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PRELIMINARY: PLEASE DO NOT CITE

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Abstract

We examine the period of national lockdown beginning in March 2020 using an integrated epidemiological-econometric framework in which health and economic outcomes are jointly determined. We augment a state-level compartmental model with behavioral responses to non-pharmaceutical interventions (NPIs) and to local epidemiological conditions. To calibrate the model, we construct daily, county-level measures of contact rates and employment and estimate key parameters with an event study design. We have three main findings: First, NPIs introduced by state and local governments explain a small fraction of the nationwide decline in contact rates but nevertheless reduced COVID-19 deaths by almost 30% percent---saving about 33,000 lives---over the first 3 months of the pandemic. However, NPIs also explain nearly 15% of the decline in employment---around 3 million jobs---over the same period. Second, NPIs that target individual behavior (such as stay-at-home orders) were more effective at reducing transmission at lower economic cost than those that target businesses (shutdowns). Third, an aggressive and well-designed response in the early stages of the pandemic could have improved both epidemiological and economic outcomes over the medium-term.

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The COVID-19 pandemic led to an unprecedented collapse in social and economic activity in the United States. Widespread social distancing – undertaken voluntarily and in response to government interventions – succeeded in containing the initial outbreak, but at a significant cost. Over the course of the middle two weeks of March 2020, employment fell by 30 million, triggering the deepest recession of the postwar period.

This paper attempts a comprehensive assessment of the early response to COVID-19. We address three key questions:

- How big a role did government mandates play relative to voluntary action in the shift to social distancing and the collapse in employment?
- How effective were the major non-pharmaceutical interventions (NPIs) deployed in response to the pandemic – stay-at-home orders, school closures, and non-essential business closures – at reducing disease transmission while minimizing economic costs?
- How could the policy response to COVID-19 have been improved and, more broadly, how should NPIs be used in response to pandemic?

To answer these questions, we extend a state-level compartmental model of the pandemic with behavioral responses to NPIs and to local epidemiological conditions. To calibrate the model, we develop novel measures of daily social contact rates and employment at the county level and estimate key parameters directly with a difference-in-differences approach. We then use our empirical estimates and simulations of the model to assess the determinants of epidemiological and economic outcomes from March through the end of May.

We find that NPIs account for only 9% of the sharp fall in contact rates over this period. This relatively modest effect, however, led to a reduction of nearly 30% in deaths from COVID-19 by May 31st. At the same time, we estimate that NPIs reduced employment by about 3 million, nearly 15% of the total decline. We also find significant differences in the effectiveness of different NPIs, with interventions that target businesses delivering less epidemiological benefit at greater economic cost than those that target individual behavior.

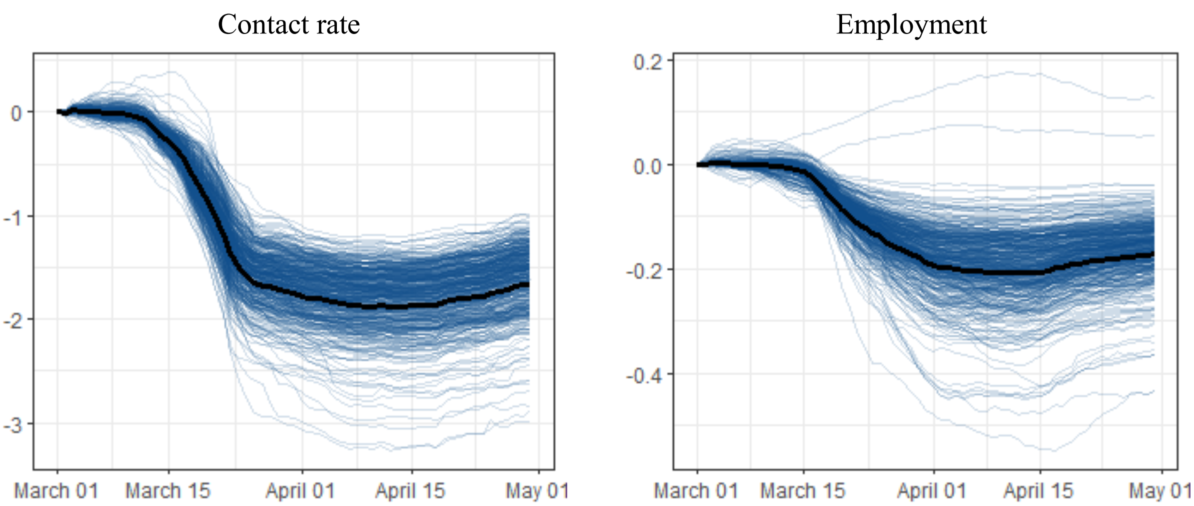
This paper joins a growing literature on the epidemiology of COVID-19 and the effects of NPIs.[1] We make three main contributions. First, we relax the conventional assumption in epidemiological models that contact rates are independent of dynamics of the epidemic and

[1] See, for example, Goolsbee and Syverson (2020), Gupta, Simon, and Wing (2020) and the literature cited therein.

allow agents to respond endogenously to local infection risk by changing their social behavior. Second, we extend the model with an explicit role for NPIs, so that our empirical specification arises directly from the model. Third, we combine data from a many different sources to construct comprehensive daily measures of contact rates and employment. With these measures, we are able frame our analysis directly in terms of the key outcomes (for example, total employment) rather than rely on the idiosyncratic proxies commonly used for high-frequency analysis of COVID-19.

Figure 1. The response to COVID-19 by county

Log difference from March 1st, 7-day average



Source: Authors' calculations; see section V.

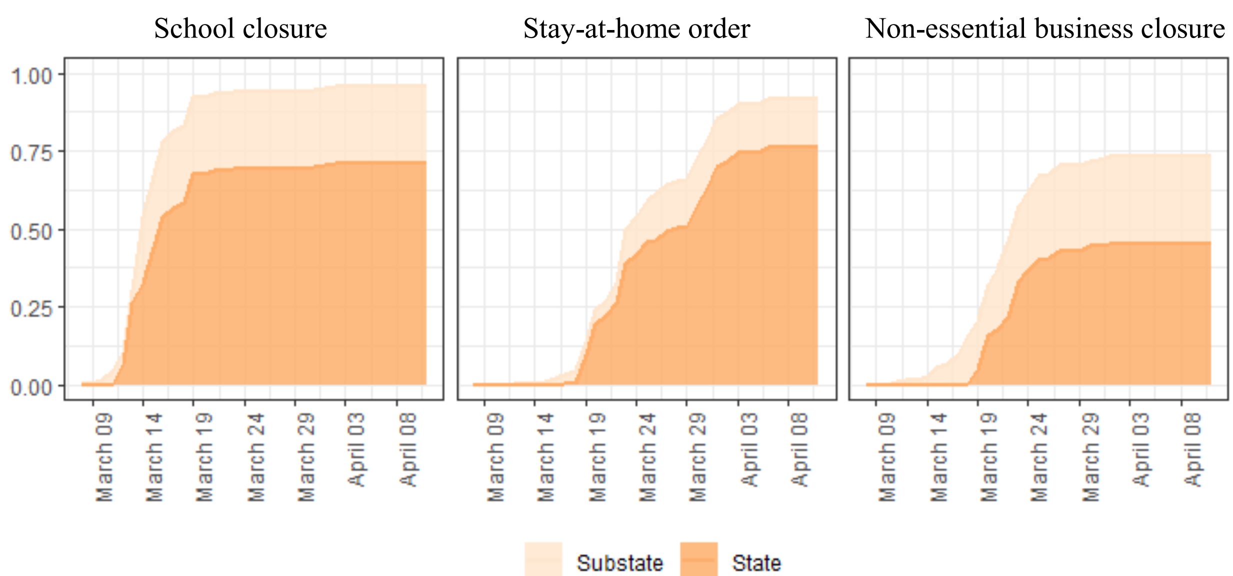
Notes: The contact rate is the probability of being in close physical proximity to someone who is not a member of the same household. Employment is the number of people working on a given day.
Each thin blue line represents one US county. The solid black line is the population-weighted US average.

I. Background

In response to exponential growth in the number of COVID-19 cases, social and economic activity in the US collapsed in the second and third weeks of March. The average social contact rate – defined as the probability of being in close physical proximity to someone who is not a member of the same household – declined more than 80% by the end of the month, while total US employment fell by 30 million. Figure 1 plots the evolution of contact rates and employment at the county level over the course of March and April, expressed as log changes relative to the beginning of March.[2] Both the contact rate and employment fell in almost every US county, though the magnitude of the declines varied widely.

State and local governments largely sought to encourage social distancing and to that end, implemented an array of non-pharmaceutical interventions – policies that attempt to reduce disease transmission by changing behavior. While most individual government actions were idiosyncratic and limited (for example, closing casinos or limiting certain close-contact person serves), three broadly restrictive NPIs were eventually enacted in most of the country: stay-at-home (or shelter-in-place) orders, school closures, and non-essential business closures.[3] Figure 2 plots the share of the share of the US population covered by each the three NPIs over time.

Figure 2. Share of US population covered by NPIs, by level of government



Sources: Fullman and others (2020); Keystone Strategy; authors' calculations.

Notes: Substate governments include school districts, municipal governments, and county governments.

NPI = non-pharmaceutical intervention

School closures expanded rapidly beginning in the second week of March to cover more than 90% of the population by March 20th. The number of non-essential business closures and stay-at-

[2] We discuss the construction of these measures in section V.

[3] Stay-at-home orders are mandates that individuals remain at home for all "non-essential" activities. Both stay-at-home orders and non-essential business closures were typically – though not always – issued with a listing of the activities or businesses considered "essential."

home orders grew rapidly from the third week of March, extending over more than 70% of the population by the end of the month. Notably, though NPIs issued by state governments would eventually cover more of the population, the earliest NPIs were generally issued by county or municipal governments.

II. Model

This section presents the augmented epidemiological framework that forms the basis of our empirical analysis. Because of the nonlinear and spatial dynamics of infectious spread, direct estimation of the epidemiological effects of NPIs using conventional methods is impractical. Instead, we extend a compartmental model of infectious disease with behavioral responses to health outcomes and an explicit role for NPIs. We model each state-level epidemic independently, allowing for heterogeneity in epidemiological and behavioral parameters.

II.A. Epidemiological Framework

We begin with the canonical Susceptible-Exposed-Infected-Removed (SEIR) model. To account for the significant role of pre-symptomatic and asymptomatic transmission in the spread of COVID-19, we divide the *infected* group into *symptomatic (I)* and *asymptomatic (A)*. A fraction of symptomatic cases become terminal (*T*), at which point effective infectiousness ceases (because they are isolated and can no longer infect members of *S*). After some period, all terminal cases die and transition to group *D*. Non-terminal symptomatic cases and all symptomatic cases eventually recover and transition to group *R*.

The following system of ordinary differential equations governs population (the total of which is represented by *N*) movement between compartments *S*, *E*, *I*, *A*, *R*, *T*, and *D* for US state *i* at time *t*:

$$\frac{dS_{it}}{dt} = -\beta_{it}(\alpha A_{it} + I_{it})\frac{S_{it}}{N_i}$$

$$\frac{dE_{it}}{dt} = \beta_{it}(\alpha A_{it} + I_{it})\frac{S_{it}}{N_{it}} - \sigma E_{it}$$

$$\frac{dA_{it}}{dt} = (1-\psi)\sigma E_{it} - \gamma^A A_{it}$$

$$\frac{dI_{it}}{dt} = \psi\sigma E_{it} - \gamma^I I_{it}$$

$$\frac{dR_{it}}{dt} = \gamma^I I_{it}\left(1 - \frac{\mu_{i(t-1/\gamma^I)}}{\psi}\right) + \gamma^A A_{it}$$

$$\frac{dT_{it}}{dt} = \gamma^I I_{it}\left(\frac{\mu_{i(t-1/\gamma^I)}}{\psi}\right)$$

$$\frac{dD_{it}}{dt} = \frac{\mu_{i(t+\tau_F+1/\gamma^I)}}{\psi}\left(\frac{I_{it}}{\tau_F - (\gamma^I)^{-1}}\right)$$

β_{it} is the transmission rate (secondary infections caused per primary infection per day). α_{it} represents the ratio of symptomatic to asymptomatic transmission rates. σ is the inverse of the COVID-19's latent period – the duration between infection and onset of infectiousness. Ψ is the share of infections during which the infected person will at some point show symptoms. γ^I and γ^A represent the rate at which symptomatic and asymptomatic infections lose infectiousness, respectively.

Note that the latent period σ differs from the incubation period – the duration between infection and onset of symptoms – which conventionally appears in the SEIR framework in its place. The incubation period is appropriate when only symptomatic cases are infectious and is preferred because it is, in principle, observable. Given the significant role of pre-symptomatic infectiousness in COVID-19 transmission, however, the latent period is the relevant concept for epidemic dynamics. In our model, the timing of symptom onset plays no role in disease transmission, all else equal, and only affects the eventual outcome of an infection.

A share of symptomatic infections are fatal. The infected population transitions into the terminal (*T*) group according to the infection fatality ratio μ_{it} (scaled by Ψ because asymptomatic infections are non-fatal by definition). After a period, these terminal infections end in death. τ_F represents the number of days between symptom onset and death in fatal cases. Note that the *T* and *D* compartments are used only to calculate the death toll with the appropriate lag between infection and death; these populations do not feed back into other parts of the system.

II.B. Behavioral Responses

We extend the traditional compartmental model by relaxing the assumption that the transmission rate is independent of the dynamics of an epidemic. Motivated by the strong empirical evidence of a fear-driven behavioral response to local outbreaks[4] – which we confirm in section 7 – we allow agents in the model to adjust their exposure risk based on the progression of their local epidemic. This extension of the model is important for generating plausible policy counterfactuals, as we attempt to do in section 9. Successful interventions to lower disease transmission improve epidemiological outcomes but consequently reduce the fear of infection, inducing an offsetting behavioral response. Ignoring this offset leads to overstatement of the effects of interventions.

The transmission rate β_{it} is the product of the contact rate κ_{it} and the infection rate ζ_{it}:

$$\beta_{it} = \kappa_{it}\zeta_{it} \tag{1}$$

We define κ_{it} as the daily probability that two persons residing in state *i* at time *t* will be in sufficiently close physical proximity to each other for a sufficient period of time to enable disease transmission – an event we refer to as a contact. We define ζ_{it} as the probability that disease transmission actually occurs in one contact between a susceptible person and an infectious person. The effective reproduction number $\mathcal{R}_{it}$ – the number of secondary infections per infection – is given by:

$$\mathcal{R}_{it} = \frac{\beta_{it}}{\gamma_{it}} \tag{2}$$

where γ_{it} is the duration of infectiousness weighted by state *i*'s relative proportion of compartments *A* and *I* at time *t*.

We model the contact rate as a function of an endogenous response to local infection risk and two exogenous behavioral factors: precautionary social distancing and the response to NPIs. The precautionary component captures changes in the contact rate driven by general fear and uncertainty about the pandemic, as opposed to specific concerns about local infection risk. The NPI component captures the impact of state and local social distancing mandates and other interventions.

