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Epidemiological and Economic Effects of Lockdown

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 about 25 percent—saving about 39,000 lives—over the first three months of the pandemic. However, NPIs also explain nearly 15 percent 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 nonessential 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 a pandemic?

To answer these questions, we extend a state-level compartmental model of the COVID-19 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 the beginning of March through the end of May.

We find that NPIs account for only 9 percent of the sharp fall in contact rates over this period. This relatively modest effect, however, led to a 25 percent reduction in deaths from COVID-19 by May 31. At the same time, we estimate that NPIs reduced employment by about 3 million, nearly 15 percent 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. Based on simulations from our model, we argue that enacting NPIs earlier and prioritizing the least costly NPIs could have saved more lives than the actual policy response with substantially lower economic costs.

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

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

the conventional assumption in epidemiological models that contact rates are independent of dynamics of the epidemic and 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 many different sources to construct comprehensive daily measures of contact rates and employment. With these measures, we are able to 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.

I. Background

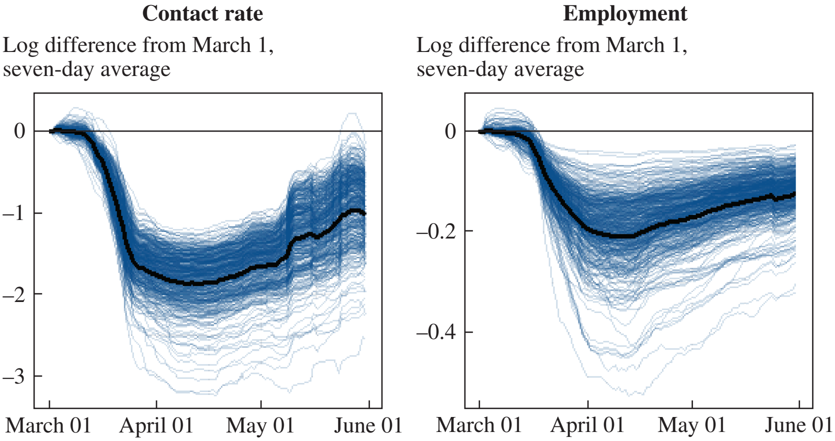
In response to exponential growth in the number of COVID-19 cases, social and economic activity in the United States collapsed in the second and third weeks of March. The average social contact rate—defined as the probability of being in close physical proximity to someone who is not a member of the same household—declined more than 80 percent 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 responded to the pandemic with an array of non-pharmaceutical interventions—policies that aim to prevent disease transmission through social distancing and other behavioral changes. By reducing the frequency of physical proximity between potentially infected and susceptible persons, social distancing limits opportunities for the virus to spread. While most individual government actions were idiosyncratic and limited (for example, closing casinos or limiting certain close-contact personal services), three broadly restrictive NPIs were eventually enacted across most of the country: school closures, stay-at-home (or shelter-in-place) orders, and nonessential business closures.[3]

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

3. School closures are orders to cease in-person teaching at public schools (at least) in a county. Stay-at-home orders are mandates that individuals remain at home for all "nonessential" activities. Both stay-at-home orders and nonessential business closures were typically—though not always—issued with a listing of the activities or businesses considered essential.

Figure 1. The Response to COVID-19 by County



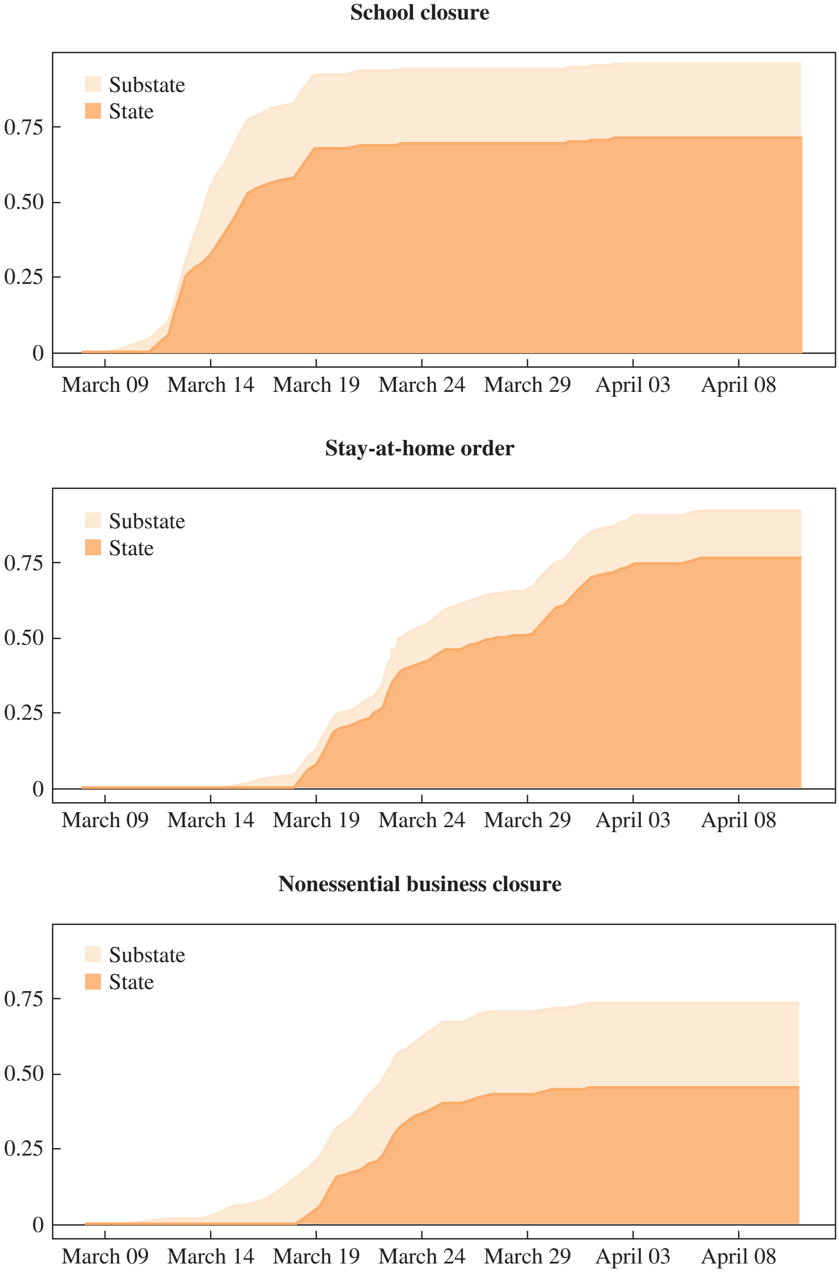
Source: Authors' calculations.
Notes: Each thin line represents one US county. The solid black line is the weighted US average. The contact rate is the probability of being in close physical proximity to someone who is not a member of the same household; the US average is weighted by county population. Employment is the number of people working in a county on a given day; the US average is weighted by the average of county employment in December 2019, January 2020, and February 2020.

Figure 2 plots the share of the US population residing in a county covered by each of these three NPIs over time. School closures expanded rapidly beginning in the second week of March to cover more than 90 percent of the population by March 20. The number of nonessential business closures and stay-at-home orders grew rapidly from the third week of March, extending over more than 70 percent of the population by the end of the month. Notably, though NPIs issued by state governments would eventually cover a greater share 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.

Figure 2. Share of the US Population Covered by NPIs, by Level of Government



Sources: Data from COVID19StatePolicy and Keystone Strategy; authors' calculations.
Note: Substate governments include school districts, municipal governments, and county governments.

II.A. Epidemiological Framework

We begin with the canonical susceptible-exposed-infected-removed (SEIR) model. A fraction of the population is susceptible (S), and this group interacts with those who are infectious (I).[4] Those who are infected with the virus but not yet infectious—that is, able to transmit the virus—are said to be exposed (E). A fraction of 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. Nonterminal cases eventually recover and transition to group R and are assumed to be immune to the virus.

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

$$\frac{dS_{it}}{dt} = -\beta_{it} I_{it} \frac{S_{it}}{N_i},$$

$$\frac{dE_{it}}{dt} = \beta_{it} I_{it} \frac{S_{it}}{N_{it}} - \sigma E_{it},$$

$$\frac{dI_{it}}{dt} = \sigma E_{it} - \gamma I_{it},$$

$$\frac{dR_{it}}{dt} = \gamma I_{it} \left(1 - \mu_{i(t-1/\gamma)}\right),$$

$$\frac{dT_{it}}{dt} = \gamma I_{it} \mu_{i(t-1/\gamma)},$$

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

The transmission rate (secondary infections caused per primary infection per day) is β_{it}. The inverse of COVID-19's latent period is σ; that is, the duration between infection and onset of infectiousness. Note that the latent period is distinct from the incubation period—the duration between infection and onset of symptoms—which conventionally appears in the SEIR

4. Our framework assumes homogeneous population mixing wherein every individual is equally likely to come into contact with every other individual. See the online appendix for the results of a stylized experiment where we relax this assumption using a two-group SEIR model with heterogeneous contact rates and NPI effects.

