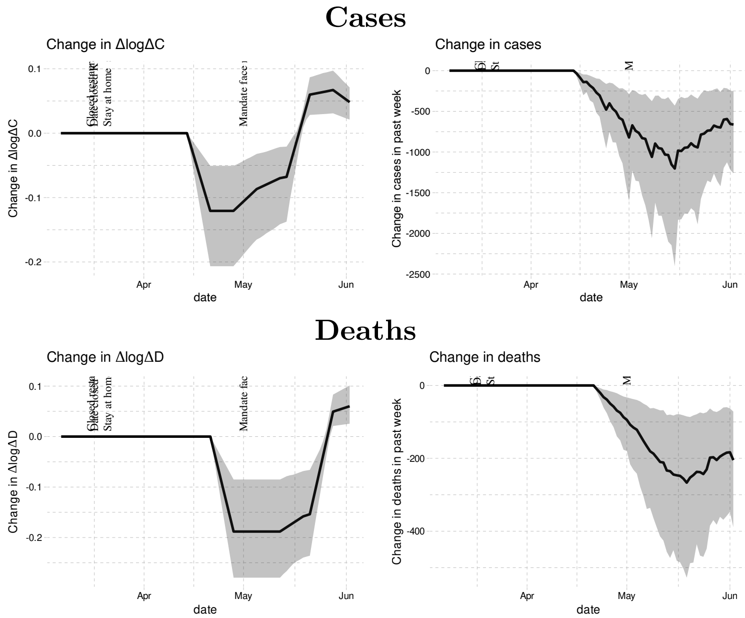
A.7. **Counterfactuals for Massachusetts and Illinois.** Figures 25 and 26 present the fit of estimated cases as well as the counterfactual effect of mandating masks on April 1st in Massachusetts and Illinois, respectively. Figures 27 and 28 show the counterfactual effect of leaving non-essential business open in Massachusetts and Illinois, respectively.

FIGURE 25. Effect of mandating masks on April 1st in Massachusetts



To compute the estimated and counterfactual paths we use the average of two estimated coefficients as reported in column "Average" of Table 7. 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. The shaded region is a point-wise 90% confidence interval.

FIGURE 26. Effect of mandating masks on April 1st in Illinois



To compute the estimated and counterfactual paths we use the average of two estimated coefficients as reported in column "Average" of Table 7. 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. The shaded region is a point-wise 90% confidence interval.