We assume the contact rate takes the following functional form:

[4] See Goolsbee and Syverson (2020).

$$\kappa_{it} = \exp(\Omega_{it} \cdot \Phi_{it} \cdot (C_{it})^{\rho}) \tag{3}$$

where Ω_{it} is the precautionary component of behavior, Φ_{it} is the response to NPIs, and C_{it} is the total number of confirmed COVID-19 cases. The parameter ρ determines the responsiveness of the contact rate to perceptions of infection risk. We assume agents assess infection risk on the basis of confirmed cases rather the true number of infections, which is unknown to agents in the model.[5] The relationship between the underlying epidemiological dynamics and the observed dynamics of confirmed cases C_{it} is given by,

$$C_{it} = \sum_{t=0}^{T} \lambda_{it} \sigma E_{i(t-\tau_S-\tau_P)}$$

where λ_{it} measures the share of new infections that are eventually confirmed through a diagnostic test, τ_S is the duration from the onset of infectiousness to the onset of symptoms, and τ_P is the duration from symptom onset to a positive test result.[6]

The precautionary response Ω_{it} varies over time and across states as a function of the characteristics of the local population. For example, older populations may respond more strongly to news of a novel infectious respiratory disease. The response to NPIs Φ_{it} depends on the set of interventions that have been implemented in a state and on parameters governing the impact of different NPIs on the contact rate. We define,

$$\Omega_{it} = \boldsymbol{\omega}_t X_i$$
$$\Phi_{it} = \boldsymbol{\phi} P_{it}$$

[5] We considered several alternatives for which observed outcome drives perceptions of local infection risk: new cases (instead of or in addition to total cases), including total or new deaths, and normalizing by population. We view this an empirical question. In our empirical estimates (see section VI.B) we found that all choices imply roughly the same aggregate response. We therefore select the most straightforward option: total confirmed cases.
[6] Note that $\alpha^{-1} + \tau_S$ is equal to the incubation period – the time between infection and the onset of symptoms.

where X_i is a set of fixed attributes characterizing the local population and P_{it} is a set of indicators characterizing the set of NPIs in effect in i. Taking logs of (1) and substituting for Ω_{it} and Φ_{it} yields,

$$\ln \kappa_{it} = \boldsymbol{\omega}_t X_i + \boldsymbol{\phi} P_{it} + \rho c_{it} \tag{4}$$

Relating behavior back to disease transmission, substituting (1) and (3) into (2) and taking logs yields the following expanded definition of the reproduction number:

$$\ln \mathcal{R}_{it} = \boldsymbol{\omega}_t X_i + \boldsymbol{\phi} P_{it} + \rho c_{it} + \ln \zeta_{it} - \ln \gamma_{it} \tag{5}$$

Throughout our analysis, we take the infection rate ζ_{it} as exogenous and given. In practice, ζ_{it} is likely affected by the same kinds of precautionary and endogenous responses as κ_{it}. While the NPIs we consider below explicitly target the contact rate, other significant interventions (such as mask mandates) target the infection rate. Ideally, we would specify an expression analogous to (4) for ζ_{it} and estimate its parameters explicitly. This is not possible, however, due to the limitations of available epidemiological data from the early stages of the pandemic. These limitations also pose serious challenges for direct estimation of (5). We discuss these data issues in section VI.B.

II.C. Employment

The necessity of physical proximity for a wide range of economic activities means that voluntary or governmental efforts to limit contacts in response to a pandemic impose unavoidable economic costs. Indeed, many studies of the effects of COVID-19 use measures of economic behavior, such as visits to retail establishments, as proxies for the contact rate. More broadly, there is some tradeoff between epidemiological gains and economic costs. The response to COVID-19 provides ample evidence that policymakers view this tradeoff as a meaningful constraint on their ability to deploy NPIs to combat a pandemic.

No analysis of this tradeoff can answer the question of whether the economic costs of a particular intervention are “worth it” given some epidemiological benefits, which is not an analytical question. However, understanding the relative tradeoffs offered by different types of interventions allows policymakers to design a pandemic response that maximizes the ratio of gains to costs. In order to assess these tradeoffs, we incorporate local employment outcomes into our behavioral SEIR framework. Reasoning that the same factors that drive κ – precautionary behavior, NPIs, and local infection risk – are also the key determinants of economic behavior, we posit an analogous relationship to (2) for employment, which we denote by W_{it} and define as the number of people working in state *i* at time *t*:

$$\ln W_{it} = \boldsymbol{\omega}_t^W X_i + \boldsymbol{\phi}^{\boldsymbol{W}} P_{it} + \rho^W c_{it} \tag{6}$$

The addition of (3) allows us to assess the epidemiological and the economic effects of interventions in a single, integrated framework. In addition, (3) takes into account the relationship between local infection risk fears and economic outcomes, which – like the relationship with contact measures – emerges clearly in empirical studies. This allows for the possibility that effective suppression of an epidemic with economically costly NPIs may yield economic benefits over the long run.

III. Data

This section provides an overview of the data underlying our analysis. We rely on mainly three types of data: daily counts of COID-19 cases, tests, and deaths; daily measures of social behavior and employment; and information on NPIs implemented by state and local governments.

III.A. Epidemiological Data

Confirmed COVID-19 cases and deaths form the starting point of our epidemiological estimates. A number of organizations track the spread and death toll of COVID-19 in the United States over time. Rather than rely on a single source for our analysis, we draw on four separate sources: Johns Hopkins's Center for Systems Science and Engineering, the New York Times, the COVID Tracking Project, and USAFacts. These sources employ different data collection methods and assumptions and often differ in terms of the number and timing of new cases or deaths. We obtain counts of the number of COVID-19 tests from the COVID Tracking Project.

We correct for data reporting anomalies resulting from changes in states' standards for reporting of deaths, causing large single-day spikes.[7] On those days, the value for deaths is linearly interpolated across previous and future observations, and the number of deaths in excess of this value reported on that day are distributed to all previous days in proportion to measured deaths. To avoid potential bias from idiosyncrasies in one source's estimates, we isolate the common trend in confirmed cases and deaths by taking the first principle component of all four sources' estimates.

III.B. Contact and Employment Data

Our model requires state-level, daily data on contact rates and employment. To estimate parameters reliably, we require greater geographic detail than the state level. However, there are no standard, high-frequency measures of population contact rates, let alone official statistics. Official measures of employment, meanwhile, are available only at monthly frequency and geographic detail only with a long lag. We therefore rely on a range of nontraditional data sources. We collect a dozen daily, county-level measures derived primarily from mobile device location data, business and financial services software, payroll service providers, and web search activity. As we describe in section V, we combine these various indicators to construct composite indexes of the contact rate and employment. Here we provide an overview of our sources and the measures underlying those indexes.

Couture and others (2020)/PlaceIQ We use a county-level measure of mobile device "exposure" developed by Couture and others (2020) based on mobile device location data from PlaceIQ. The device exposure index (DEX) reflects the average number of devices that visited locations also visited by residents of a county. It is an indirect measure of the extent to which individuals are congregating in common locations.

SafeGraph We construct county-level measures of time spent at home, time spent at a fixed location outside the home during regular workday hours (a proxy for work), and distance

[7] For New Jersey, an anomaly appears on June 25th in the New York Times and COVID Tracking Project data, and on June 27th for USAFacts. For New York, an anomaly appears on June 30th in the New York Times and USAFacts data. For Texas, all sources report an anomaly on July 27th.

travelled using mobile device location data from SafeGraph.[8] SafeGraph assigns each device a "home" based on "common nighttime location." Data are available at the census block group-level. We aggregate to county-level weighting by number of devices.

Google Mobility We use county-level measures of time spent at residential locations and time spent at workplace locations from the Google *Community Mobility Reports*.[9]

Unacast We use county-level measures of "encounter density" and distance travelled derived from mobile device location data from Unacast.[10] Encounter density is a measure of physical proximity between persons defined as average number of times an individual is within 50 meters another person, normalized by a county's physical size and relative to the pre-COVID national average.

Homebase We construct county-level measure of small business employment using data from Homebase, an employee scheduling and time-tracking software company. Homebase provides anonymized daily data at individual worker level. We limit our sample to workers at firms with at least 200 hours worked between January 12 and February 22.[11] We define employment as the number of workers with positive hours and aggregate to the county level based on firm zip code.

Opportunity Insights We use a county-level measure of employment workers from the Opportunity Insights Economic Tracker developed by Chetty and others (2020).[12] This measure is based on data from payroll service providers Paychex and Intuit; Earnin, a personal financial management company with access to clients' payroll information; and Kronos, which provides employee time management services to business. We obtain this measure as a seven-day average and estimate daily values based on the pseudoinverse of the moving average matrix.

Google Trends We construct daily proxies for job loss and hiring based on web search intensity from Google Trends. For job loss, we obtain data on searches that contain any of the

[8] https://www.docs.safegraph.com/docs/social-distancing-metrics
[9] https://www.google.com/covid19/mobility
[10] https://www.unacast.com/covid19/social-distancing-scoreboard
[11] We define a "firm" as the aggregate of all of a single company's establishments in the same industry and county.
[12] https://www.tracktherecovery.org

terms, “file for unemployment,” “unemployment benefits,” or “unemployment insurance.” For hiring we obtain data on searches that contain any of the terms, “W-4,” “W-9,” or “I-9” (with or without hyphens). Google Trends provides indexes of search intensity by Nielsen designated market area (DMA), which are considerably broader than counties. We use the same index for all counties within a DMA.

III.C. Non-Pharmaceutical Interventions

We use information on NPIs issued by state governments from Fullman and others (2020) and NPIs issued by county, municipal, or other substate government entities from Keystone Strategy.[13] We extend the Fullman and others (2020) state data to the county level for state government NPIs that applied only to specified counties. We exclude advisory policies and recommendations, as well as mandates that apply to specific subpopulations (typically “vulnerable” persons or those above a certain age).

State and local governments enacted a wide range of NPIs in response to COVID-19. We focus on three major interventions: school closures, stay-at-home (or shelter-in-place) orders, and closures of all non-essential businesses. While most individual government actions were idiosyncratic and limited (for example, closing casinos or limiting indoor restaurant service), these three NPIs were widely adopted (see Figure 2) and imposed meaningful constraints on a broad range of social and economic activities. Although there is some variation in the procedures for closing schools, the types of activities permitted under stay-at-home orders, and the classification of businesses as essential or non-essential, the key features of each NPI are consistent across jurisdictions and across data sources.

IV. Case Confirmation Rate and Infections

The number of confirmed COVID-19 cases understates the true number of infections. Asymptomatic cases are unlikely to be detected in the absence of widespread preventative testing and individuals experiencing mild COVID-19 symptoms may choose not to seek a test, especially when testing capacity is limited and restricted to severe cases (as in the early days of the outbreak in the US). If underreporting of infections is constant over time, it does not affect our modeling outside of herd immunity dynamics, which are not important in the early months of

[13] https://www.keystonestrategy.com/coronavirus-covid19-intervention-dataset-model

an epidemic (the focus of this paper). But variation over time in the extent of underreporting leads to spurious changes in transmission rates inferred from case counts even if growth in actual infections is unchanged. Such variation is almost certainly present in the period we examine, which saw a rapid increase in the number of people being tested for COVID-19. Estimates of the spread of SARS-CoV-2 over this period based on case counts alone are therefore likely to be biased upwards.

Confirmed COVID-19 deaths are less likely than cases to suffer from time-varying mismeasurement. For that reason, some COVID-19 modelers eschew confirmed cases altogether and rely entirely on counts of confirmed deaths (Gu 2020). Our approach lies somewhere in the middle and draws from both case and death data.

First, for each state i at time t, we estimate the case confirmation rate λ_{it}:

$$\lambda_{it} = \frac{C_{it} - C_{i(t-1)}}{\left(D_{i(t+\tau_F-\tau_P)} - D_{i(t-1+\tau_F-\tau_P)}\right)\mu_t^{-1}}$$

where C_{it} is cumulative confirmed cases, D_{it} is cumulative confirmed deaths, τ_F is the average number of days from symptom onset to death in fatal cases, τ_P is the average number of days from symptom onset to a positive test result, and μ_t is the current infection fatality ratio. Following clinical evidence, we assign a value of 19 days to τ_F and a value of 7 days for τ_P. We assume the infection fatality ratio begins at 0.8 percent and falls linearly to 0.025 percent from mid-April to mid-August. See Section VI.A for further details on parameter selection.

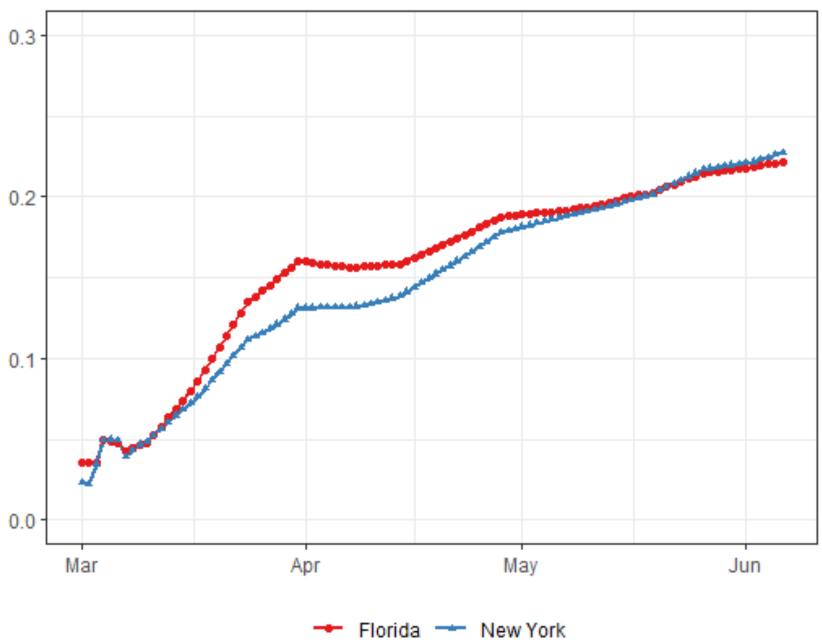
Using state-level data on cases, deaths, and tests, we model the case confirmation rate as a function of national-level variation over time (reflecting nationwide trends in testing infrastructure and capacity) and the test positivity rate (the share of tests with a positive result). When testing capacity is limited relative to the size of the current outbreak, tests are reserved for the most severe cases, leading to high positivity rates. As relative capacity expands, we expect to positivity rate to fall as the eligibility criteria for testing broadens.

We estimate the following regression:

$$\ln \lambda_{it} = w_t + \theta \frac{C_{it}}{T_{it}} + \varepsilon_{it}$$

Where the w_t are calendar week fixed effects, T_{it} is the number of tests performed, and $\frac{C_{it}}{T_{it}}$ is the test positivity rate. We smooth both λ_{it} and $\frac{C_{it}}{T_{it}}$ with a centered two-week moving average.[14] We estimate a value (standard error) of -0.57 (0.06) for θ, which represents the semi-elasticity of confirmation rate with respect to the positivity rate. To estimate the true number of new infections, we fit values of λ_{it} for each state over time and scale the number confirmed new cases by its inverse. We then shift values backwards in time by τ_P (set to one week) to reflect the date of symptom onset rather than the date of case confirmation.

Figure 3. Estimated daily case confirmation rate



Source: Authors' calculations.

In the initial days of the epidemic, the true number of new infections was nearly 20 times the number of new confirmed cases. This figure fell rapidly as testing infrastructure expanded: by early June, the ratio was around 5, with the median state confirming 22 percent of new

[14] In reality, time from symptom onset to death follows a wide distribution of outcomes rather than a deterministic average; using a moving average allows us to pool deaths and positive tests across a broader span and thus capture some of that variation.

infections.[15] To illustrate the common trend in reporting rates and deviations from that trend arising from local conditions, Figure 3 plots our estimates of case confirmation rate for New York (a state with a severe early outbreak) and Florida (a state with a severe, more recent outbreak).

V. Contact Rate and Employment Indexes

To specify the parameters and historical inputs of the model in section II, we require geographically detailed, daily data on the contact rate κ_{it} and employment W_{it}. To our knowledge, no such data exists. Instead, we have an array of unconventional indicators described in section III.B. Rather than consider each of these individually, we divide them into two sets, one containing measures related to the contact rate and the other containing measures related to employment. We then take the first principal component of each set of related indicators and interpret the resulting indexes as direct proxies for the daily contact rate and daily employment.

Underlying measures related to the contact rate include frequency of close physical proximity to other mobile devices, time spent at home, and distance travelled. Underlying measures related to employment include time spent at workplaces, web searches related to job loss and hiring, and direct measures of the number of persons working. For measures derived from mobile device data, we generally have multiple versions based on different samples of mobile devices.

Principal components is a convenient means of summarizing information from multiple indicators and extracting common variation.[16] Each of our measures captures only one dimension of the outcomes we are actually interested in and on its own may contain a misleading signal. Moreover, daily measures at the county level are inevitably noisy. Taking the first principal component of several measures filters out both misleading idiosyncratic patterns and noise using information from all of the inputs. It also allows for geographic variation in the relevance of particular indicators, which might depend on place characteristics.[17] We construct indexes independently for each county, so the weight assigned to any one underlying measure is determined by its relationship to the other measures in that county alone.

[15] Our estimates show a similar though more pronounced trend compared with those of Gu (2020), who estimates a national "prevalence ratio" that fell from about 18 on March 1st to 7 on August 1st.

[16] See Lewis, Mertens, and Stock (2020) for a recent application to weekly economic activity.

[17] For example, distance travelled is more closely related to time spent at home in less dense counties.

Figure 4. Daily employment index and monthly official employment: US total

Millions

Sources: Bureau of Labor Statistics (BLS); authors' calculations.