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 presymptomatic 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 being equal, and only affects the eventual outcome of an infection.

The recovery rate, the inverse of the average infectious period, is represented by γ. A share of symptomatic infections are fatal. The infected population transitions into the terminal (T) group according to the infection fatality ratio μ_{it}. After a period, these terminal infections end in death. The number of days between symptom onset and death in fatal cases is represented by τ_F. 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—which we confirm in section VII—we allow agents in the model to adjust their exposure risk based on the progression of their local epidemic.[5] This extension of the model is important for generating plausible policy counterfactuals, as we attempt to do in section VIII. 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

5. See Goolsbee and Syverson (2020).

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:

$$\text{(2)} \qquad \mathcal{R}_{it} = \frac{\beta_{it}}{\gamma_{it}},$$

where γ_{it} is the duration of infectiousness.

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:

$$\text{(3)} \qquad \kappa_{it} = \exp\left(\Omega_{it} \cdot \Phi_{it} \cdot (C_{it})^{\rho}\right),$$

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 than the true number of infections, which is unknown to agents in the model.[6] The relationship between the underlying epidemiological dynamics and the observed dynamics of confirmed cases C_{it} is given by

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

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

6. 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 as 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.

to the onset of symptoms, and τ_P is the duration from symptom onset to a positive test result.[7]

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 $\Omega_{it} = \omega_t X_i$ and $\Phi_{it} = \phi P_{it}$, 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 equation (1) and substituting for Ω_{it} and Φ_{it} yields

$$\ln \kappa_{it} = \omega_t X_i + \phi P_{it} + \rho c_{it}. \tag{4}$$

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

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

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 equation (4) for ζ_{it} and estimate its parameters explicitly. This is not possible, however, due to the limitations of available epidemiological data from the initial stages of the pandemic.

Data limitations also pose serious challenges for direct estimation of equation (5), as daily $\mathcal{R}_{it}$ is not observed and must be estimated historically. We therefore focus our empirical analysis on equation (4). We discuss these issues in more detail in section VI.

II.C. Employment

The necessity of physical proximity for a wide range of economic activities means that voluntary or governmental efforts to limit contacts lead to unavoidable economic disruption. Indeed, many studies of the effects

7. Note that $\alpha^{-1} + \tau_S$ is equal to the incubation period—the time between infection and the onset of symptoms.

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 trade-off between epidemiological gains and economic costs. The response to COVID-19 provides ample evidence that policymakers view this trade-off as a meaningful constraint on their ability to deploy NPIs to combat a pandemic.

No analysis of this trade-off 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 trade-offs 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 trade-offs, 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 equation (2) for employment, which we denote by W_{it} and define as the number of people working in state i at time t:

$$\ln W_{it} = \omega_t^W X_i + \phi^W P_{it} + \rho^W c_{it}. \tag{6}$$

The addition of equation (3) allows us to assess the epidemiological and the economic effects of interventions in a single, integrated framework. In addition, equation (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 mainly on three types of data: daily counts of COVID-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 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.[8] 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 any one source's estimates, we isolate the common trend in confirmed cases and deaths by taking the first principal 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 from mobile device location data, business and financial services software, payroll service providers, and web search activity. As we describe in section V, we combined 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.

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.

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

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 traveled using mobile device location data from SafeGraph.[9] 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.[10]

UNACAST We use county-level measures of "encounter density" and distance traveled derived from mobile device location data from Unacast.[11] Encounter density is a measure of physical proximity between persons defined as average number of times an individual is within 50 meters of another person, normalized by a county's physical size and relative to the pre-COVID-19 national average.

HOMEBASE We construct a 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.[12] 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).[13] 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.

9. SafeGraph, Social Distancing Metrics, https://docs.safegraph.com/docs/social-distancing-metrics.

10. Google, COVID-19 Community Mobility Reports, https://www.google.com/covid19/mobility.

11. Unacast, COVID-19 Toolkit, Social Distancing Scoreboard, https://www.unacast.com/covid19/social-distancing-scoreboard.

12. We define a "firm" as the aggregate of all of a single company's establishments in the same industry and county.

13. Opportunity Insights Economic Tracker, https://www.tracktherecovery.org.

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 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 COVID19StatePolicy and NPIs issued by county, municipal, or other substate government entities from Keystone Strategy.[14] We extend the 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 nonessential 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 nonessential, 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

14. COVID19StatePolicy, State-Level Social Distancing Policies in Response to the 2019 Novel Coronavirus in the US, https://github.com/COVID19StatePolicy/SocialDistancing; Keystone Strategy, City and County Non-pharmaceutical Intervention Rollout Dates, https://www.keystonestrategy.com/coronavirus-covid19-intervention-dataset-model.

days of the outbreak in the United States). 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 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 upward.

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 the positivity rate to fall as the eligibility criteria for testing broaden.

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.[15] 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 of confirmed new cases by its inverse. We then shift values backward in time by τ_P (set to one week) to reflect the date of symptom onset rather than the date of case confirmation.

In the initial days of the epidemic, the true number of new infections was nearly twenty times the number of new confirmed cases. This figure fell rapidly as testing infrastructure expanded: by early June, the ratio was around five, with the median state confirming 22 percent of new infections.[16] 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 outbreak later).

V. Contact Rate and Employment Indexes

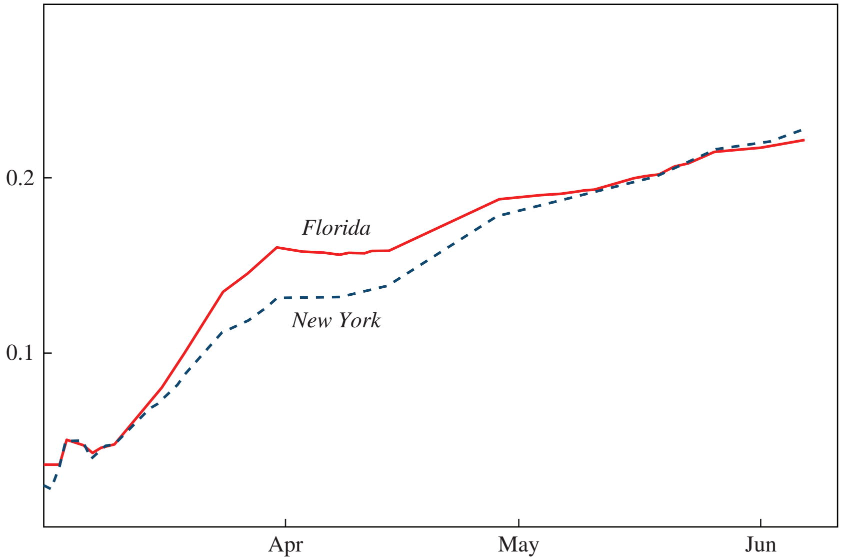
To specify the parameters and historical inputs of the model in section II, we require geographically detailed, daily data on the contact rate κ_{it} and employment W_{it}. To our knowledge, no such data exist. Instead, we have an array of unconventional indicators described in section III.B. Rather 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 traveled. Underlying measures related to employment include time spent at workplaces, web searches related to job loss and hiring, and

15. 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.

16. 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 eighteen on March 1 to about seven on August 1.

Figure 3. Estimated Daily Case Confirmation Rate in Florida and New York



Source: Authors' calculations.
Note: The figure compares the estimated daily case confirmation rate in states with different epidemic curves.

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.[17] 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.[18] We construct indexes independently for each county, so the weight assigned to any one underlying

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

18. For example, distance traveled is more closely related to time spent at home in less dense counties.

measure is determined by its relationship to the other measures in that county alone.