FIGURE 27. Effect of leaving businesses open in Massachusetts

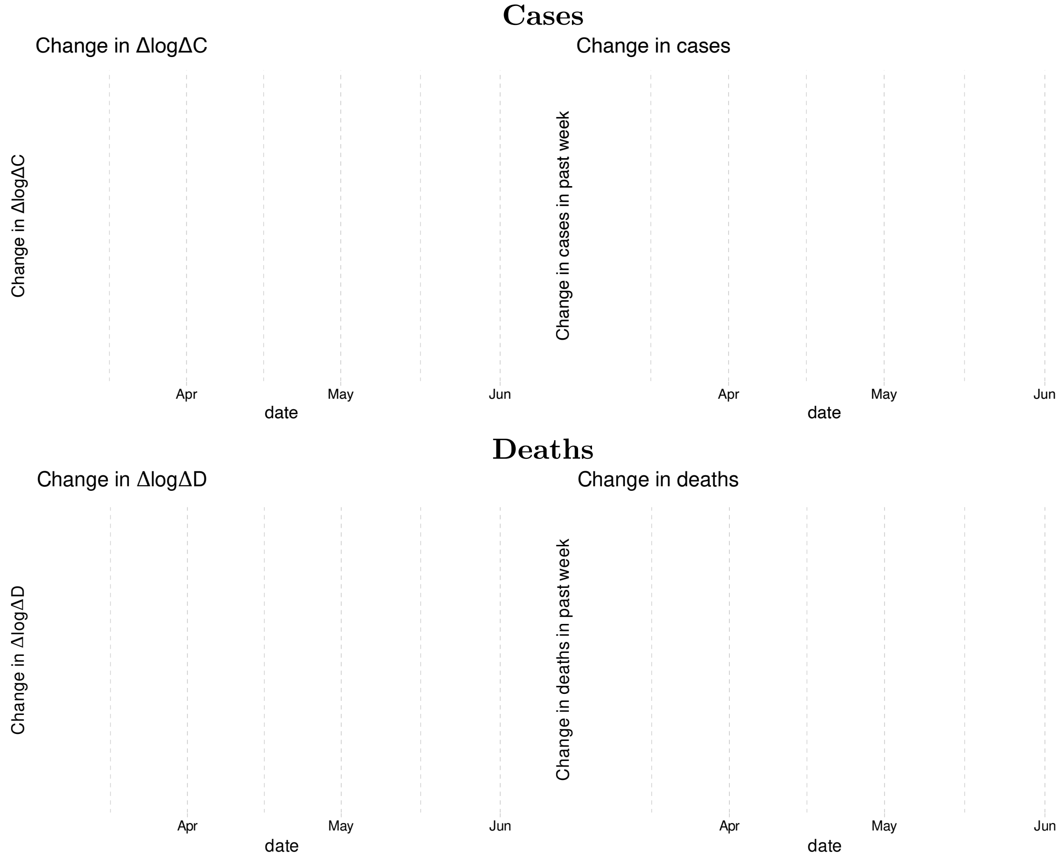
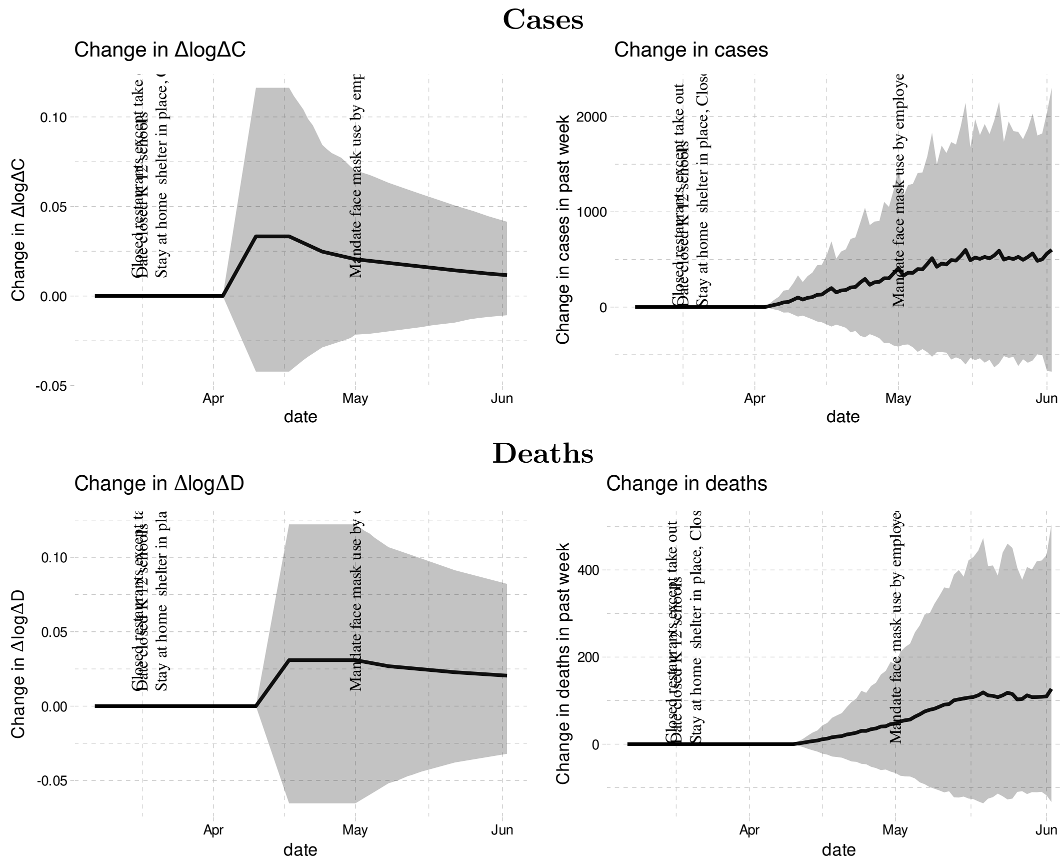


FIGURE 28. Effect of leaving businesses open in Illinois



A.8. **Counterfactuals with National Cases as Information Variables.** Figures 29-31 present the results of counterfactual analyses that include the national cases/deaths as the information variables. To create this figure, we repeat the same counterfactual simulation that we did for Washington with each state. For each state, we hold national cases constant, but endogenize state specific information. Thus, these figures should be interpreted as an average of state specific counterfactuals, and not a national counterfactual.

The counterfactual results of mask policies, shelter-in-place, and closing non-essential businesses remain robust with respect to the inclusion of national case/death variables. This contrasts to the resulting counterfactual of removing all policies discussed in section 6.

FIGURE 29. Effect of mandating masks for employees on April 1st under a specification with both state-level cases/deaths and national-level cases/deaths as information

Cases

Deaths

Figure 30. Effect of leaving non-essential businesses open under a specification with both state-level cases/deaths and national-level cases/deaths as information

Cases

Deaths

Figure 31. Effect of having no stay-at-home orders under a specification with both state-level cases/deaths and national-level cases/deaths as information

Cases

Deaths

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