Notes: Daily employment index values are aggregated from county-level indexes. Monthly official employment through July is aggregated from county-level employment from the BLS Local Area Unemployment Statistics. The value for August is from the BLS news release. Monthly official employment values are placed on the 12th of each month to align with the BLS reference week.

Before constructing the indexes, we normalize all measures relative to their average for the same day of the week in early 2020 – generally the 6-week period from January 12 to February 22, 2020.[18] For series with sufficient historical data to identify seasonal patterns, we normalize relative to the same day one year earlier. Not all measures are available for counties with small populations. We aggregate counties with incomplete data into a single residual county unit by state, using whatever data is available and weighting by population.[19]

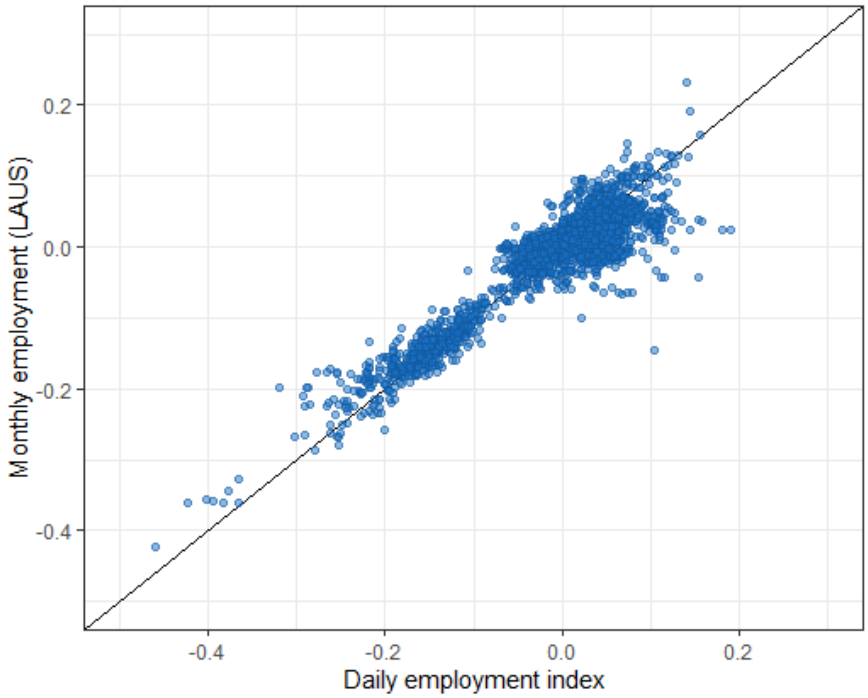
[18] Measures from Unacast and Google Mobility Reports are already normalized relative to the same day of the week over different base periods in early 2020. Measures from SafeGraph are available only from January 20th.

[19] For some small states, the residual "county" is the entire state, for which data is always available. Excluding all aggregated counties with incomplete data has no discernible impact on any of the results presented below.

To construct the contact rate index, we take the first principal component of two measures of physical proximity, two measures of time spent at home, and two measures of distance travelled. Given these inputs, we interpret the index as reflecting contacts between persons who do not live together. To construct the employment index, we use two direct measures of the number of persons working, two measures of time spent at workplaces, and measures of unemployment- or hiring-related web searches. We then scale the indexes into interpretable units by adjusting the (county-level) mean and standard deviation to match those of a series expressed in the desired unit. For the contact rate, no such series exists, so we use the measure of encounter density from Unacast, which is the closest of our available indicators to a direct measure of contacts. For employment, we scale indexes to monthly employment by county in 2020 from the Local Area Unemployment Statistics (LAUS). We have sufficient data to construct both indexes beginning in late January.

Figure 1 plots the evolution of the two indexes across counties during the early stages of the pandemic. While there is no external data source against which to validate our measure of the contact rate, our employment index is effectively a daily proxy for the official monthly estimates of county employment. Figures 4 and 5 compare our employment index with official estimates from LAUS. Figure 4 plots total US daily employment aggregated from our county employment indexes against actual monthly employment since January. Figure 5 plots county-level monthly changes in the log of the daily employment index (using the mean for the official employment reference week) against actual monthly changes in the log of employment from LAUS. Although the underlying indicators are all indirect and partial measures of overall employment, the combined index tracks the dynamics of the official series over the first half of 2020 both in aggregate and at the county level.

Figure 5. Daily employment index and monthly official employment: monthly log change in county employment, February-July 2020



Sources: Bureau of Labor Statistics (BLS); authors' calculations.

Notes: To align with the BLS reference week, monthly changes in the daily employment index are calculated based on the weekly average for week containing the 12th of each month.

VI. Parameters

This section reviews the selection and estimation of the epidemiological and behavioral parameters of the model in section II. For the former, we draw on the clinical literature on COVID-19 as well as methods from empirical epidemiology. For the latter, we adopt a difference-in-differences approach using county-level data.

VI.A. Epidemiological Parameters

We first select values for parameters that are largely biological in nature – that is, least likely to vary according to behavior or policy. We draw on the early and developing clinical COVID-19 literature where available. Parameter values and sources are shown in Table 1.

Table 1. Exogenous parameter definitions and values

Parameter	Definition	Value	Source
$\boldsymbol{\alpha}$	ratio of asymptomatic to symptomatic transmission rates	1	Lee and others (2020), Tan and others (2020)
$\boldsymbol{\sigma}$	$1/\tau_E$, where τ_E is the noninfectious latent period in days	1/2	Peng and others (2020)
$\boldsymbol{\psi}$	symptomatic share of new infections	0.84	He and others (2020)
$\boldsymbol{\gamma^A}$	$1/\tau_A$, where τ_A is the infectious period for asymptomatic cases in days	1/7	Peng and others (2020)
$\boldsymbol{\gamma^I}$	$1/\tau_I$, where τ_I is the infectious period for symptomatic cases in days	1/7	Peng and others (2020)
$\boldsymbol{\tau_S}$	duration from infectiousness onset to symptom onset	3	Lauer and others (2020), Peng and others (2020)
$\boldsymbol{\tau_F}$	duration from symptom onset to death for severe cases in days	19	Zhou and others (2020)
$\boldsymbol{\tau_P}$	duration from symptom onset to positive test result for confirmed cases	7	Assumed
$\boldsymbol{\mu_t}$	infection fatality ratio	0.008-0.025	Gu (2020)

We assume that transmission rates and duration of infectiousness parameters are the same for symptomatic and asymptomatic cases. In reality, it is likely that infected persons who are not experiencing symptoms transmit the virus as different rates, but the sign of any such difference is ambiguous. Some COVID-19 symptoms – such as coughing – directly increase the probability the transmission. However, symptomatic individuals may exhibit greater precautionary behavior, voluntarily limiting their contacts. Clinical evidence so far does not resolve this ambiguity; see Lee and others (2020) and Tan and others (2020). We retain the division of the infected population into these two groups to allow for extension of the model as additional evidence becomes available.

Of the parameters included in Table 1, only the infection fatality ratio μ_t is time-dependent. The infection fatality ratio depends not just on the biology of the disease but also on policy, medical advances, and epidemic dynamics. We base our assumption on the work of Gu (2020), one of the most consistently accurate COVID-19 forecast models.[20] We assume the infection fatality rate was 0.8 percent through mid-April and then declined linearly to a terminal value of 0.025 percent in mid-August. This decline reflects improvements in COVID-19 outcomes over time due to a number of factors, including compositional shifts in the demography of new infections, improved treatments, and expanded hospital capacity.

μ_t is used to estimate case confirmation rates as described in Section IV. Recall that infections are imputed using estimated case confirmation rates, which capture averages of time- and positivity rate effects across states. This means that *effective* infection fatality ratios, calculated as actual new deaths divided by estimated new infections, vary slightly by state (hence the indexation by i in the differential equations presented in Section 3). When calculating marginal deaths in counterfactual scenarios, we use the simple average of the overall headline infection fatality ratio and the state-specific effective infection fatality ratio.

The final SEIR parameter is the daily transmission rate β_{it}. This parameter varies with behavior and is responsive to local epidemiological conditions, and thus varies widely across time and place. To obtain historical estimates of β_{it}, we first estimate the effective reproduction number $\mathcal{R}_{it}$. From (2), β_{it} is given by,

$$\beta_{it} = \mathcal{R}_{it}\gamma_{it}$$

We estimate $\mathcal{R}_{it}$ using the method described in Cori and others (2013) and implemented using the authors' software package *EpiEstim*. The estimation framework is parsimonious and only requires data on new infections and an estimate of the distribution of serial intervals (the time between symptom onset in successive cases) for the virus. For each state, we iterate over hundreds of possible combinations of gamma-distributed serial interval means and standard deviations. We then simulate the SEIR model for each possible path of R_{it}, choosing the serial interval distribution that best matches the observed trajectory of each state-level epidemic.[21]

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[20] See https://www.covid19-projections.com/about/#historical-performance for a review of model accuracy.

[21] The loss function minimizes the weighted mean of absolute error in two measures of infections: cumulative infections for the most recent date of data (80 percent weight) and new cases over the most recent three days of data (20 percent weight). This arbitrary weighting scheme is chosen to target both the level and slope of the epidemic curve.

VI.B. Behavioral Parameters

We now turn to the estimation of the behavioral parameters $\boldsymbol{\phi}$, ρ, and $\boldsymbol{\omega}_t$ from sections II.B and II.C. We adopt an event study design to estimate the effects of policy interventions $\boldsymbol{\phi}$, using variation in the implementation of NPIs across counties and over time to capture the dynamic response during the month following an intervention. We estimate the response to local infection risk ρ directly based on the number of confirmed COVID-19 cases by county. The time path of precautionary behavior $\boldsymbol{\omega}_t$ is captured by calendar date fixed effects interacted with county characteristics.

Ideally, we would estimate the relationship between behavior and COVID-19 transmission directly based on county-level $\mathcal{R}_{it}$ and (5). However, the limitations of our data make this impractical. The procedure for obtaining historical estimates of $\mathcal{R}_{it}$ (described in sections IV and VI.A) is only feasible given a sufficient number of confirmed cases. For many counties, this threshold is not reached until late March – by which time most NPIs had already been implemented – and for a substantial number it is never reached.[22] Altogether, our sample for estimates on $\mathcal{R}_{it}$ is less than half the size of the full sample and drops most school closure and non-essential business closure events and many stay-at-home order events. We therefore estimate $\boldsymbol{\phi}$, ρ, and $\boldsymbol{\omega}_t$ using the contact rate κ_{it} and (4) instead and include estimates from (5) only for comparison.

Reformulating the policy component in equations (4) and (6) as event studies of the three NPIs – and adding superscript κ to the parameters in (4) – leads to the following estimating equations for the contact rate and employment,

$$\ln \kappa_{it} = \eta_i^{\kappa} + \sum_x \omega_{xt}^{\kappa} X_{xi} + \sum_{j \in NPIs} \left(\sum_{\substack{k=-31, \\ k \neq -1}}^{31} \phi_{jk}^{\kappa} P_{it}^{jk} \right) + \rho^{\kappa} c_{it} + v_{it}^{\kappa} \tag{7}$$

$$\ln W_{it} = \eta_i^{W} + \sum_x \omega_{xt}^{W} X_{xi} + \sum_{j \in NPIs} \left(\sum_{\substack{k=-31, \\ k \neq -1}}^{31} \phi_{jk}^{W} P_{it}^{jk} \right) + \rho^{W} c_{it} + v_{it}^{W} \tag{8}$$

[22] This problem is much less severe for the state-level estimates of $\mathcal{R}_{it}$ we use in the SEIR model.

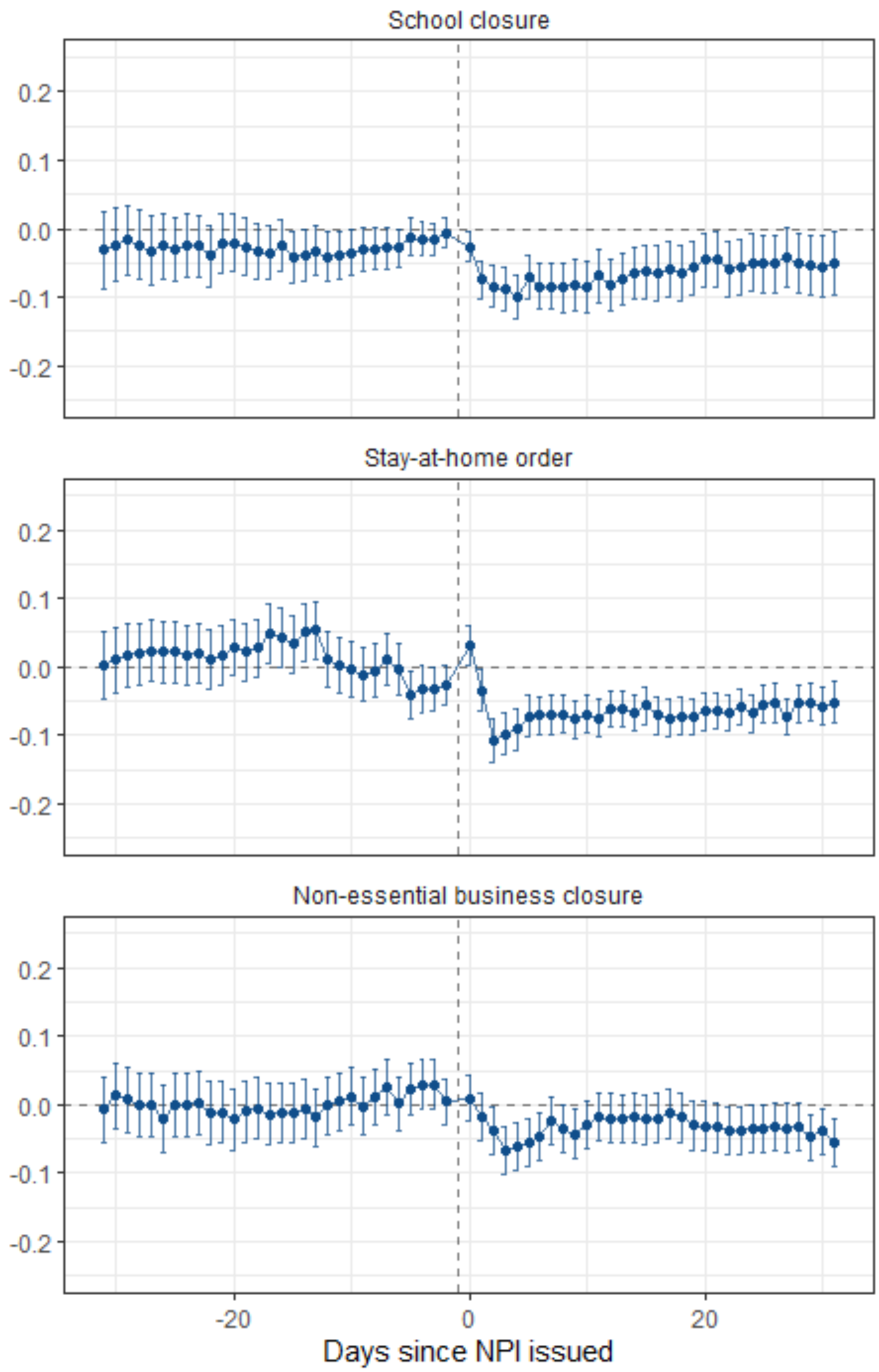
κ_{it} is the contact rate index and W_{it} is the employment index for county *i* on day *t* (see section V). η_i and ω_{xt} are county and calendar date fixed effects, respectively. X_{xi} contains a column of ones and a set of county characteristics indexed by *x*. The three NPIs are indexed by *j*. The number of days before or after an NPI is issued is indexed by *k*. P_{it}^{jk} is an indicator equal to one if NPI *j* is in effect in county *i* on date *t*, which is *k* days from the date issued. For $k \geq 0$, the coefficients ϕ_{jk} trace out the dynamic response to *j* over the 30 days following announcement of the NPI. For $k < 0$, the coefficients ϕ_{jk} capture systematic differences between counties that issued NPIs and those that did not over the month immediately before the NPI was issued. Dates more than 31 days from the issuance of the NPI are binned in *k = -31* and *k = 31* and reflected in the coefficients $\phi_{j,-31}$ and $\phi_{j,31}$. c_{it} is the inverse hyperbolic sine of C_{it}, the total number of confirmed COVID-19 cases in county i.[23]

X_{xi} contains information on the demographic, economic, and political characteristics of counties. In our main estimates, it includes the shares of the population aged 5 to 17 and aged 65 or over; the shares of workers in leisure and food services, in essential industries, and in educational services; and the Republican Party vote share in the 2016 presidential election.[24] The precautionary behavior terms $\omega_{xt}X_{xi}$ capture nationwide common variation as well as county-specific patterns driven by heterogeneity across the characteristics in X_{xi}. These terms also absorb the average effects of all government actions not in Φ_{it}, the event study component. This includes non-mandatory guidance and an array of restrictions on particular social and economic activities (such as public events or close-contact personal services). Unlike the broad mandated closures we consider in our analysis of NPIs, the details of these limited actions vary widely across jurisdictions and generally defy classification into distinctive treatments, and so cannot be separately identified. Though we will refer to the estimated $\omega_{xt}X_{xi}$ simply as "precautionary behavior" in our discussion, it is important to keep in mind that our concept of "precaution" encompasses a range of government actions.