Before constructing the indexes, we normalize all measures relative to their average for the same day of the week in early 2020—generally the six-week period from January 12 to February 22.[19] For series with sufficient historical data to identify seasonal patterns, we normalized relative to the same week 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 are available and weighting by population.[20]

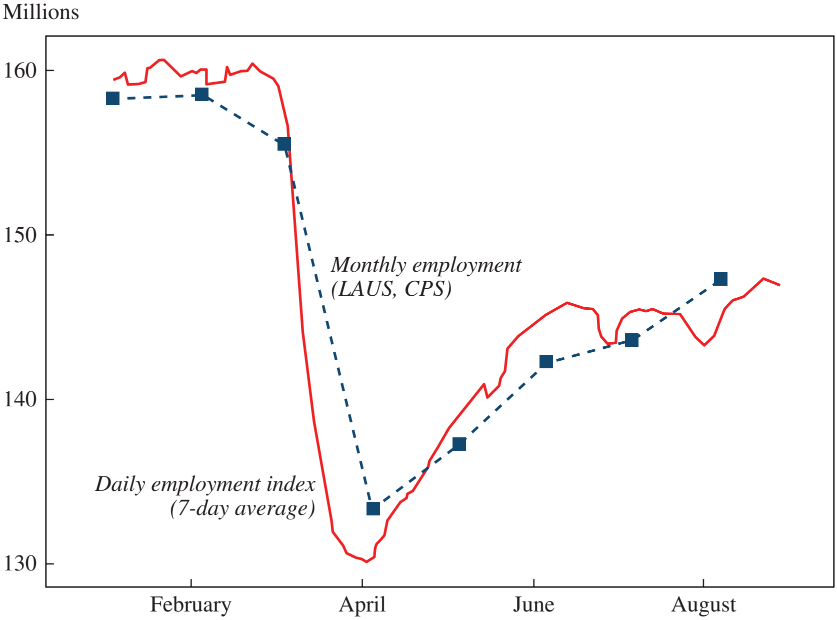
To construct the contact rate index, we take the first principal component of two measures of physical proximity, two measures of time spent at home, and two measures of distance traveled. Given these inputs, we interpret the index as reflecting contacts between persons who do not live together. To construct 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 Bureau of Labor Statistics Local Area Unemployment Statistics (LAUS). We had 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. Figure 4 plots total US daily employment aggregated from our county employment indexes against official estimates of monthly employment. Figure B1 in the online appendix compares county-level monthly changes in the daily employment index against actual monthly changes from LAUS. Although the underlying indicators are all indirect

19. 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 20.

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

Figure 4. Daily Employment Index and Monthly Official Employment



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 monthly value for August is from the BLS news release. Monthly official employment values are placed on the 12th of each month in the plot to align with the BLS reference week.

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.

VI. Parameters

This section reviews the selection or 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 estimate behavioral responses with 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

Table 1. Exogenous Parameter Definitions and Values

Parameter	*Definition*	*Value*
σ	$1/\tau_E$, where τ_E is the noninfectious latent period in days	1/2
γ	$1/\tau_I$, where τ_I is the infectious period in days	1/7
τ_S	Duration from infectiousness onset to symptom onset	3
τ_F	Duration from symptom onset to death for severe cases in days	19
τ_P	Duration from symptom onset to positive test result for confirmed cases (assumed)	7
μ_t	Infection fatality ratio	0.0025–0.008

Sources: Peng and others (2020); Lauer and others (2020); Zhou and others (2020); Gu (2020).

early and developing clinical COVID-19 literature where available. Parameter values and sources are shown in table 1.

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.[21] 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 improved treatments, expanded hospital capacity, and possible compositional shifts in the demography of new infections (Boehmer and others 2020).

The variable 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 III). 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 it varies widely across time and place. To obtain historical

21. See COVID-19 Projections Using Machine Learning, "About /Historical Performance," https://covid19-projections.com/about/#historical-performance, for a review of model accuracy.

estimates of β_{it}, we first estimate the effective reproduction number $\mathcal{R}_{it}$. From equation (2), β_{it} is given by $\beta_{it} = \mathcal{R}_{it}\gamma_{it}$.

We estimate $\mathcal{R}_{it}$ using the method developed by 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.[22]

VI.B. Behavioral Parameters

We now turn to the estimation of the behavioral parameters ϕ, ρ, and ω_t from sections II.B and II.C. We adopt a daily event study design to estimate the effects of policy interventions ϕ, 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 ω_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 equation (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.[23] Altogether, our sample for estimation of equation (5) is less than half the size of the full sample and drops most school closure and nonessential business closure events and many stay-at-home order events. In addition, historical estimation of $\mathcal{R}_{it}$ is based on an arbitrary time window and imposes a degree of smoothing, making it difficult to identify the timing of responses in a daily event study. We therefore estimate ϕ, ρ, and ω_t using

22. 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.

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

the contact rate κ_{it} and equation (4) instead. Where feasible, we also show estimates from equation (5) 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 equation (4)—leads to the following estimating equations for the contact rate and employment:

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

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

The contact rate index is κ_{it}, and W_{it} is the employment index for county i on day t. The county and calendar date fixed effects are η_i and ω_{xt}, respectively. The variable 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. The variable 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 thirty 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 thirty-one days from the issuance of the NPI are binned in $k = -31$ and $k = 31$ and reflected in the coefficients $\phi_{j,-31}$ and $\phi_{j,31}$. The variable c_{it} is the inverse hyperbolic sine of C_{it}, the total number of confirmed COVID-19 cases in county i.[24]

The variable X_{xi} contains information on the demographic, economic, and political characteristics of counties. In our main estimates, it includes the shares of the population age 5 to 17 and age 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.[25] The precautionary behavior terms $\omega_{xt}X_{xi}$ capture nationwide

24. 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.

25. Essential industries are defined based on guidance from the Department of Homeland Security. Election data are from the MIT Election Data and Science Lab.

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.

The event study coefficients ϕ_{jk} reflect the direct impact of NPIs on opportunities for social contact or economic activity as well as any other changes in behavior indirectly induced by NPIs. Both the announcement of NPIs and observation of their effects convey information to the public about the importance of social distancing.[26] Individuals may respond to this information by adjusting their behavior in ways that are not directly related to specific limitations imposed by NPIs. For example, an announcement that all nonessential businesses must close may lead some households to purchase groceries online for delivery instead of at a store, even if grocery stores are considered essential businesses and remain open.

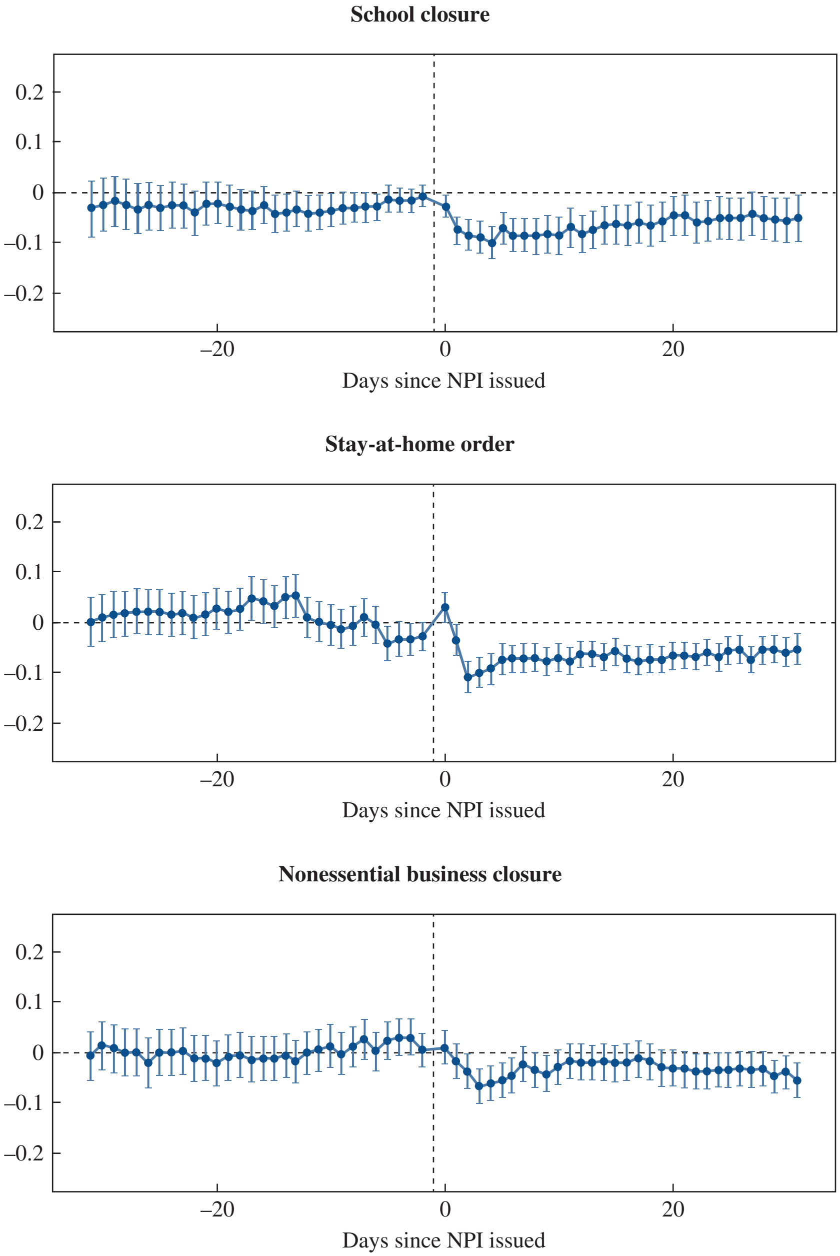
The relationship between the contact rate κ_{it} and COVID-19 cases C_{it} described in section II implies potential simultaneity in equation (7) and—to the extent employment W_{it} is related to κ_{it}—in equation (8). Identification of the causal parameters ϕ_{jk} and ρ depends on the lag between κ_{it} (or W_{it}) and C_{it}. Given the disease's incubation period and the time from symptom onset to a positive test result, the effects of a change in behavior are not reflected in the number of cases for more than a week. Hence, we treat the contemporaneous case count as exogenous with respect to behavioral outcomes.