[23] The inverse hyperbolic sine $c = \ln\left(C + \sqrt{1 + C^2}\right)$ has similar properties to a log transformation but is defined at zero.

[24] Demographic and employment data are from the American Community Survey. Essential industries are defined based on guidance from the Department of Homeland Security. Election data are from the MIT Election Data and Science Lab.

Figure 5. Event study estimates: contact rate

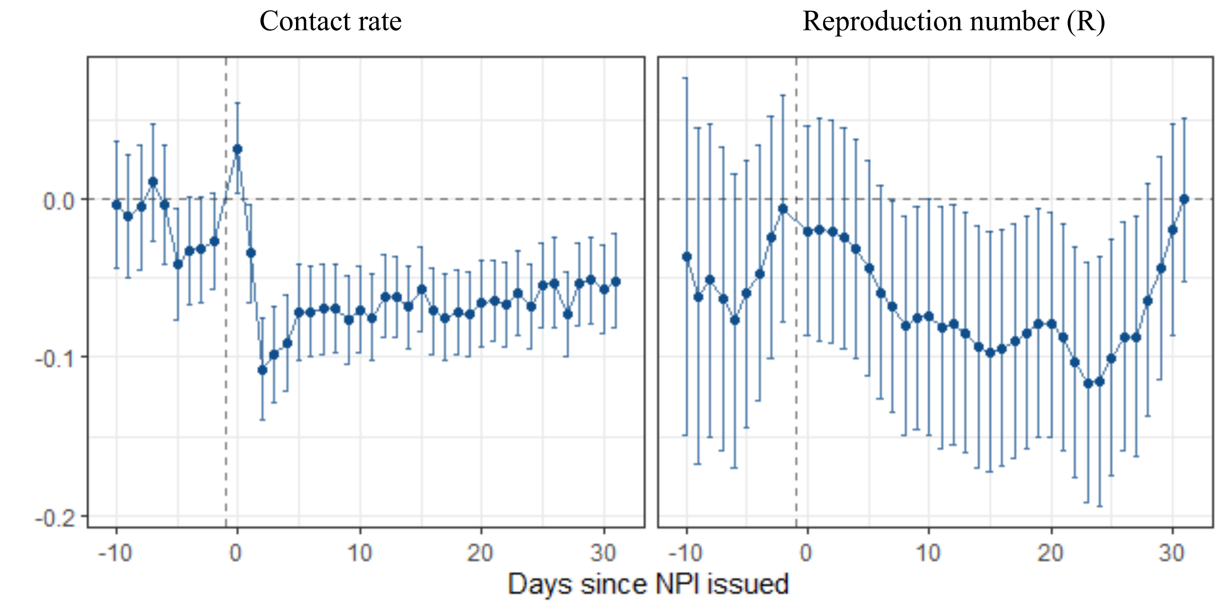


Source: Authors' calculations.

Notes: This figure shows coefficient estimates and 95% confidence intervals for ϕ_{jk}^{κ} from (7). Standard errors are clustered at the county level.

Figure 5 reports NPI event study estimates for the contact rate from (7).[25] Over the week following an order to close schools, the contact rate declined between 5 and 10%. Stay-at-home orders had larger and more immediate effects, with a sharp fall in contacts of more than 10% two days after the order was issued – generally corresponding to the day after the order went into effect. For both school closures and stay-at-home orders, roughly half the decline persisted after 30 days. The effects of non-essential business closures were smaller – a decline of around 5% – but somewhat more persistent.

Figure 6. Event study estimates for stay-at-home orders



Source: Authors' calculations.

Notes: The left panel shows coefficient estimates and 95% confidence intervals for ϕ_{jk}^{κ} from (7) for *j* = stay-at-home order. The right panel shows analogous estimates based on (5) instead of (4).
Standard errors are clustered at the county level.

Figure 6 compares the response to stay-at-home orders estimated from the contact rate and (4) with estimates from the reproduction number and (5). Because stay-at-home orders were typically enacted later than the other two NPIs, the sample available for estimates using $\mathcal{R}_{it}$ is larger than for the other two NPIs, though still much smaller than the full sample.[26] For readability, we limit the plot to 10 pre periods, as the standard errors of the $\mathcal{R}_{it}$ estimates become

[25] Appendix Figure A1 reports estimates from the model excluding county characteristics, i.e. $X_{xi} = \vec{\mathbf{1}}$.

[26] We report estimates for $\mathcal{R}_{it}$ for all three NPIs in Appendix Figure A3.

very large in earlier periods. We estimate that $\mathcal{R}_{it}$ declined about 10% over the weeks following a stay-at-home order – roughly the same magnitude as the estimated response of κ_{it}, though with a different time pattern.[27] Given the degree of uncertainty, which makes it impossible to assess prior trends in the estimates for $\mathcal{R}_{it}$, this comparison is at best suggestive, but is nevertheless reassuring.

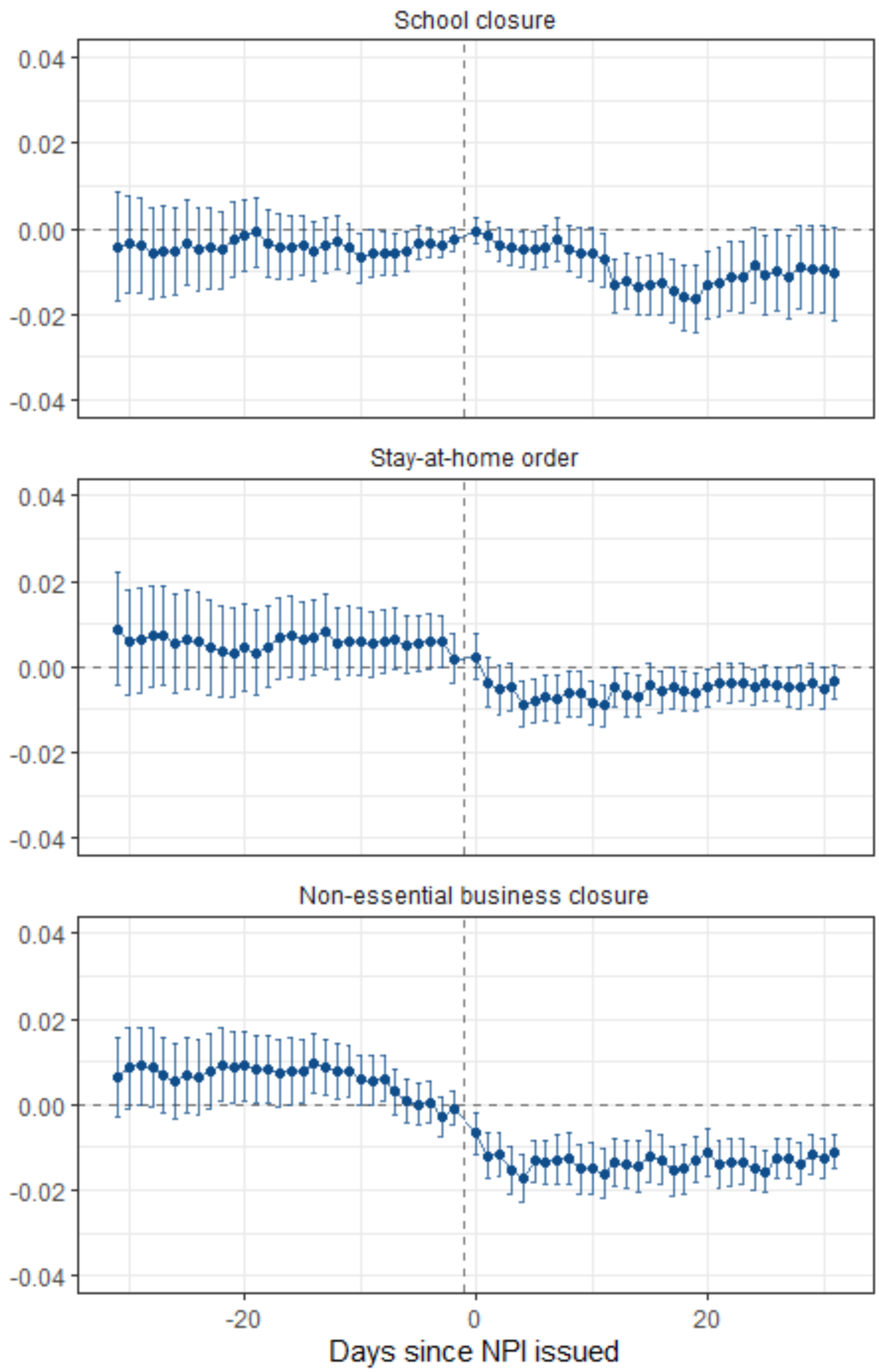
Figure 7 reports NPI event study estimates for employment.[28] Employment fell gradually following the announcement of school closures, eventually reaching a persistent decline of around 1% after two weeks. Stay-at-home orders had somewhat larger effects, with employment falling nearly 1.5% in the days following an order, though one third of the decline was reversed after three weeks. Non-essential business closures had the largest employment effects, inducing a persistent decline of 2%.

The estimates for non-essential business closures indicate that employment began falling in the days before an order was issued. We attribute this to the effectively phased introduction of the policy in many jurisdictions. State and local governments issued a broad range of restrictions on businesses and public venues that were more limited than blanket non-essential business closures, including highly targeted interventions affecting only a handful of businesses (such as closing casinos or fairgrounds), restrictions on particular activities (such as in-person dining), and mandated closure of entire classes of business (such as beauty salons, hairdressers, and other close-contact personal services). In most cases, implementation of the full non-essential business closures we consider in our analysis was immediately preceded by one or more of these more limited restrictions. For example, Connecticut issued a statewide non-essential business closure on March 20th. This followed three prior orders closing particular types of businesses: on March 16th, fitness studios and movie theaters were ordered to close; on March 18th, this was expanded to shopping malls, bowling alleys, and other public venues; on March 19th, this was expanded to hairdressers, estheticians, and other personal services. This example is typical. In the jurisdictions for which we have reliable data on all forms of business restriction, three quarters of non-essential business closures were preceded by lesser restrictions.

[27] The difference in timing arises at least in part from the construction of historical values for $\mathcal{R}_{it}$, which are based on a rolling time window.

[28] Appendix Figure A2 reports estimates from the model excluding county characteristics, i.e. $X_{xi} = \vec{\mathbf{1}}$.

Figure 7. Event study estimates: employment



Source: Authors' calculations.

Notes: This figure shows coefficient estimates and 95% confidence intervals for ϕ_{jk}^{W} from (8). Standard errors are clustered at the county level.

Table 2 reports estimates for ρ^{κ} and ρ^{W}, the elasticity of the contact rate and of employment with respect to local infection risk.

Table 2. Estimated response to local infection risk

	Estimate	Std. Err.
Contact rate (ρ^{κ})	-0.0541	0.0045
Employment (ρ^{W})	-0.0048	0.0011

Here we note only that these estimates have the expected sign and the magnitudes are plausible. We discuss the implied local infection risk response in the next section.

VII. The Response to COVID-19

In this section, we assess the initial policy response to COVID-19 using the epidemiological and empirical framework described above. We have two objectives: First, to estimate what benefits and harms can reasonably be attributed to government as opposed to voluntary action. Second, to provide useful insights to policymakers managing the current and any future infectious disease outbreaks.

VII.A. Social and Economic Responses to the Pandemic

Using the estimated coefficients from (7) and (8), we decompose the aggregate declines in the contact rate and employment since the beginning of March into contributions from the three behavioral components: state and local NPIs, response to local infection risk, and precautionary behavior.[29] Figure 8 shows the results of this decomposition. We find that the early declines in the contact rate and employment in mid-March were primarily precautionary.[30] The contact rate fell rapidly before there were substantial numbers of confirmed cases and before the introduction of most NPIs. We estimate that these precautionary changes in behavior explain 80% of the total decline in the contact rate in the middle two weeks of March.

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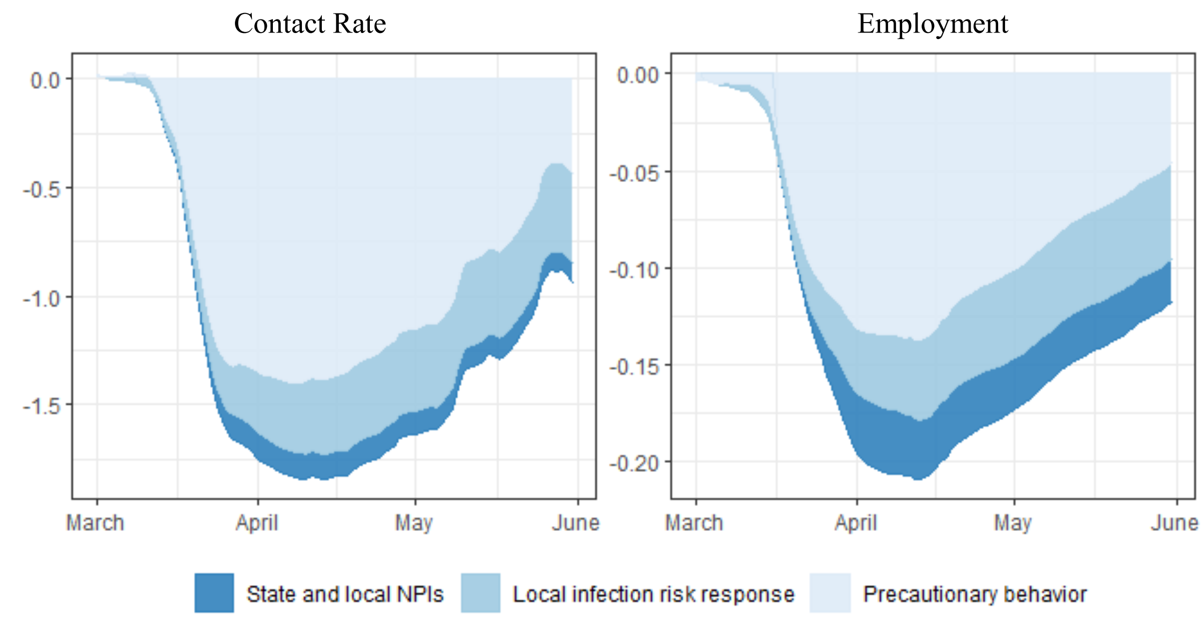
[29] Aggregated values for the contact rate are weighted by county population. Aggregated vales for employment are weighted by average county employment from December 2019 to February 2020.

[30] Recall that the precautionary component also includes the effects of state and local government actions other than three major NPIs considered explicitly in the analysis, such as issuing warnings and advice or imposing narrow restrictions on commercial activity.

As the number of COVID-19 cases surged in the second half of March and the geographic concentration of cases became apparent, the behavioral response shifted from nationwide fears to localized concerns reflecting the severity of local outbreaks. When the contact rate reached its lowest point in mid-April – a fall of almost 85% from the beginning of March – about 73% of the cumulative decline was attributable to precautionary behavior and 20% to local infection risk. The final component, state and local NPIs, explains only 7% of the change in the contact rate through mid-April.

Figure 8. Decomposition of the response to COVID-19

Contribution to log difference from March 1st, 7-day average

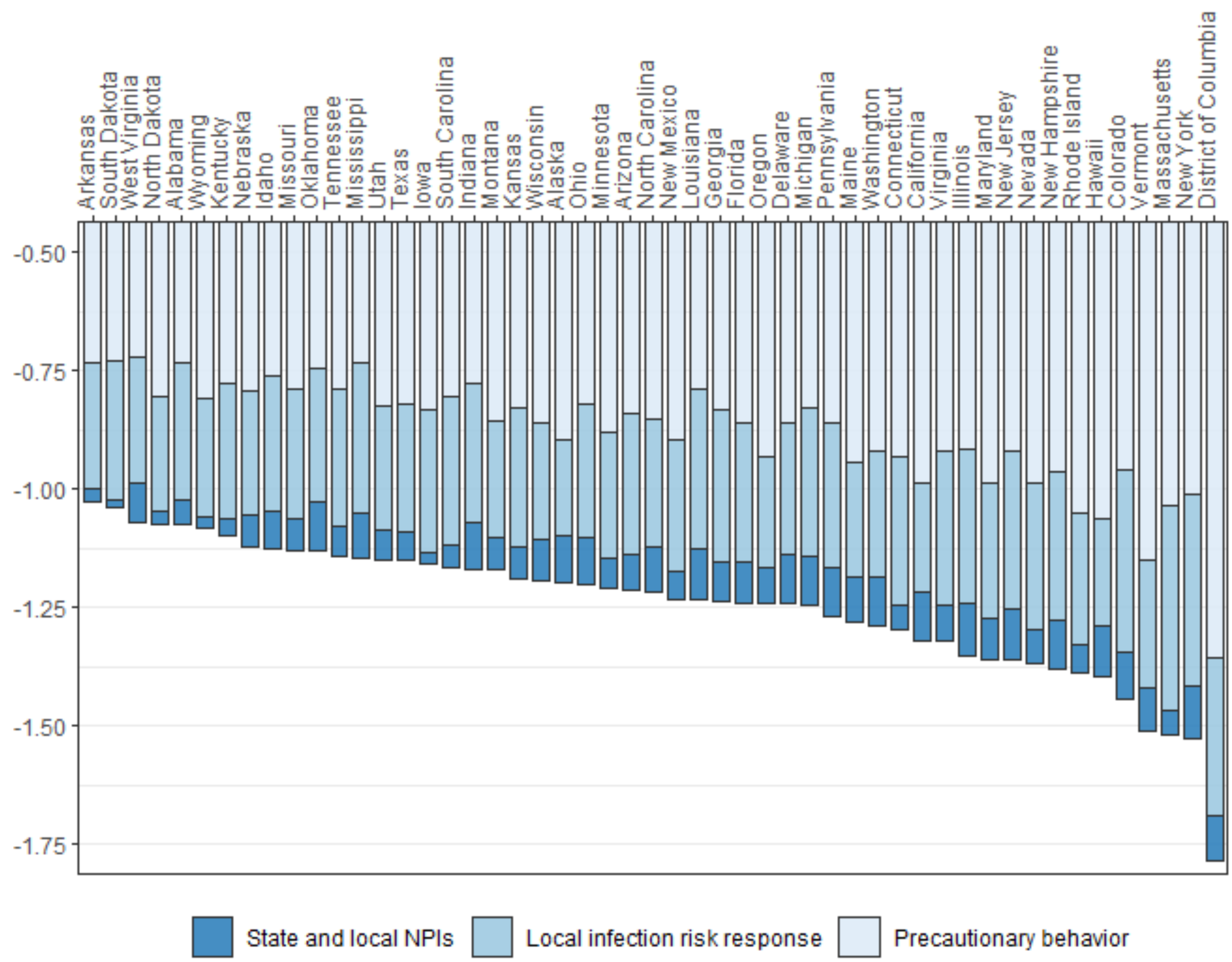


Source: Authors' calculations.

The decline in employment initially followed a pattern similar to the contact rate, lagging a few days behind. Precautionary behavior explains about 80% of the 11% fall in employment between March 8th and March 22nd. The two outcomes diverge beginning in late March due to the effects of NPIs – in particular, the employment impact of mandated business closures. By mid-April, employment was 20% below its level in early March. The response to local infection risk explains one fifth of this decline, the same as its contribution to the fall in the contact rate. State and local NPIs explains nearly 15%, more than double their contribution to the fall in the contact rate. Thus, on average NPIs appear to have been somewhat inefficient in terms of employment loss relative to social distancing gains. We return to this subject below.

Figure 9. Decomposition of the contact rate response to COVID-19 by state

Average contribution to log difference from March 1st

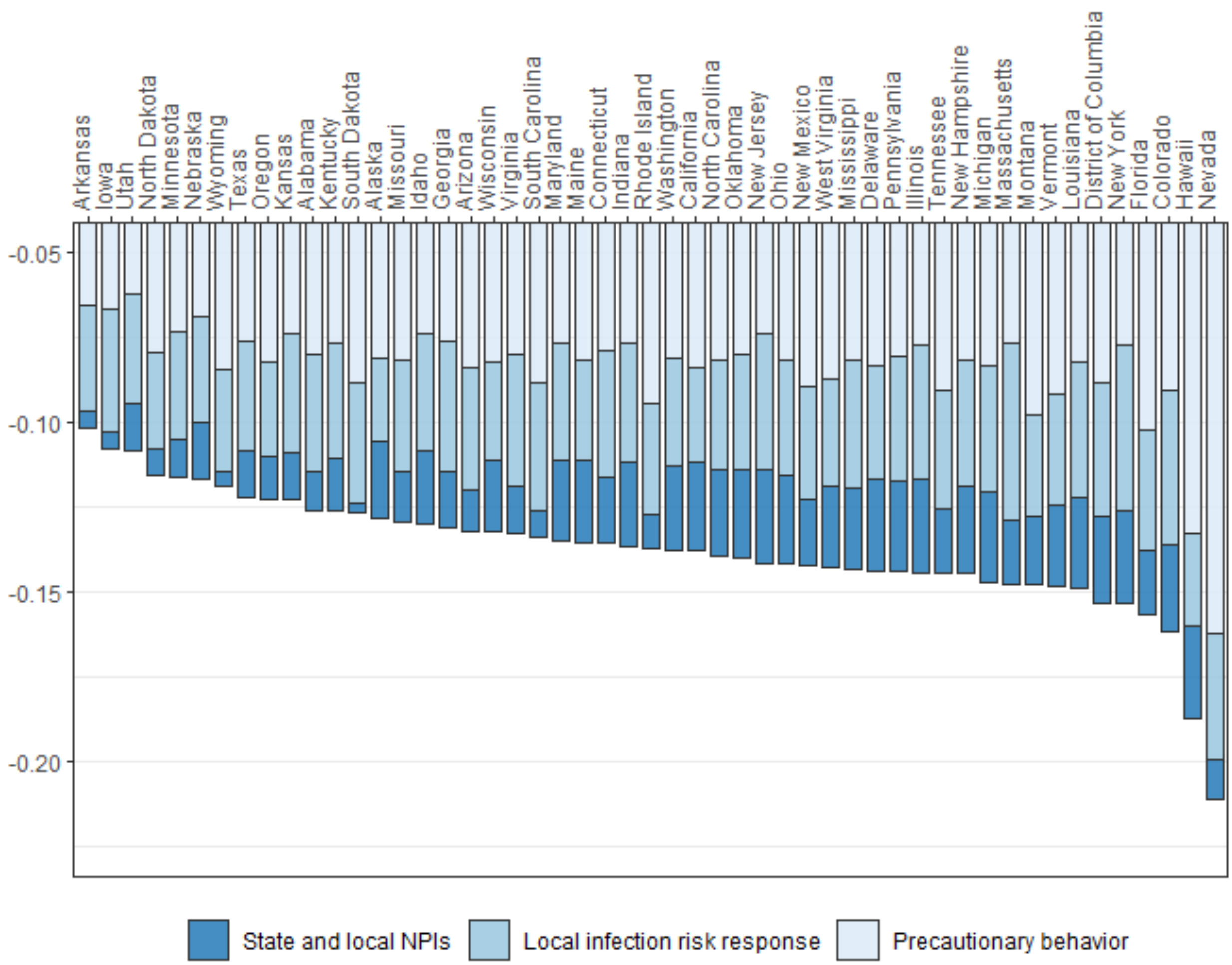


Source: Authors' calculations.

Figures 9 and 10 present the same decomposition of the contact rate and employment at the state level, averaging contributions over the period March 1st to May 31st. In general, plains states and the south central region experienced the smallest declines, while northeastern states – along with Nevada, Colorado, and Hawaii – experienced the largest. Cross-state variation in the magnitude of decline in contact rates and, to a lesser extent, employment is driven largely by differences in the precautionary component. Variation in the contribution of NPIs is much greater for employment than for the contact rate. This difference reflects the role of non-essential business closures, which were less widely adopted than the other NPIs (see Figure 2) and had small effects on the contact rate but large effects on employment.

Figure 10. Decomposition of the employment response to COVID-19 by state

Average contribution to log difference from March 1st



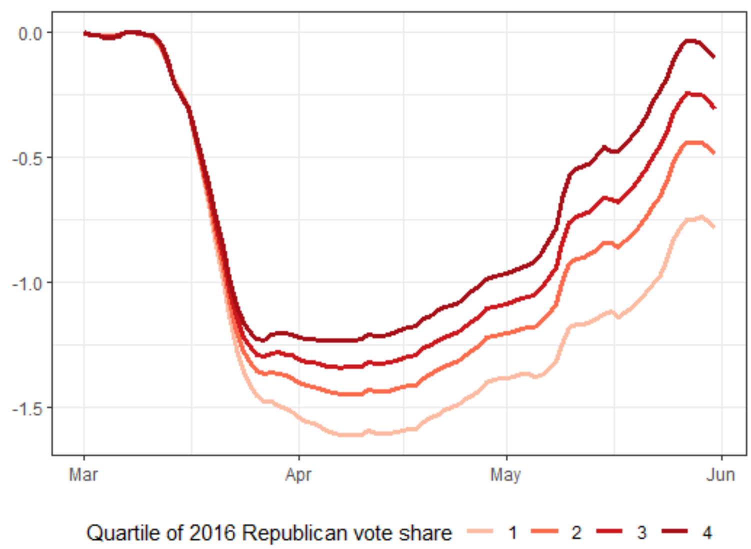
Source: Authors' calculations.

Figures 11 and 12 highlight two key drivers of heterogeneity in precautionary behavior: political preferences and industry mix. Figure 11 plots the average (county-level) contribution of precautionary behavior to the change in the contact rate by quartile of Republican Party vote share in the 2016 presidential election. The initial precautionary decline in contact rates in mid-

March occurred at roughly the same rate nationwide but diverged along political lines beginning in the last week of March. The most Republican-leaning counties experienced no further declines after mid-March, while the least Republican-leaning counties continued reducing contacts through early April. Precautionary concerns began to recede across all counties in the second half of April, with recovery proceeding somewhat faster in more Republican-leaning counties. By the end of May, the precautionary effect on contact rates had largely dissipated in the most Republican-leaning counties even as it depressed contact rates by around 50% in the least Republican-leaning.

Figure 11. Political preferences and precautionary changes in the contact rate

Contribution to log difference from March 1st, 7-day average

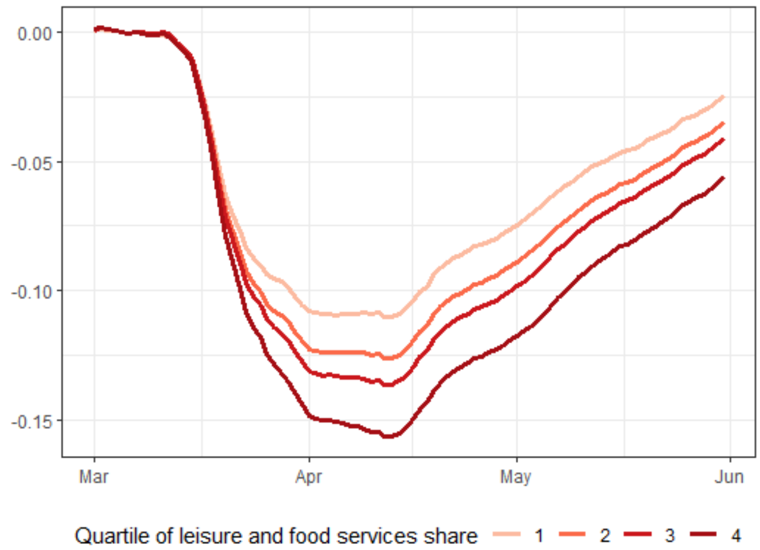


Source: Authors' calculations.

Figure 12 plots the average precautionary behavior contribution to the change in the employment by quartile of the share of county employment in leisure and food services. Because these industries provide largely discretionary services that typically require physical proximity, they are particularly likely to suffer as a result of voluntary social distancing. We find that the precautionary decline in employment was indeed substantially larger and more persistent in counties with more workers in leisure and food services. The importance of these industries to the economies of Nevada and Hawaii in particular explains the unusually large contribution of precautionary behavior the decline in employment in those states in Figure 10.

Figure 12. Industry composition and precautionary changes in employment[a]

Contribution to log difference from March 1st, 7-day average



Source: Authors' calculations.

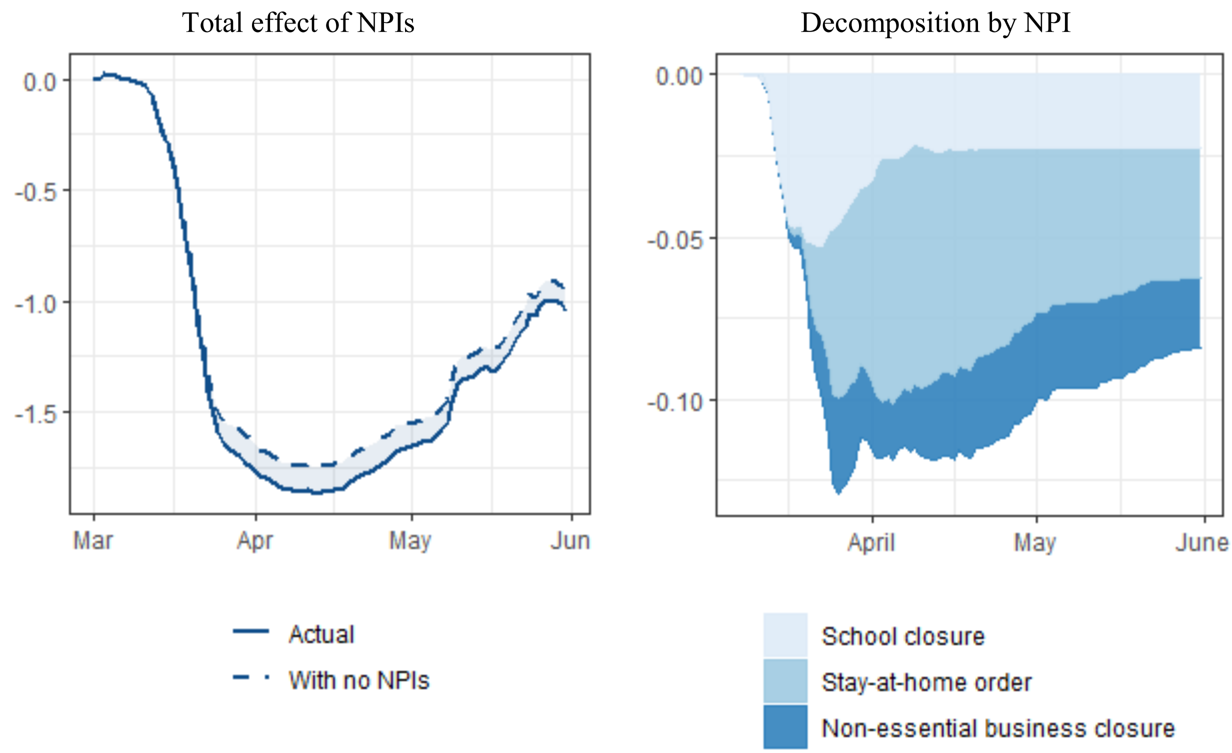
Appendix Figures A4 and A5 show variation in precautionary behavior across the five other county characteristics we include in our analysis. Figures A6 and A7 shows analogous plots for the contribution of NPIs. In general, we do not find strong patterns in the size of the policy response. The response was somewhat slower, smaller, and less persistent in the most Republican-leaning districts, but these differences are small compared with political variation in precautionary behavior.