Figure 5 reports NPI event study estimates for the contact rate from equation (7).[27] Over the week following an order to close schools, the contact rate declined between 5 and 10 percent. Stay-at-home orders had larger and more immediate effects, with a sharp fall in contacts of more than

26. Gupta, Simon, and Wing (2020) highlight the informational aspect of NPIs and provide a detailed discussion.

27. We report estimates from the model excluding county characteristics (i.e., $X_{xi} = \vec{1}$) in figures B2 and B3 in the online appendix.

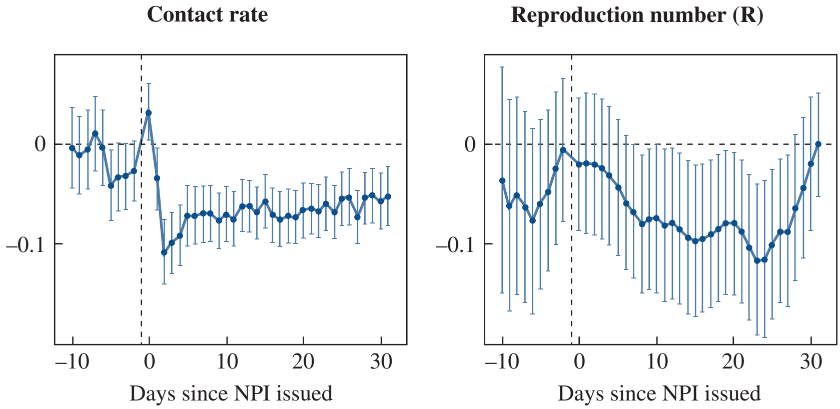
Figure 5. NPI Event Study Estimates: Contact Rate



Source: Authors' calculations.

Notes: The figure shows coefficient estimates and 95 percent confidence intervals for ϕ^k_{jk}, the effect of each NPI on the log of the contact rate. Standard errors are clustered at the county level.

Figure 6. NPI Event Study Estimates for Stay-at-Home Orders



Source: Authors' calculations.

Notes: The left panel shows coefficient estimates and 95 percent confidence intervals for $\phi^k_{SAH,k}$, the effect of stay-at-home orders on the log of the contact rate. The right panel shows analogous estimates based on equation (5) instead of equation (4): the effect of stay-at-home orders on the log of the reproduction number. Standard errors are clustered at the county level.

10 percent 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 thirty days. The effects of nonessential business closures were smaller—a decline of around 5 percent—but somewhat more persistent.

Figure 6 compares the response to stay-at-home orders estimated from the contact rate and equation (4) with estimates from the reproduction number and equation (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.[28] For readability, we limit the plot to ten pre periods, as the standard errors of the $\mathcal{R}_{it}$ estimates become very large in earlier periods. We estimate that $\mathcal{R}_{it}$ declined about 10 percent 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.[29] 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.

28. We report estimates for $\mathcal{R}_{it}$ for all three NPIs in figure B4 in the online appendix.

29. 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 of arbitrary width.

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

The estimates for nonessential 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 nonessential 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 nonessential 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 nonessential business closure on March 20. This followed three prior orders closing particular types of businesses: on March 16, fitness studios and movie theaters were ordered to close; on March 18, this was expanded to shopping malls, bowling alleys, and other public venues; on March 19, 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 nonessential business closures were preceded by lesser restrictions.

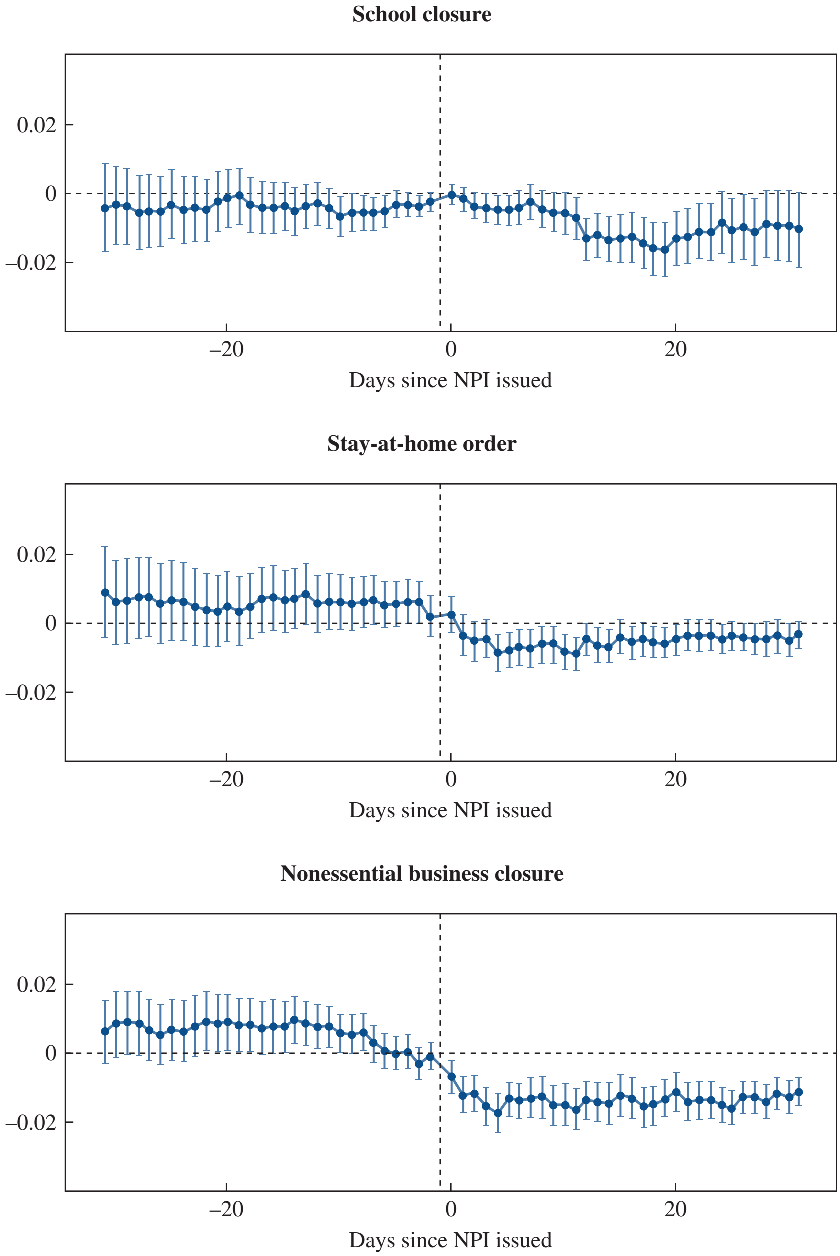
Table 2 reports estimates for ρ^{κ} and ρ^{W} and the elasticity of the contact rate and of employment with respect to local infection risk.

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

Figure 7. NPI Event Study Estimates: Employment



Source: Authors' calculations.

Notes: The figure shows coefficient estimates and 95 percent confidence intervals for ϕ^{w}_{jk}, the effect of each NPI on the log of the employment. Standard errors are clustered at the county level.

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

Source: Authors' calculations.

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 equations (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.[30] 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.[31] 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 percent of the total decline in the contact rate in the middle two weeks of March.

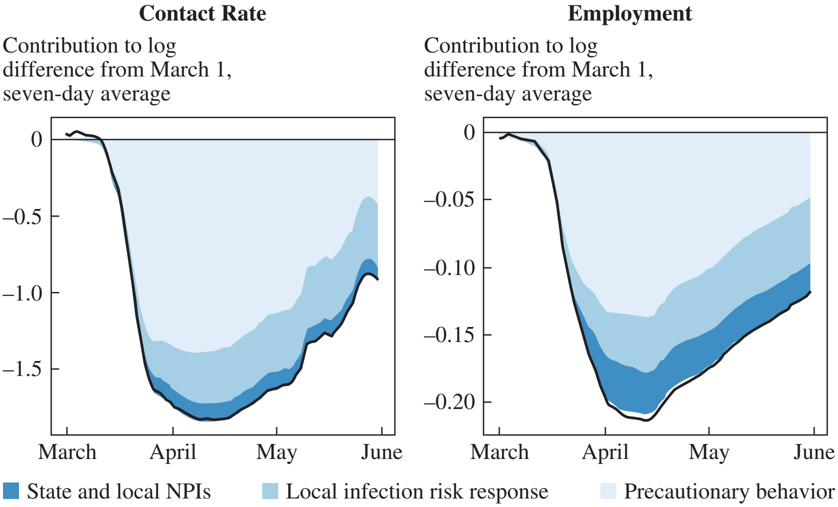
As the number of COVID-19 cases surged in the second half of March and the geographic concentration of cases became apparent, the behavioral response shifted from nationwide fears to localized concerns reflecting the severity of local outbreaks. When the contact rate reached its lowest point in mid-April—a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

The decline in employment initially followed a pattern similar to the contact rate, lagging a few days behind. Precautionary behavior explains

30. 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.

31. 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.

Figure 8. Decomposition of the Response to COVID-19



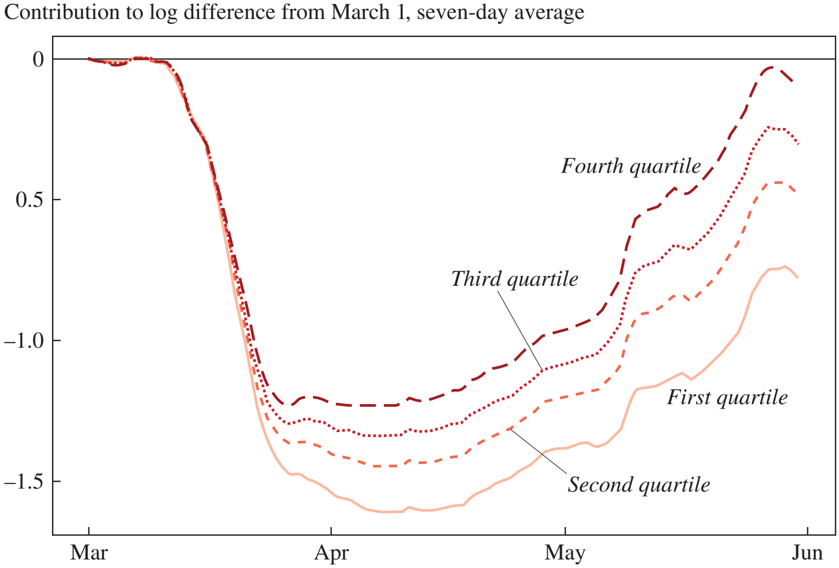
Source: Authors' calculations.

Notes: The figure shows the impact of the three components of behavior on the contact rate and employment. The solid black lines show actual changes relative to March 1. The difference between the actual change and the sum of the three components is the regression residual.

about 80 percent of the 11 percent fall in employment between March 8 and March 22. 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 around 20 percent below its level in early March. The response to local infection risk explains about one-fifth of this decline, the same as its contribution to the fall in the contact rate. State and local NPIs explain nearly 15 percent, 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.

Figures B5 and B6 in the online appendix present the same decomposition of the contact rate and employment at the state level. 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 nonessential business closures, which were

Figure 9. Republican Vote Share and Precautionary Changes in the Contact Rate

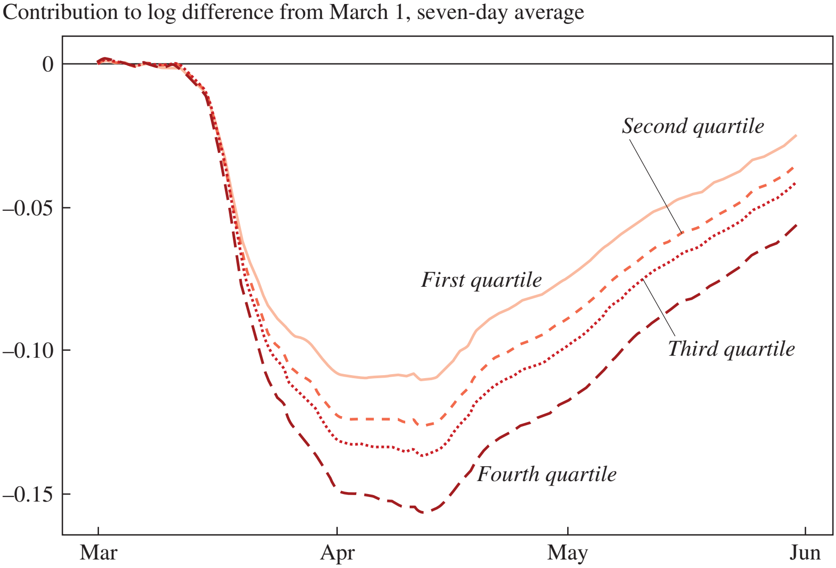


Source: Authors' calculations.
Note: The figure shows the county-level contribution of precautionary behavior to the change in the contact rate relative to March 1, averaged by quartile of county-level Republican vote share in the 2016 presidential election.

less widely adopted than the other NPIs (see figure 2) and had small effects on the contact rate but large effects on employment.

Figures 9 and 10 highlight two key drivers of heterogeneity in precautionary behavior: political preferences and industry mix. Figure 9 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 percent in the least Republican-leaning.

Figure 10. Employment in Leisure and Food Services and Precautionary Changes in Employment



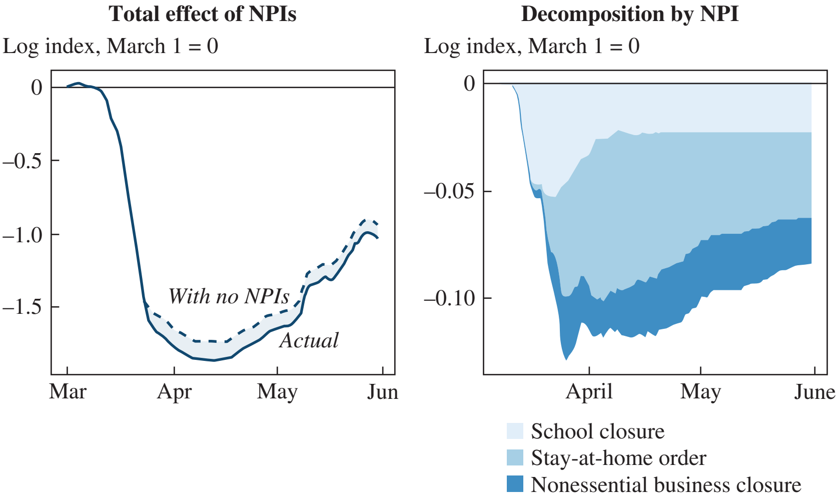
Source: Authors' calculations.

Note: The figure shows the county-level contribution of precautionary behavior to the change in the employment relative to March 1, averaged by quartile of county-level share of employment in leisure and food services.

Figure 10 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 to the decline in employment in those states in figure 10.

Figures B7 and B8 in the online appendix show variation in precautionary behavior across the five other county characteristics we include in our analysis. Figures B9 and B10 show 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.

Figure 11. Effect of NPIs on the Contact Rate



Source: Authors' calculations.

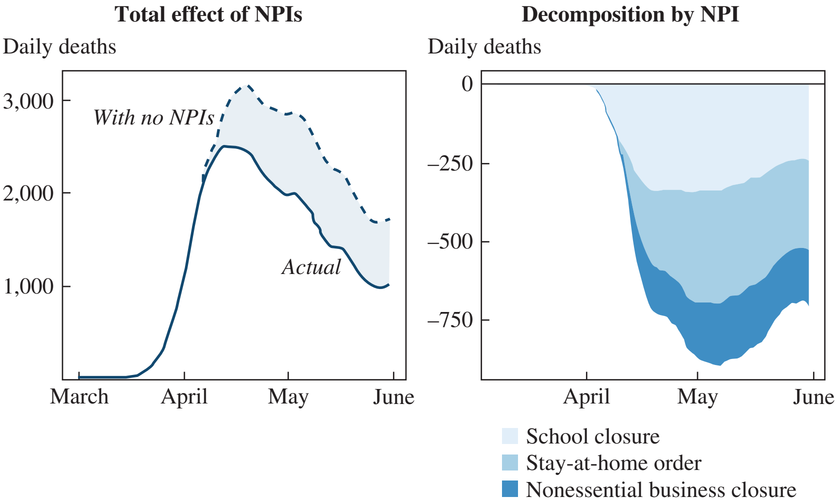
Notes: The left panel shows the actual change in the contact rate (solid line) and the estimated change in the absence of any NPIs (dashed line). The right panel decomposes the difference between the two into contributions from the three NPIs.

VII.B. The Impact of NPIs

Narrowing our focus to the role of policy, we now consider the three types of interventions separately and review their epidemiological and economic effects. Figure 11 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 percent of the population by March 20. By the end of March, more than 70 percent of the population was also under either a stay-at-home-order, nonessential business closure, or both (see figure 2). We estimate that together these policies reduced the daily contact rate by an average of 9 percent between early March and the end of May, accounting for 12 percent of the total fall in the contact rate. Of this, half was explained by stay-at-home orders, 28 percent by school closures, and 22 percent by nonessential business closures.

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 12 shows the

Figure 12. Effect of NPIs on Daily COVID-19 Deaths



Source: Authors' calculations.