VII.B. The Impact of NPIs

Narrowing our focus to the role of policy, we now consider the three types of intervention separately and review their epidemiological and economic effects. Figure 1 decomposes the estimated effect of state and local NPIs on the contact rate from the previous subsection into contributions from each of the three NPIs. The initial policy response consisted largely of school closures, which expanded rapidly to cover more than 90% of the population by March 20th. By the end of March, more than 70% of the population was also under either a stay-at-home-order, non-essential business closure, or both (see Figure 2). We estimate that together these policies reduced the daily contact rate by an average of 9% between early March and the end of May, accounting for 12% of the total fall in the contact rate. Of this, half was explained by stay-at-home orders, 28% by school closures, and 22% by non-essential business closures.

Figure 13. Effect of NPIs on the contact rate

(Log index, March 1st = 0)

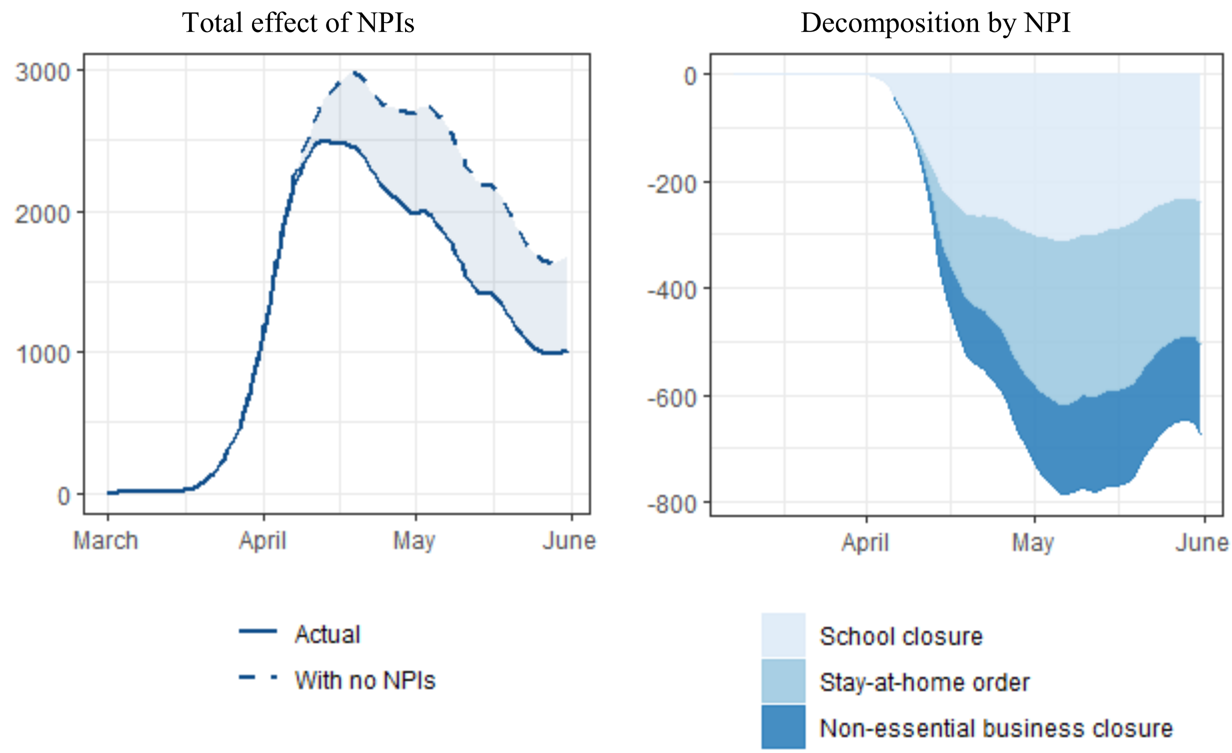


Source: Authors' calculations.

To estimate the epidemiological effects of these responses, we use the SEIR model described in section II to simulate each state's epidemic under a counterfactual path for the contact rate (and thus for the transmission rate β_{it}) that removes the effects of one or more NPIs. Figure 14 shows the results for daily COVID-19 deaths. In the absence of NPIs, we estimate daily deaths would have reached a peak of nearly 3,000 in mid-April instead of the actual peak of 2,500. In total, we estimate that NPIs lowered confirmed COVID-19 deaths through May 31st by more than 33,000, 29% of the actual cumulative total of nearly 115,000. Taking into account the lag between infection and death, we estimate that policy-induced changes in behavior through May 31st lowered confirmed deaths through mid-June by 48,000, or 37% of the actual total. School closures and stay-at-home orders each explain about 40% of these reductions; non-essential business closures account for 21%

Figure 14. Effect of NPIs on daily COVID-19 deaths

(Daily deaths)

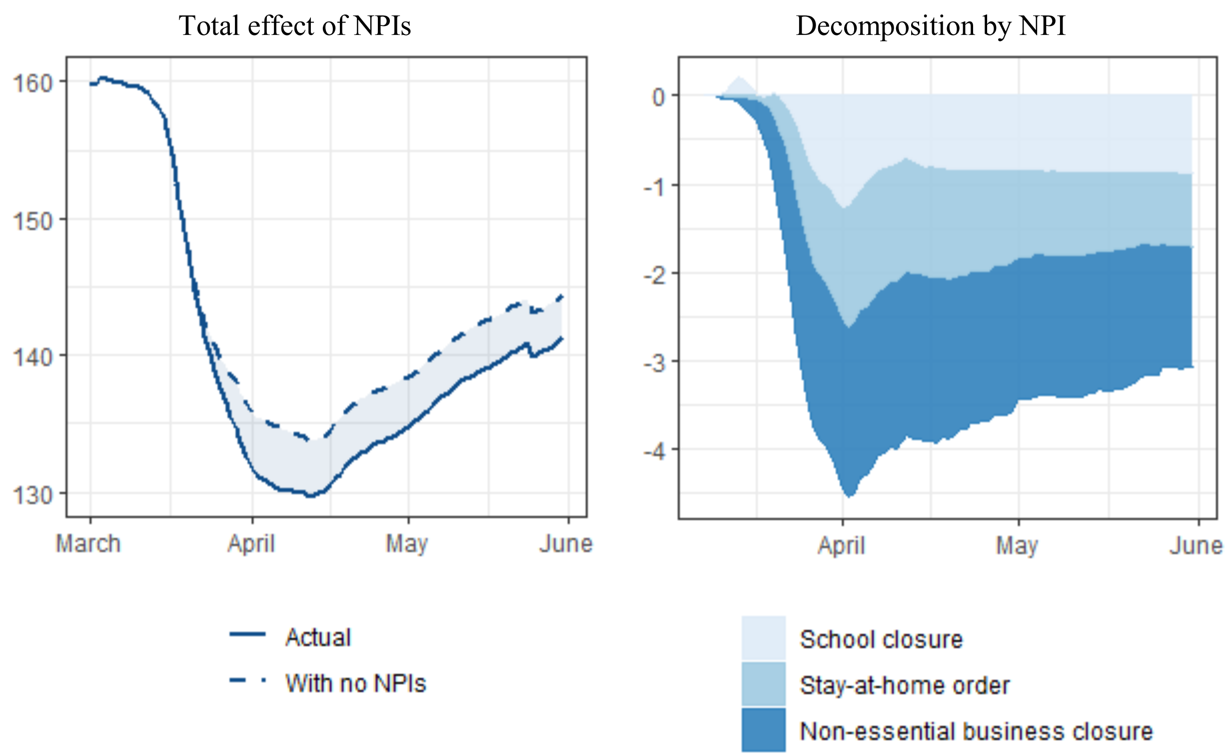


Source: Authors' calculations.

Comparing results for the contact rate and for deaths, we note two significant differences. First, the 9% decline in contacts in response to NPIs is considerably smaller than the resulting decline in deaths of about one third. Second, school closures accounted for a larger share of the reduction in the deaths than the reduction in contact rates (41% vs. 28%), with a corresponding and opposite difference in the contributions of stay-at-home orders (37% vs. 50%). Both outcomes reflect the nonlinear dynamics of infectious disease transmission. Reductions in contacts in the early stages of an epidemic may prevent long chains of transmission from ever emerging, leading to disproportionate reductions in infections and deaths. The relatively greater effect of school closures on deaths than contacts is thus explained by their relatively early enactment (on average, one week before non-essential business closures and ten days before stay-at-home orders).

Figure 15. Effect of NPIs on employment

(Millions)



Source: Authors' calculations.

Figure 15 shows the impact of NPIs on employment. We estimate that the policy response to COVID-19 reduced employment by an average of 3 million between early March and the end of May – 13% of the total fall employment. Almost half of this decline was attributable to non-essential business closures, 30% to stay-at-home orders, and 22% to school closures. Notably, business closures account for a much larger share of the decline in employment than of the fall in contact rates (48% vs. 22%), while the opposite is true of stay-at-home orders (30% vs. 50%). This suggests large cost-benefit differences across the different NPIs. We discuss these differences in the next section.

VIII. Counterfactuals

In this section, we use the augmented SEIR model to examine alternative responses to the pandemic. We first present a set of illustrative scenarios to help calibrate expectations of what NPIs can plausibly accomplish. We then consider alternative policy responses to the outbreak of COVID-19. Drawing on the results from the previous sections, we ask what could have been gained by responding more aggressively and deploying a more efficient mix of NPIs.

VIII.A. Seven Days

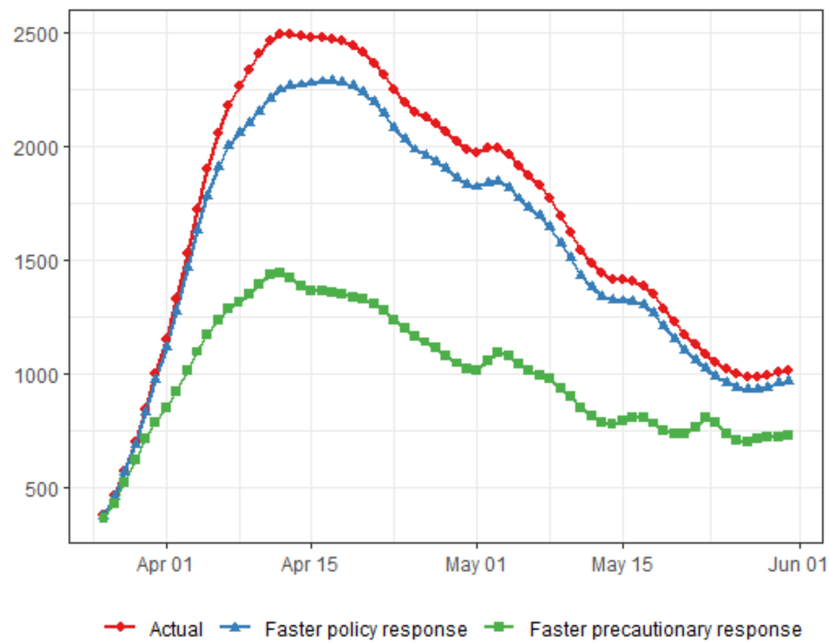
Figure 16 compares actual daily COVID-19 deaths with simulated paths for two illustrative scenarios. First, we assume that state and local governments adopt the same set and sequencing of NPIs but implement them all seven days earlier than they actually did. Second, we assume a precautionary response to the pandemic of the same magnitude as actually occurred but beginning seven days earlier. We find that a faster policy response would have reduced daily deaths by around 200 through much of April, preventing a cumulative 8,000 deaths by May 31st. By the end of the period, however, the epidemic largely converges back to its original path. A faster precautionary response, by contrast, dramatically alters the dynamics of the epidemic. The initial surge in deaths between late March and mid-April is substantially muted, and daily deaths never exceed 1500. In total, COVID-19 deaths are lower by 47,000 – or 40% – at the end of May.

We next consider the opposite scenarios, assuming that either the policy response or the precautionary response occurred seven days later than it actually did. Figure 17 reports the results. The effects of a one week delay in the introduction of NPIs are roughly symmetrical with those of faster action, leading a cumulative increase in deaths of 8,100. The effects of a slower precautionary response are of a different order of magnitude entirely. An additional week of effectively unabated transmission in mid-March dramatically increases the death rate over the subsequent months. Daily deaths reach a peak of more than 13,000 in mid-April, almost five times the actual peak. In total, COVID-19 deaths are higher by 242,000 – or 111% – at the end of May.

These results highlight the qualitative difference in the impact of marginal changes in voluntary behavior and that of marginal changes in policy. While NPIs produce meaningful gains, it is unlikely that any policy response based on the set of interventions we consider here –

which are the most stringent enacted in the US – could have altered the fundamental epidemiological dynamics of COVID-19. Effective suppression of the pandemic would have required either earlier voluntary action or substantially more coercive government interventions.

Figure 16. Daily COVID-19 deaths given 7 days faster response

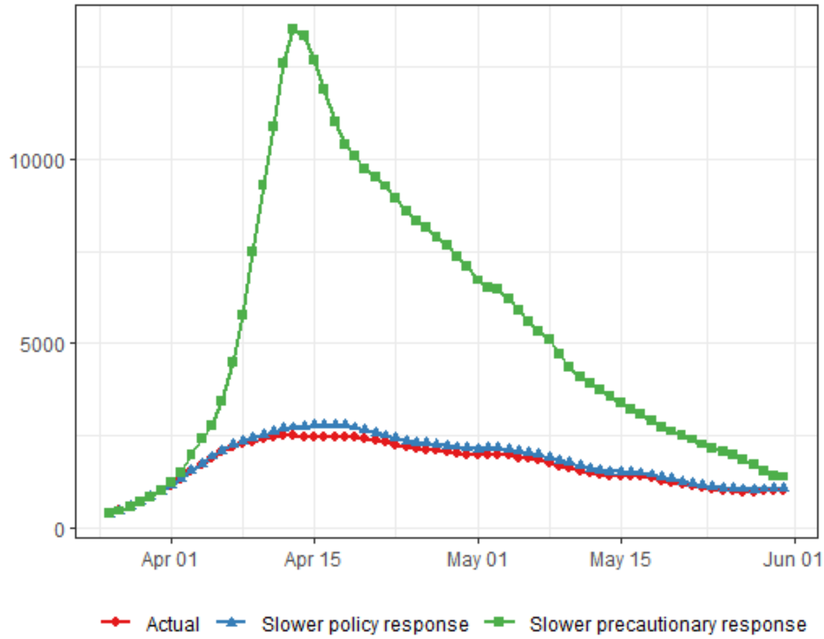


Source: Authors' calculations.

VIII.B. Efficient Pandemic Response

We now consider the potential gains from a more efficient policy response to the outbreak of COVID-19. We define policy efficiency in terms of the reduction in deaths attributable to an NPI relative to the corresponding reduction in employment. Our analysis of the actual response in section VII suggests two principles to guide the deployment of NPIs: first, action should be taken as early as possible; second, the interventions with the highest benefit-to-cost ratios should be prioritized.

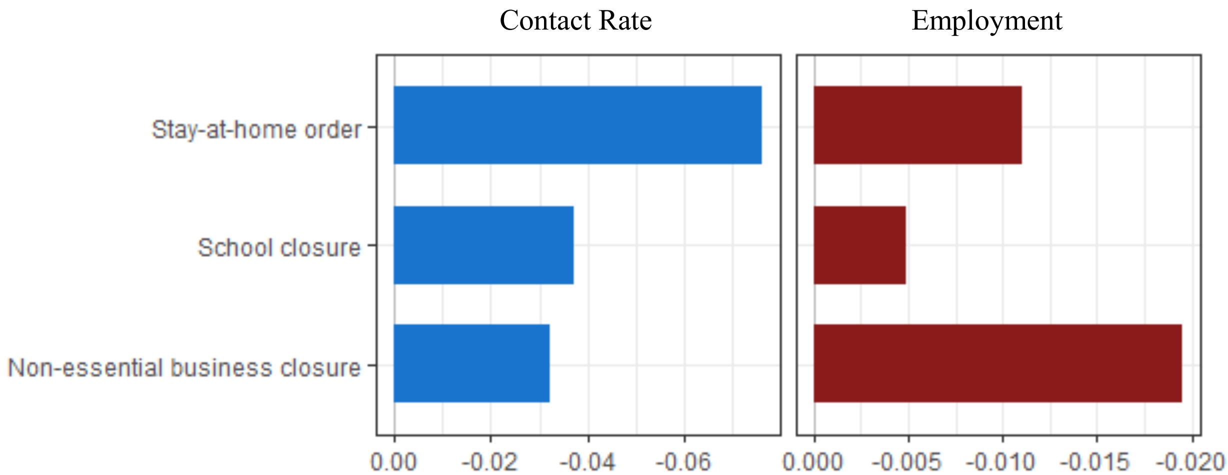
Figure 17. Daily COVID-19 deaths given 7 days slower response



Source: Authors' calculations.