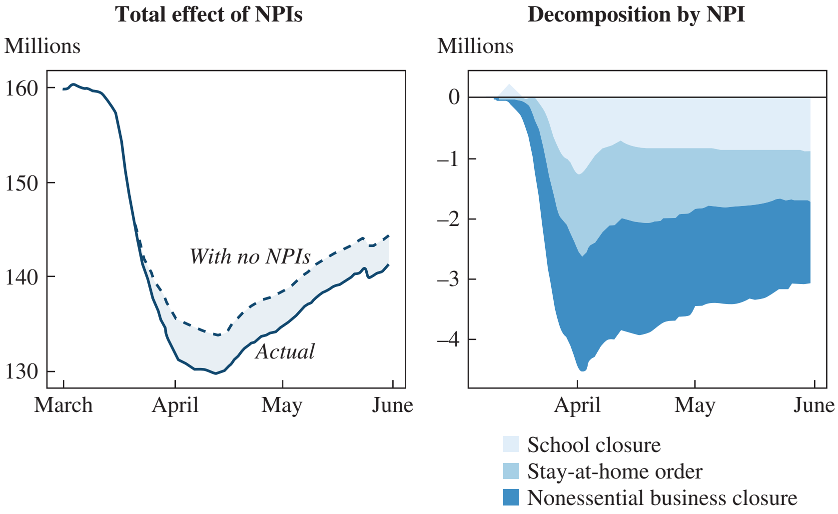
Notes: The left panel shows actual daily COVID-19 deaths (solid line) and estimated deaths in the absence of any NPIs (dashed line). The right panel decomposes the difference between the two into contributions from the three NPIs.

results for daily COVID-19 deaths. In the absence of NPIs, we estimate daily deaths would have reached a peak of roughly 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 31 by more than 39,000, bringing the cumulative total down by about 25 percent to its actual level of nearly 115,000. Taking into account the lag between infection and death, we estimate that policy-induced changes in behavior through May 31 lowered confirmed deaths through mid-June by 55,000. School closures and stay-at-home orders each explain about 40 percent of these reductions; nonessential business closures account for 21 percent.[32]

Comparing results for the contact rate and for deaths, we note two significant differences. First, the 9 percent decline in contacts in response

32. Note that our homogeneous-mixture framework assumes that the NPI-driven change in the overall contact rate is consistent across population subgroups. To illustrate how this assumption has a directional impact on our headline epidemiological results, we conduct a stylized experiment using a two-group SEIR model that allows for heterogeneous contact rates and heterogeneous responses to NPIs. See the online appendix for details.

Figure 13. Effect of NPIs on Employment

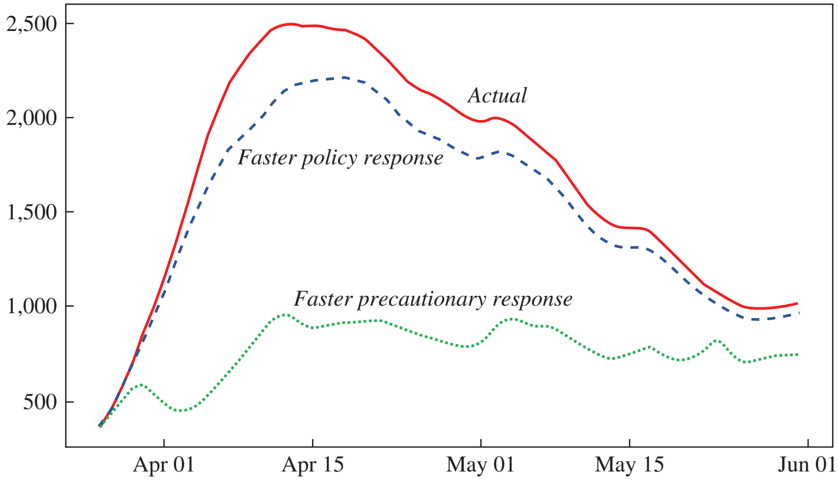


Source: Authors' calculations.
Notes: The left panel shows actual employment (solid line) and estimated employment in the absence of any NPIs (dashed line). The right panel decomposes the difference between the two into contributions from the three NPIs.

to NPIs is considerably smaller than the resulting decline in deaths of about one-quarter. Second, school closures accounted for a larger share of the reduction in the deaths than the reduction in contact rates (41 percent vs. 28 percent), with a corresponding and opposite difference in the contributions of stay-at-home orders (37 percent vs. 50 percent). 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 nonessential business closures and ten days before stay-at-home orders).

Figure 13 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 percent of the total fall employment. Almost half of this decline was attributable to nonessential business closures, 30 percent to stay-at-home orders, and 22 percent to school closures. Notably, business closures account for a

Figure 14. Daily COVID-19 Deaths Given Seven Days Faster Response



Source: Authors' calculations.

much larger share of the decline in employment than of the fall in contact rates (48 percent vs. 22 percent), while the opposite is true of stay-at-home orders (30 percent vs. 50 percent). This suggests large cost-benefit differences across the different NPIs. We discuss these differences in the next section.

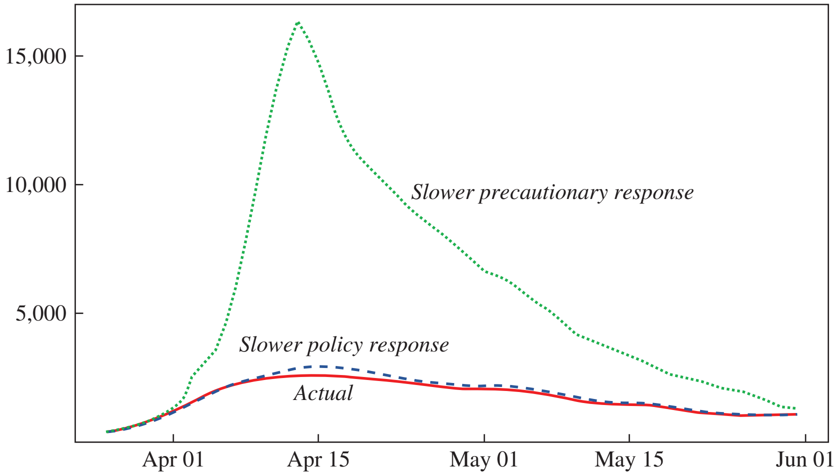
VIII. Counterfactuals

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 14 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

Figure 15. Daily COVID-19 Deaths Given Seven Days Slower Response



Source: Authors' calculations.

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 11,000 deaths by May 31. 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 1,000. In total, COVID-19 deaths are lower by 62,000 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 15 reports the results. The effects of a one-week delay in the introduction of NPIs are roughly symmetrical with those of faster action, leading to a cumulative increase in deaths of nearly 10,000. 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 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 United States—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.

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, interventions with the largest effect on the contact rate relative to employment should be prioritized.

On the second principle, we noted above that nonessential business closures accounted for a markedly larger share of the decline in employment than of the decline in contact rates, while the reverse was true for stay-at-home orders. The reason for this difference is clear from the event study estimates of equations (7) and (8) shown in figures 5 and 7. Of the three NPIs, nonessential business closures have the largest estimated effect on employment while delivering the smallest reduction in contacts. The trade-off is similar for stay-at-home orders and school closures, though stay-at-home orders have substantially larger overall 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.

With this in mind, we construct two sets of alternative policy response scenarios. First, we consider a federal, nationwide response on March 13, 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

Table 3. Counterfactual Policy Response Simulation Results

	Cumulative COVID-19 deaths through May 31[a]		*Difference in employment from March 1*[b]	
	Deaths	*Difference from actual*	*Millions*	*Difference from actual*
Actual	114,423		–20.5	
No NPIs	153,667	39,244	–17.8	2.67
Seven days				
Seven days slower	124,341	9,918	–20.3	0.17
Seven days faster	103,364	–11,059	–20.7	–0.15
Federal response on March 13				
Stay-at-home order	121,866	7,443	–18.9	1.62
Stay-at-home order and school closure	109,318	–5,105	–19.5	1.01
Stay-at-home order, school closure, and nonessential business closure	99,835	–14,588	–21.6	–1.08
Local response to confirmed cases				
Stay-at-home order	120,695	6,272	–18.8	1.76
Stay-at-home order and school closure	111,374	–3,049	–19.3	1.21
Stay-at-home order, school closure, and nonessential business closure	104,484	–9,939	–21.1	–0.62

Source: Authors' calculations.
a. Excludes differences in deaths after May 31 attributable to differences in infections through May 31.
b. March 1–May 31 average.

its first, second, and third NPI.[33] 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 nonessential 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.