On the second principle, we noted above that non-essential business closures accounted for a markedly larger share of the decline employment than of the decline in contact rates, while the reverse was true for stay-at-orders. Figure 18 highlights the reason for this difference, plotting the average effect of each intervention on the two outcomes estimated from (7) and (8). Non-essential business closures are the costliest of the three NPIs in terms of employment while delivering the smallest reduction in contacts. For stay-at-home orders and school closures, the tradeoff is similar, though stay-at-home orders have substantially larger effects. Given the nonlinear benefits of earlier reductions in contact, as well as the negative externalities of removing children from schools, we view stay-at-home orders as preferred over school closures. Thus, we argue that the NPI of first resort should be a stay-at-home order, followed first by closing schools and then by closing businesses.

Figure 18. Average change in the contact rate and employment by NPI



Source: Authors' calculations.

Notes: The plotted values are averages of the estimated effect of each NPI over the 31 days after the NPI is issued.

With this in mind, we construct two sets of alternative policy response scenarios. First, we consider a federal, nationwide response on March 13th, the date on which the president declared COVID-19 a national emergency. We simulate this scenario for responses consisting of only a stay-at-home order, a stay-at-home order and school closure, and all three NPIs issued on the same date. Second, we consider a local government (county-level) response based on the number of confirmed cases in a county. We calculate confirmed cases per capita on the date a state or substate government issued its first, second, and third NPI.[31] We take the 25th percentile of each and use the three values as thresholds to specify when a county government issues (first) a stay-at-home order, (second) an order closing schools, and (third) an order closing non-essential businesses. Hence, this scenario represents a relatively aggressive response to local outbreaks, with NPIs reordered based on efficiency. As with the federal response, we run simulations adding each of the NPIs incrementally.

[31] For NPIs issues by state governments, we use state-level cases per capita. For NPIs issues by substate governments, we use county-level cases per capita.

Table 3. Counterfactual policy response simulation results

	Cumulative COVID-19 deaths through May 31st [a]		Difference in employment from March 1st [b]	
	Deaths	Difference from actual	Millions	Difference from actual
Actual	114,423		-20.5	
No NPIs	147,661	33,238	-17.8	2.67
Seven days				
Seven days slower	122,569	8,146	-20.3	0.17
Seven days faster	106,375	-8,048	-20.7	-0.15
Federal response on March 13th				
Stay-at-home order	120,314	5,891	-18.9	1.62
Stay-at-home order and school closure	110,037	-4,386	-19.5	1.01
Stay-at-home order, school closure, and non-essential business closure	102,293	-12,130	-21.6	-1.08
Local response to confirmed cases				
Stay-at-home order	120,385	5,962	-18.8	1.76
Stay-at-home order and school closure	112,798	-1,625	-19.3	1.21
Stay-at-home order, school closure, and non-essential business closure	107,102	-7,321	-21.1	-0.62

Source: Authors' calculations.

a. Excludes differences in deaths after May 31st attributable to differences in infections through May 31st.
b. March 1st – May 31st average.

Table 3 presents our results for cumulative confirmed COVID-19 deaths through May 31st and for the change in employment relative to March 1st, averaged over the period March 1st to May 31st. The first two rows show historical values and our estimates of what would have happened in the absence of any NPIs at all. The next two rows report results for the illustrative policy scenarios discussed in VIII.A, which we include for comparison. The remainder of the table reports results for the federal response and local response scenarios.

We highlight three main results. First, the most aggressive response we consider – nationwide enactment of all three NPIs on March 13th – leads to a reduction in deaths of more than 12,000 relative to the actual response, as well as an additional employment loss of 1.1

million. Though the number of lives is significant, it reflects a marginal change in the epidemic curve, confirming that contact-reducing NPIs alone are not sufficient to manage the epidemic.

Second, enactment of non-essential business closures led to economic costs that could have been avoided while actually improving epidemiological outcomes. Compared with the actual policy response, we estimate that wider implementation of stay-at-home orders and school closures – without any non-essential business closures – could have delivered a larger reduction in deaths while sustaining at least an additional one million jobs.

Third, we find that there is no significant advantage to geographic targeting of NPIs based on local epidemic conditions compared with blanket issuance of NPIs. Comparing the federal and local response scenarios, we estimate that the epidemiological benefits of applying interventions nationwide are roughly proportional to the economic costs. This outcome is partly attributable to the low case confirmation rate in the early stages of the epidemic. Policymakers relying on confirmed case counts to assess whether NPIs should be enacted will generally underestimate the progression of their local epidemic and react too slowly. Early, universal enactment of NPIs counters this bias, offsetting the economic losses suffered by counties with few actual infections.

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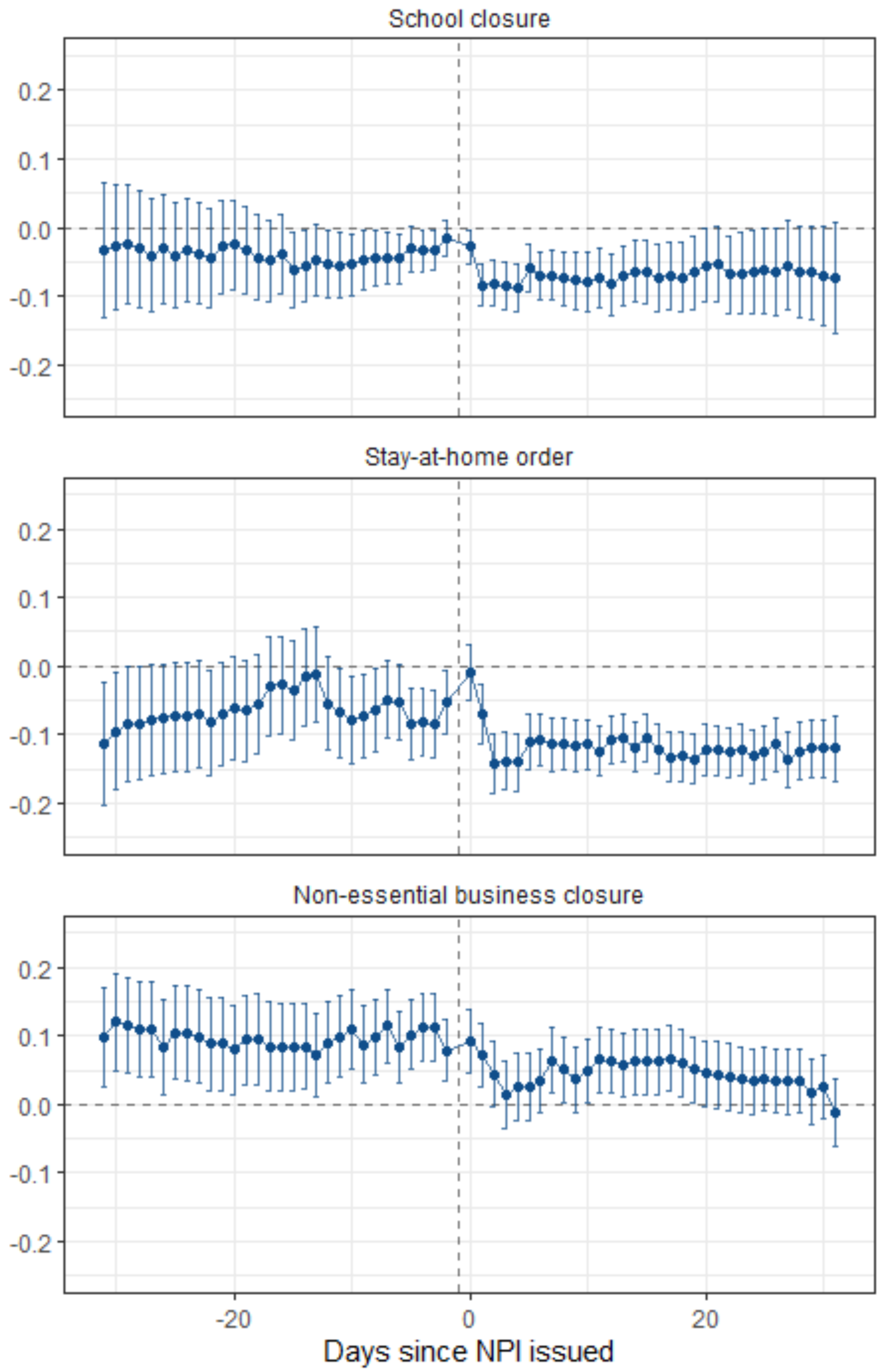
Appendix

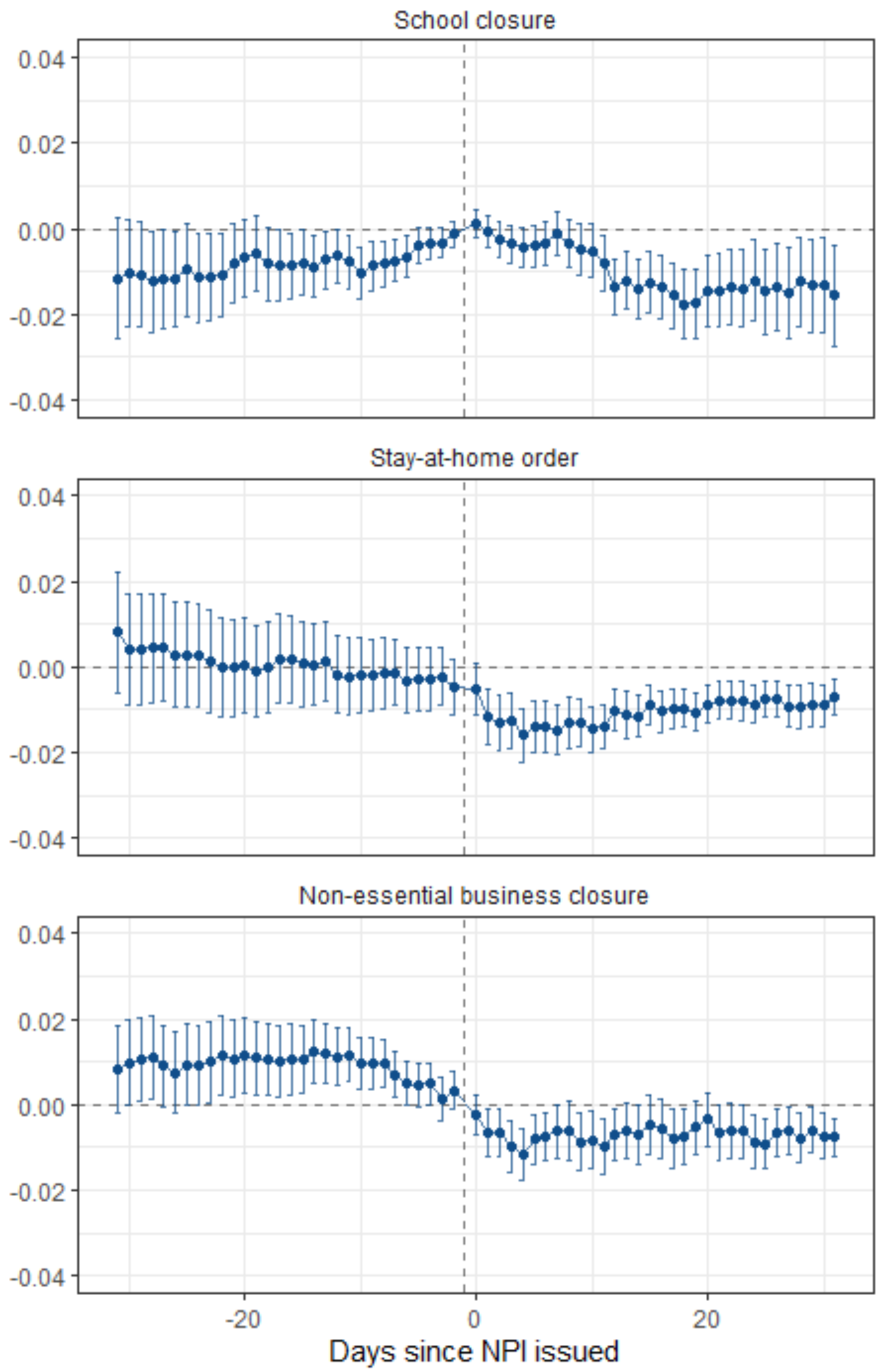
Figure A1. Event study estimates without county characteristics: contact rate



Source: Authors' calculations.

Notes: This figure shows coefficient estimates and 95% confidence intervals for ϕ_{jk}^{κ} from (7) with $X_{xi} = \vec{\mathbf{1}}$. Standard errors are clustered at the county level.

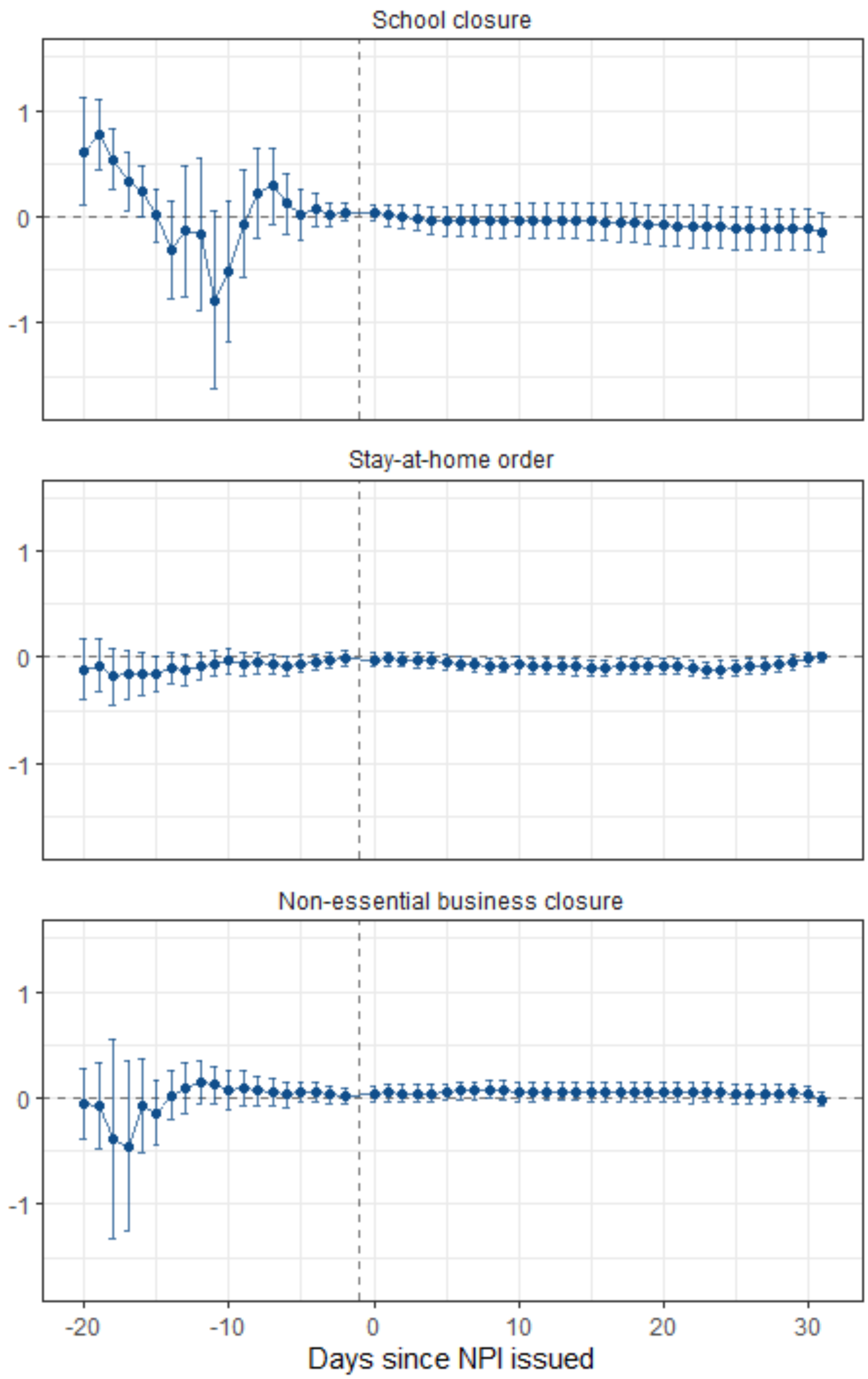
Figure A2. Event study estimates without county characteristics: employment



Source: Authors' calculations.

Notes: This figure shows coefficient estimates and 95% confidence intervals for ϕ_{jk}^{W} from (7) with $X_{xi} = \vec{\mathbf{1}}$. Standard errors are clustered at the county level.

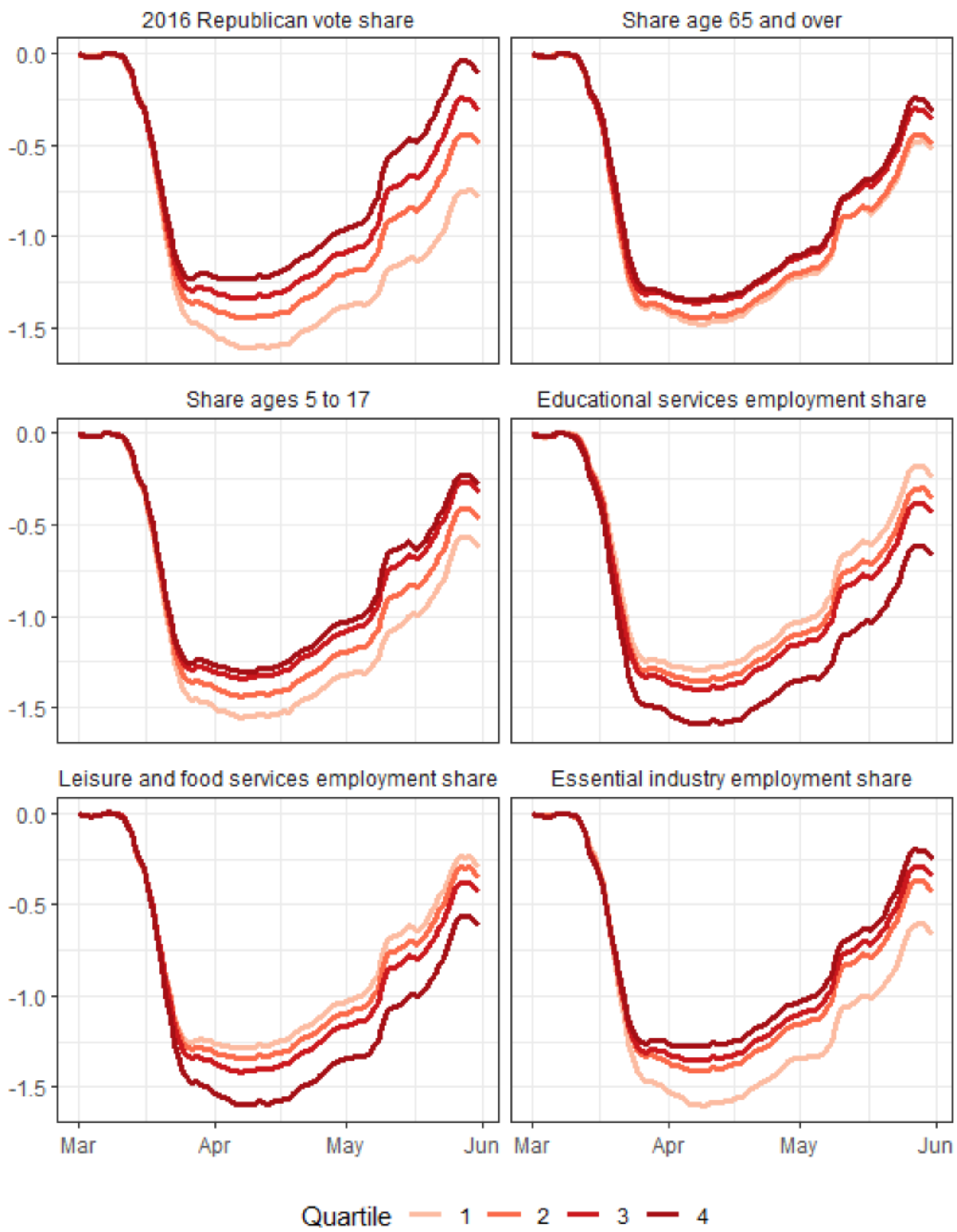
Figure A3. Event study estimates: reproduction number (R)



Source: Authors' calculations.

Figure A4. Precautionary changes in the contact rate by county characteristics

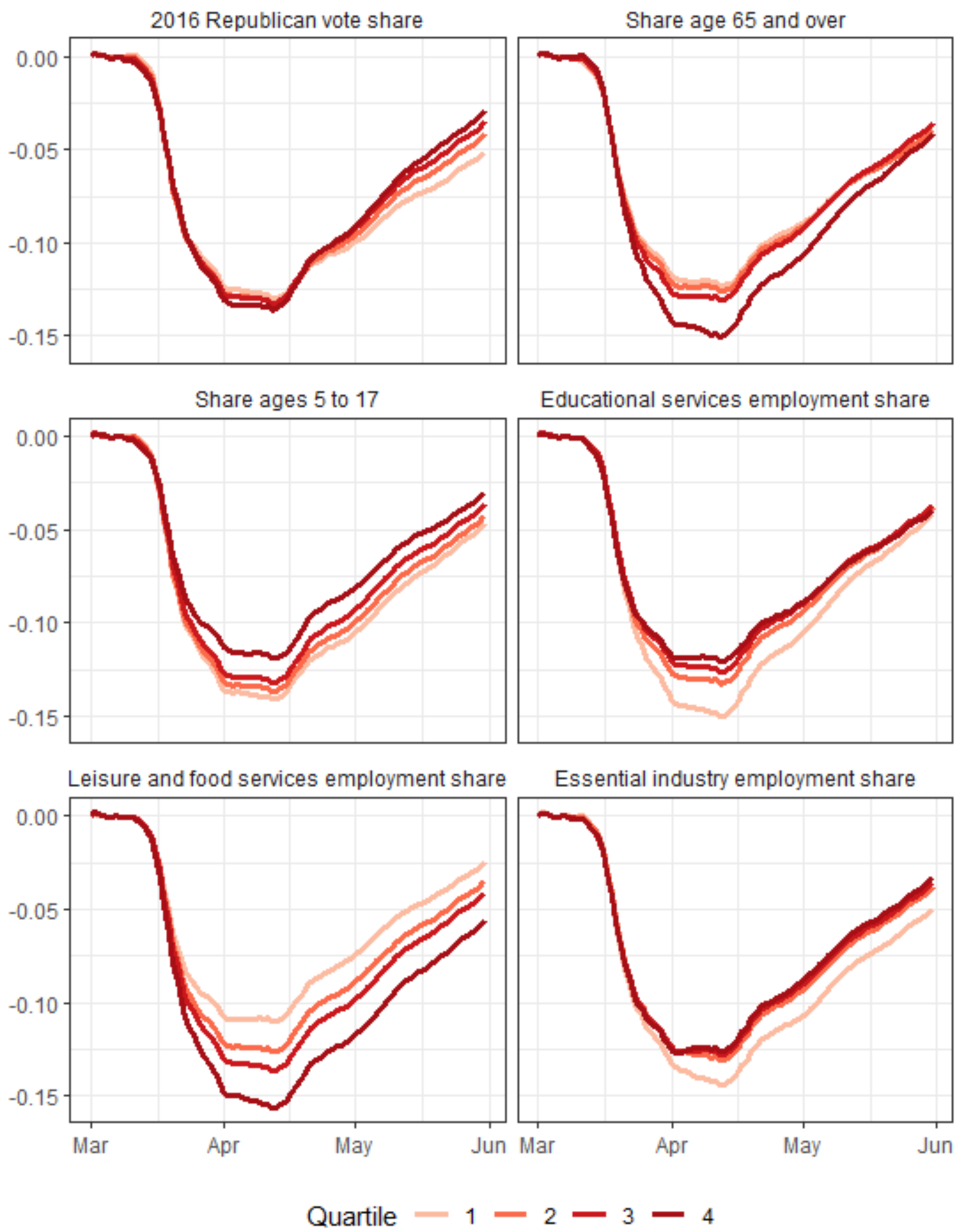
Contribution to log difference from March 1st, 7-day average



Source: Authors' calculations.

Figure A5. Precautionary changes in employment by county characteristics

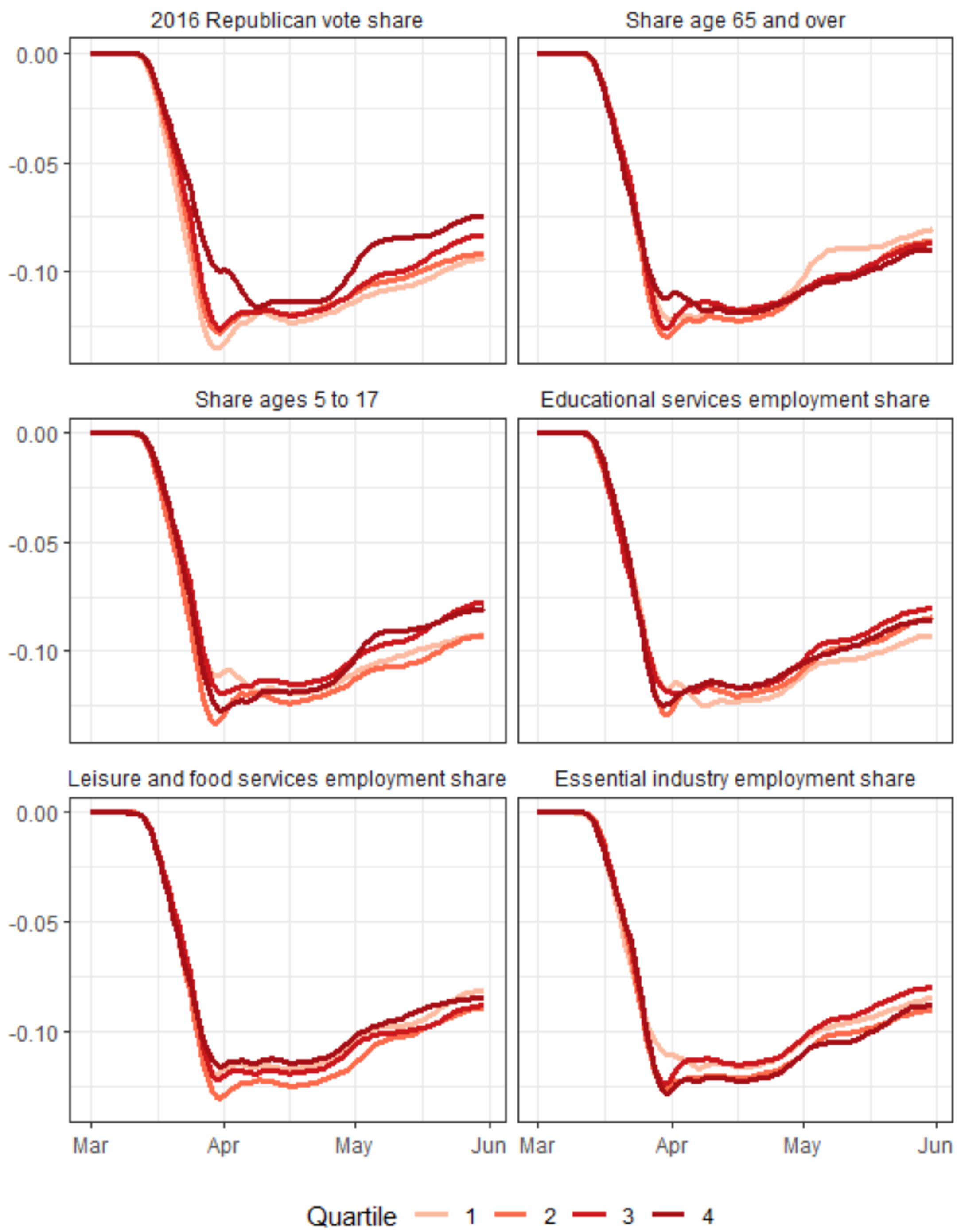
Contribution to log difference from March 1st, 7-day average



Source: Authors' calculations.

Figure A6. Contribution of NPIs to changes in the contact rate by county characteristics

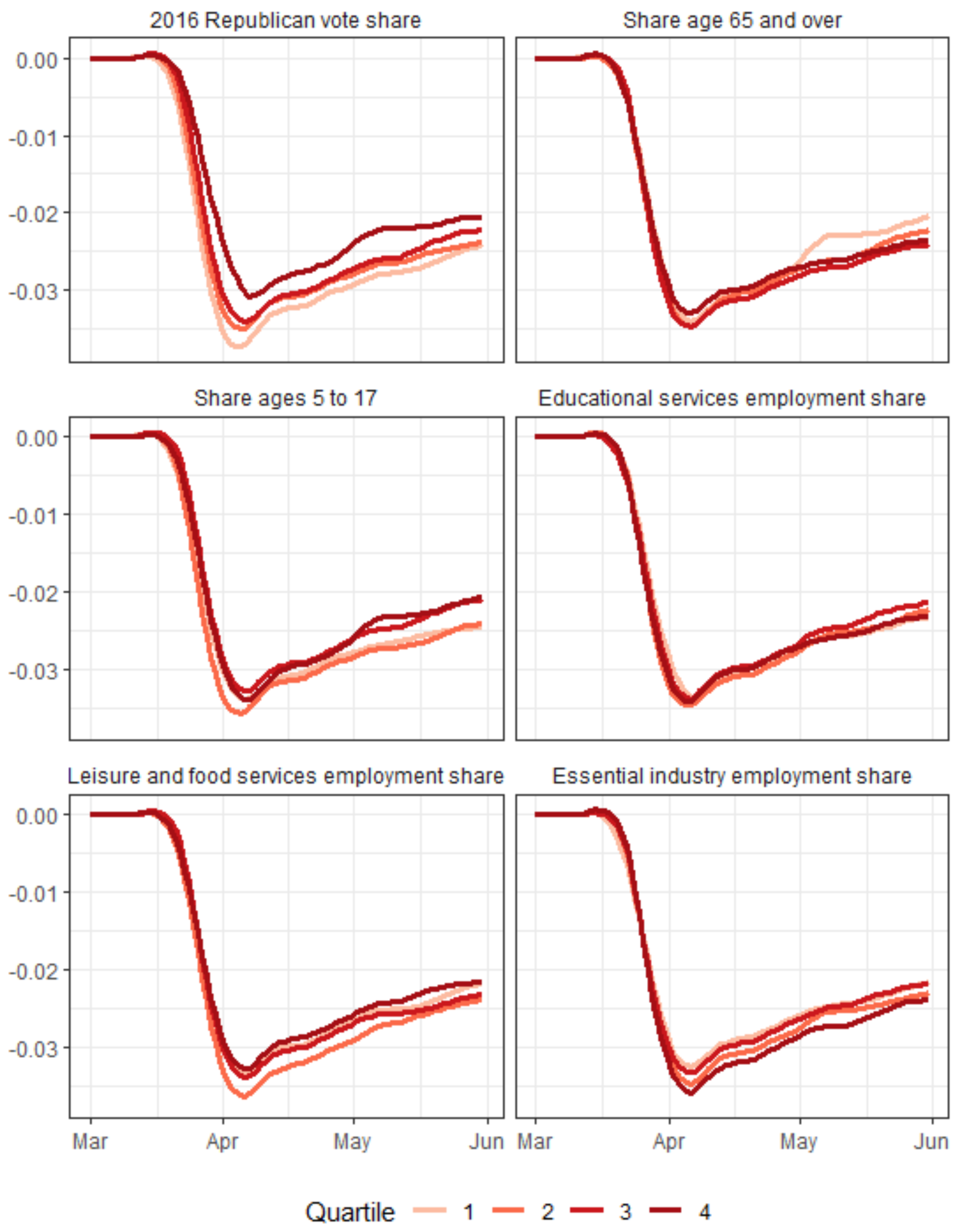
Contribution to log difference from March 1st, 7-day average



Source: Authors' calculations.

Figure A7. Contribution of NPIs to changes in employment by county characteristics

Contribution to log difference from March 1st, 7-day average



Source: Authors' calculations.