Table 3 presents our results for cumulative confirmed COVID-19 deaths through May 31 and for the change in employment relative to March 1, averaged over the period March 1 to May 31. 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

33. For NPIs issued by state governments, we use state-level cases per capita. For NPIs issued by substate governments, we use county-level cases per capita.

scenarios discussed in section 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 13—leads to a reduction in deaths of nearly 15,000 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 nonessential 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 nonessential business closures—could have delivered a larger reduction in deaths while sustaining at least an additional 1 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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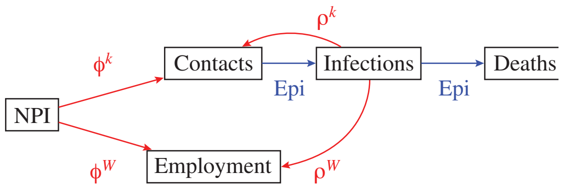
Comment and Discussion

COMMENT BY

ALESSANDRA FOGLI In 2020, the world as we knew it has been swept away in a few weeks by a major pandemic. Governments across the globe have introduced policies with the objective of reducing social interactions to save lives. Such policies have spanned from national lockdowns of all economic activities, to stay-at-home orders, to measures aimed at specific businesses or geographic regions. The combined effect of mitigation policies and the pandemic has been a dramatic fall in employment and production. Economists and epidemiologists started working together to design policies that can save the most lives at the least cost for the economy, and in a matter of a few months, a large body of literature on the topic developed.

This paper belongs to this recent and growing literature and investigates to what extent non-pharmaceutical interventions (NPIs) contribute to saving lives after controlling for the endogenous behavior of individuals who independently reduce their interactions in response to high local infection rates. Earlier research in the area (Flaxman and others 2020; Hsiang and others 2020) found a very large impact of NPIs on infection dynamics, while recent work (Goolsbee and Syverson 2020) finds a more muted impact of NPIs and a larger role for behavioral responses. The authors exploit the variation across US regions in the implementation of mitigation policies by local governments and make some important contributions. On the modeling side, they fully integrate a standard epidemiological model of disease progression in an econometric framework designed to identify the causal impact of NPIs on the contact rate and on the employment rate. On the empirical side, they combine a lot of interesting data sets to generate proxies for unobserved variables such as the contact rate, the reproduction number, and the employment rate at the daily frequency and at the

Figure 1. A Sketch of the Model



Source: Author.

county level. The main finding is that NPIs introduced by state and local governments explain only a small fraction of the observed decline in contact rates when the endogenous response of individuals to epidemiological conditions is taken into account. This is an important message since it may inform the policies of national and local governments as they face a second wave of infections possibly even more intense and widespread than the first one.

Although I am sympathetic to the overall message of the paper and the careful analysis of rich daily-by-county data, I think there are some challenges in interpreting the results. These challenges stem from the reduced form approach of the estimation that does not take into account the role played by heterogeneity. I will first describe the model and then explain why heterogeneity matters and how its exclusion may drive the results and may lead to underestimating the role of NPIs in mitigating the pandemic.

The model developed in the paper is summarized in figure 1. NPIs directly affect the number of contacts among individuals, and the effect is captured by the parameter ϕ^{κ}. Using a standard epidemiological model, contacts translate into infections according to the effective reproduction number, and a fraction of infections eventually end up in deaths. In turn, the infection rate affects contacts as individuals endogenously reduce their interactions in response to more infections. This effect is what the authors call the "fear-driven behavioral response" and is captured by the parameter ρ^{κ}. A similar relationship holds for employment, as employment is affected by NPIs (ϕ^W) and by fear (ρ^W).

As the estimation of the employment equation follows closely the estimation of the contacts equation, from here on I will focus on the latter. In order to estimate the impact of NPIs and of fear on contacts the paper adopts an event study design exploiting the variation over time and across counties in the implementation of three different NPIs. Equation (1) links contacts κ_{it} in county i at time t directly to individual fear and to the effect of a given type of NPI:

$$(1) \qquad \ln(\kappa_{it}) = \eta_i + \omega_t X_i + \sum_{k=-31}^{31} \phi_k P_{it}^k + \rho\, c_{it} + v_{it},$$

where η_i is a county fixed effect, $\omega_t X_i$ is a time varying precautionary motive, ϕ_k is the effect of an NPI implemented at time t on contacts at time $t + k$, P_{it}^k is an indicator function that captures whether the NPI is in place at time $t + k$, ρ represents the endogenous individual response to local confirmed cases (in logs) c_{it}, and v_{it} is a random shock to the contact rate. The inclusion of the individual fear factor in the estimation of the effect of NPIs on contacts is a nice feature of the paper. Estimates that do not take into account the endogenous response of agents are likely to overestimate the contemporaneous impact of NPIs on contacts and, at the same time, underestimate their lagged impact. Since NPIs are typically implemented when cases are high (and hence fear is high), estimates that do not take into account the role of fear typically attribute to NPIs the decline in contacts due to individuals reducing their interactions in response to fear. In a dynamic sense, ignoring the effect of fear can lead to underestimating the role of NPIs in reducing contacts since, when epidemiological conditions improve, individuals perceive less fear and consequently increase their interactions, partially offsetting the effect of NPIs.

The inclusion of the fear factor in the model is definitely useful to separately identify the role of NPIs. However, I am concerned that the empirical approach employed by the authors might underestimate the causal effects of NPIs on contacts. My concern stems from the role played by heterogeneity which is dismissed in the model but is likely to matter in the estimation for two reasons. First, it is reasonable to expect significant variation in the local responses to NPIs since we observe large differences in the degree of compliance across regions. Second, it is also likely that various types of contacts affect the infection rate differently. I will show how ignoring these sources of heterogeneity can lead to significantly underestimating the true importance of policies.

HETEROGENEITY IN LOCAL RESPONSES A key assumption in equation (1) is that the effect of NPIs ϕ_κ is constant across locations. The precautionary motive, on the other hand, is modeled as a time varying factor ω_t that depends on local fixed characteristics X_i. This component is the most flexible and therefore is able to explain more variation than the other components.

As a result, the estimation could understate the impact of NPIs and overstate the importance of the precautionary effect. For instance, if NPI effectiveness varies by political affiliation (because of different compliance rates or degree of enforcement), this variation would be incorrectly absorbed by the precautionary behavior. Similarly, the effect of other mitigation policies that are not included in the model (such as mask mandates or test availability) would also be absorbed by the precautionary component.

In order to illustrate to what extent unobserved heterogeneity in local responses can lead to underestimating the effect of NPIs, I report the results of a simple simulation where the contact rate is determined according to equation (1) except that in the true model the response to NPIs is allowed to vary across locations, so that the ϕ_k in equation (1) are also indexed by i.

Consider a panel of 3,000 regions (approximately the number of US counties) for twenty periods. Regions are assumed to vary across a single dimension X_i which is drawn from a normal distribution with mean 0.5 and standard deviation 0.75. The observed level of infections in each region follows a simple auto-regressive process:

$$c_{it+1} = \gamma \ln(\kappa_{it}) + \delta c_{it} + \epsilon_{it}.$$

This implies that, on average, γ contacts will turn into confirmed cases and $(1 - \delta)$ cases will resolve themselves, each period.[1] NPIs are assumed to go into effect at a random time t_0 and continue until the end of the sample.[2]

The response to the NPI (governed by ϕ_i) has two components: one is drawn uniformly from $[-1.2, 0.3]$ and the other is assumed to be $-X_i$. This results in the response to NPI usage being correlated with the regional characteristic. Larger draws of X_i result in a higher initial level of contacts but also translate into a larger decrease when an NPI is implemented.[3] In the true model the elasticity of contacts to confirmed cases ρ (the fear factor) is set equal to -0.8 while the precautionary motive ω_t is assumed to be constant and equal to $\omega = 2.2$. This implies that any estimated reduction in ω_t is a consequence of misspecification.

Ignoring the heterogeneity in local responses leads to significantly underestimating the true importance of both policies and fear: the estimates

1. In the simulation $\gamma = 0.5$ and $\delta = 0.95$. Additionally, $\nu_{it} \sim N(0, \sigma_\nu^2)$ and $\epsilon_{it} \sim N(0, \epsilon_\nu^2)$ with $\sigma_\nu = 0.1$ and $\sigma_\epsilon = 0.05$.

2. The implementation date for each region is a random draw between 3 and 13.

3. Occasionally, ϕ_i will be drawn to have a positive value. To enforce the notion that NPIs reduce contacts, positive values of ϕ_i are set equal to zero.

of the effects of NPIs and fear are respectively one-third and one-fourth of their true values.[4]

To get a sense of the magnitudes, figure 2 shows the share of the decline in contacts attributed to each component in the true model and in the misspecified model.

In the true model the precautionary motive plays no role in the decline in contacts. Fear plays a large role at the beginning of the pandemic, when no NPIs are in effect but, by the last period, NPIs account for about 60 percent of the decline. However, in the misspecified model, the precautionary motive accounts for around 65 percent of the decline in contacts, while the effect of fear and NPIs is cut by roughly two-thirds. While in the true model NPIs are very effective in reducing contacts, ignoring heterogeneity leads to mistakenly concluding that their impact is marginal.

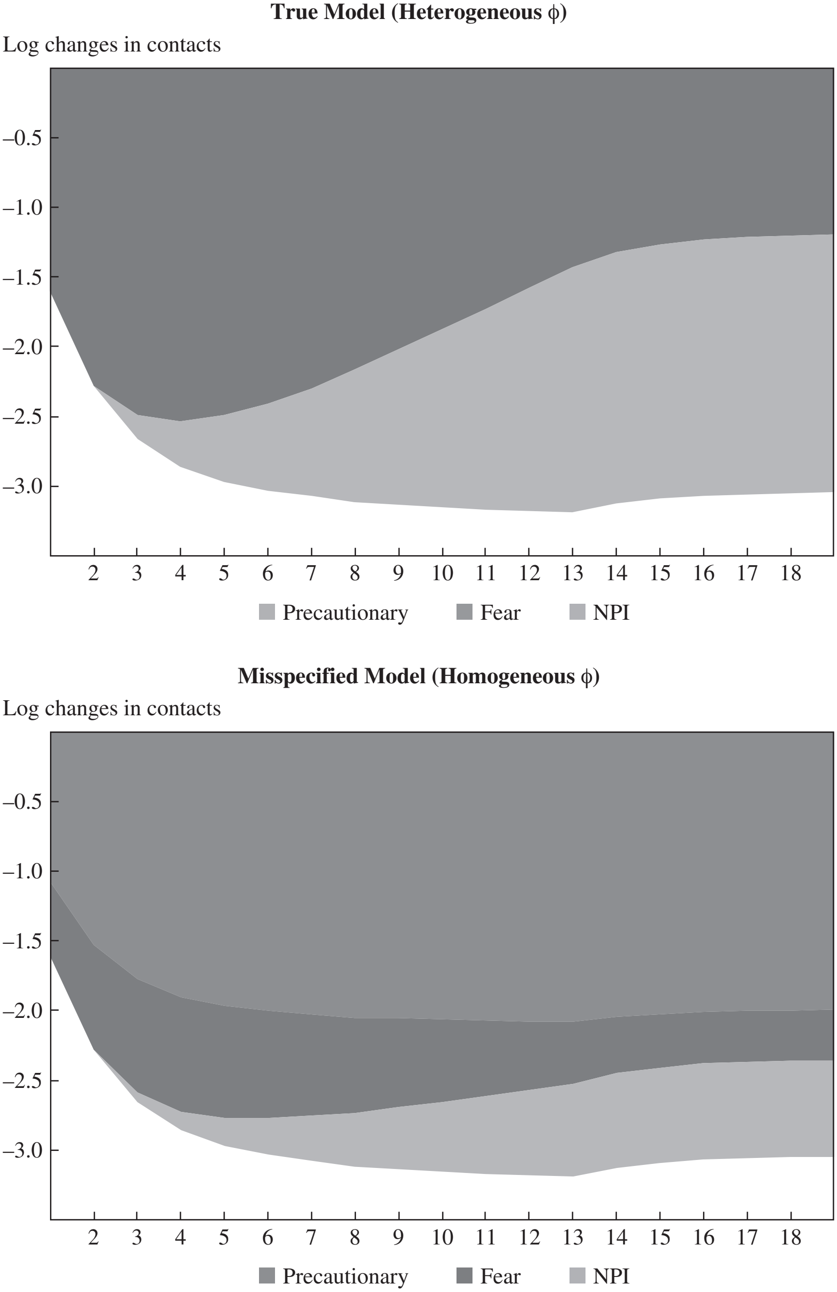
Interestingly, the extent to which abstracting from heterogeneity in local responses leads to underestimating the effect of NPIs depends on the strength of the correlation between the effectiveness of NPIs (ϕ_i) and local characteristics. Since the model includes the share of Republican voters as one of the regional controls, which has been shown to be strongly correlated with NPI compliance (Amuedo-Dorantes, Kaushal, and Muchow 2020), there is a concern that the authors significantly underestimate the role played by NPIs in reducing contacts.

Another important source of heterogeneity in the impact of policies on contacts simply stems from the heterogeneity in the initial contact structure across regions. Many NPIs (stay-at-home orders or caps on social gatherings) impose an absolute limit on the number of contacts. When these policies are introduced in regions with very different numbers of initial contacts, their implementation, even abstracting from compliance issues, leads to different reduction in contacts.

HETEROGENEITY IN THE TYPE OF CONTACTS Another important dimension of heterogeneity that the authors abstract from is the one in the type of contacts. In the model, all contacts have the same impact on infections, while recent network-based epidemiological research has highlighted that different types of contacts can have very different impacts on infections (Akbarpour and others 2020; Azzimonti and others 2020; Baqaee and others 2020). In particular contacts that are close and repeated (like those with friends and family) typically have a small effect on infections, while

4. The true ρ is equal to -0.8, but ignoring the heterogeneity results in an estimate of $\hat{\rho} = -0.22$. The mean ϕ is -1.0, but the model estimate is -0.33.

Figure 2. Implied Share of Contact Decline



Source: Author's calculations.

contacts that are far and random (like those happening, for example, at a concert or at the mall) can have a much larger impact on infections. This heterogeneity can be of crucial importance when evaluating the effects of different NPIs. For example, a policy like nonessential business closure can itself have a very small reduction of contacts but by eliminating a large fraction of the far and random contacts can have a substantial impact on infection.

The implementation of NPIs during the COVID-19 epidemic has been proven very costly, both politically and economically, and even more so during the second wave when pandemic fatigue has kicked in. For these reasons, a precise assessment of the impact of NPIs on infection reduction is of paramount importance. This paper makes important steps toward this goal and finds a limited role for NPIs. In this comment I argue that heterogeneity in the impact of NPIs across counties in the United States is likely large, and it should be taken into account when performing these evaluations. First, heterogeneity can lead to significant underestimation of the effect of NPIs. Second, heterogeneity implies that the most important question is not whether or not a central authority should implement NPIs but rather where and when NPIs should be used and where and when they should not.

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GENERAL DISCUSSION Olivier Blanchard began the discussion by complimenting the authors on their work and encouraging them to reconcile their findings on the relation between formal measures and change in behavior with the findings presented by the discussant, Alessandra Fogli. Blanchard then brought up how the government at all levels had begun scaling back some of these formal measures. He asked if we should assume symmetry and that the removal of formal measures would not make a large difference in lowering the infection rate. Blanchard noted that this might be difficult to answer at that point but hoped that the authors would be able to offer some thoughts.

Ben Friedman then asked the authors how they identified the difference between NPIs and behavioral precautionary actions that people would have taken regardless of the mandates. He stated that in his community, he saw schools and nonessential businesses being ordered to close, therefore he chose to act in a way he otherwise would not have acted if it were not for the NPIs. He asks whether this endogenous response to NPIs affects the estimate of the NPIs' effect in the model.

Jim Stock praised the authors for their paper and then asked them to refine the assumptions being made on the endogeneity of responses to NPIs and even recommended fleshing out some sort of instrumentation in their further research beyond this study. Furthermore, he continued to raise concerns about whether the NPIs or endogenous behaviors were responsible for causing the decline in infection rates. Stock brought up how, at the Summer BPEA conference, Gupta, Simon, and Wing and Bartik and colleagues concluded that the endogenous responses were a major piece of the decline, while the two *Nature* papers discussed by Fogli simply excluded them.[1] Stock said that the exclusion of the endogenous response in the

1. Sumedha Gupta, Kosali Simon, and Coady Wing, "Mandated and Voluntary Social Distancing during the COVID-19 Epidemic," *Brookings Papers on Economic Activity*, Summer (2020), 269–315; Alexander W. Bartik, Marianne Bertrand, Feng Lin, Jesse Rothstein, and Matthew Unrath, "Measuring the Labor Market at the Onset of the COVID-19 Crisis," *Brookings Papers on Economic Activity,* Summer (2020): 239–68.

Nature papers led him to have less confidence in them compared to some of the more finely tuned papers seen at BPEA.

Mervyn King also reverted to Friedman's point and questioned how cross-country differences would help disentangle the endogeneity problem, pointing to Sweden as an example where the government did not mandate as many NPIs but households took a degree of caution. Furthermore, King noted the importance of Fogli's point on heterogeneity and brought up how the level of caution associated with events and actions varies across individuals and locations, so having only a single parameter could be potentially misleading.

Alexander Arnon then addressed the question on the symmetry of reopening. He mentioned the preliminary work the authors had done and discussed how difficult it is to match a given reopening event across different jurisdictions. He noted that, to the extent the authors can estimate, they do not expect it to be symmetrical.

Moving on to address Friedman's question, Arnon said that endogenous changes in behavior will be picked up as a response to NPIs and noted that there is a lack of enforcement of these NPIs across the country, so even though the policies were mandates that were required by law, they were viewed more as information advisories or as an aggressive information push by the government.

Kent Smetters mentioned that the model will allow for heterogeneity by location and that the paper will focus on the marginal effects of NPIs. Arnon then continued by mentioning that there are a number of studies that examine stay-at-home orders in the United States and that those studies' estimates are similar to the estimates arrived at by the authors.