December 18, 2020

Current Policy Perspectives

The Roles of Mobility and Masks in the Spread of COVID-19

Daniel Cooper, Vaishali Garga, María José Luengo-Prado, and Jenny Tang

This policy brief analyzes the effects of COVID-19 mitigation policies, those that restrict movement and activity and those that advocate public health best practices. The analysis uses US state-level data to estimate the effects of mobility, mask mandates, and compliance with these mandates on the numbers of COVID-19 cases and deaths. A one-standard-deviation increase in mobility is associated with an 11 to 20 basis points greater rate of growth in case counts; a mask mandate can offset about half of this increase. Slower growth in case counts ultimately translates into slower growth in death counts. Mask mandates are more effective in states where compliance with those mandates is higher. Our estimates imply that total infections in the United States would have been 46.5 to 66.2 percent lower than they were on November 15 if mobility had remained fixed at its May 15 level. Given the actual mobility level, if a national mask mandate had been enacted on May 15, the case count would have been 26.4 to 34.3 percent lower than it was on November 15. This means that a national mask mandate potentially could have offset as many as 74 percent of the additional COVID-19 cases associated with increases in mobility.

1 Introduction

This policy brief examines the relationship between containment policies, public health measures, and the numbers of COVID-19 cases and deaths in the United States. Most containment policies, including stay-at-home orders and closures of schools and nonessential businesses, are intended to prevent the spread of the virus by limiting mobility and thus reducing interactions between people. While potentially very effective, these policies come at the cost of reducing economic transactions, especially transactions that require in-person interactions. On the other hand, public health measures, such as encouraging handwashing or mandating the wearing of masks, are intended to reduce the likelihood of infection when people do move around and interact. Therefore, a good understanding of the effectiveness of public health measures such as mask mandates is important for policymakers trying to determine how much to limit mobility and social interactions—at the potential cost of reduced economic activity—given the substantial resurgence in the spread of the virus. While the economy has adapted and evolved in response to restrictions on mobility since the start of the pandemic, the potential costs of lockdowns are large. As shown in Figure 1, economic activity, measured by the growth in credit and debit card transactions, fell sharply following the economic shutdowns in March 2020, especially in sectors where purchases require social interaction.

We use state-level variation in the numbers of COVID-19 cases and deaths, mobility, mask mandates, reported mask wearing, and other related factors to analyze the link between these containment and public health policies and COVID-19 cases and deaths. We use a variety of cellphone-based mobility indexes on location-specific visits, time at home, and contacts between people to comprehensively summarize several dimensions of containment policies.[1] For public health measures, we focus on mask mandates and compliance with these mandates. More importantly, we also quantify the extent to which mask mandates and mask wearing offset the effects of mobility on the numbers of infection cases and deaths. Our analysis produces four main findings.

First, higher mobility (less time at home) is associated with a higher rate of growth in COVID-19 case counts—a relationship that is already well documented in other studies. The effect of mobility on the growth rate of cases (and deaths) is quite similar regardless of whether we measure mobility based on "visit" (or staying at home) data from SafeGraph

[1]Visits (or lack of time at home) and contacts need not be the same. For example, an individual could visit a park and never be in close proximity with anyone else.

or "contact" indexes from Cuebiq or PlaceIQ. A one-standard-deviation increase in mobility (or decrease in staying at home) leads to roughly 11 to 20 basis points greater growth in the COVID-19 case count. The effects are strongest and most precisely estimated in specifications where mobility is lagged seven or more days relative to the growth in cases and 14 days relative to the increase in the number of deaths—a finding that is consistent with the documented incubation period for the virus.

Second, the strong positive link between mobility and the growth in COVID-19 cases appears to be mitigated to a certain extent by mask mandates. We find that a mask mandate offsets about half of the increase in case growth associated with a one-standard-deviation rise in mobility. The role of mask mandates in limiting the spread of the virus is relevant because mask wearing does not entail the same degree of economic costs as mandated reductions in mobility.

Third, we find that mandates combined with higher levels of mask compliance in a given state (measured using survey data on mask wearing and attitudes) are associated with larger reductions in the growth rate of COVID-19 cases. This conclusion holds true even when we predict (instrument for) mask compliance using relevant preexisting state-level characteristics such as the share of votes cast for the Republican party in the 2016 presidential election or beliefs about climate change.

Fourth, while higher mobility is associated with a higher growth rate of COVID-19 deaths, perhaps unsurprisingly, this effect operates entirely through the increase in the case count. That is, once we control for the growth in cases, mobility does not significantly correlate with the growth rate of deaths. By offsetting some of the effect of mobility on case-count growth rate, mask mandates and mask wearing ultimately reduce death-count growth rate.

The research examining the public health issues and economic effects related to COVID-19 is already extensive. Several papers study the relationship between mobility and COVID-19 cases—by looking at a variety of factors that likely impact cross-location differences in infection rates, such as income, inequality, weather, debt burdens, the ability to work from home, and population density, to name a few (for example, Wilson 2020, Desmet and Wacziarg 2020, Davydiuk and Gupta 2020). Related epidemiological papers that also study factors affecting the spread of the virus include Baqaee et al., Kissler et al. (2020), and Giuliani, Dickson, and Espa (2020).

We incorporate relevant controls and best practices from existing studies in constructing a comprehensive and robust empirical specification for our analysis. An important part of our approach is that we control for epidemiological-time effects, which are a key feature of epidemiological analyses. These effects account for common patterns in virus progression that start from its arrival in a location. Because the virus arrived at different times across locations, these effects are not well captured by the standard time fixed effects that are common in panel data analysis. We also account for persistence in cases/deaths, a feature of some structural epidemiological models, by including the lagged growth rate of COVID-19 cases/deaths in our regressions. This practice is not common in studies that use reduced-form regression analysis. Lagged growth rate turns out to be quite important in explaining the variation in infection rates across locations and over time, and it captures the exponential effects of changes in mobility and mask policies that occurred early on in the pandemic. Our specifications also account for differences in testing across locations, and include several other relevant controls that we discuss in more detail in Section 3.

The number of studies on the effect of mask mandates and actual mask wearing on the growth in COVID-19 cases is more limited. Lyu and Wehby (2020) use an event-study approach to analyze how state-level mask mandates affected daily county-level COVID-19 growth rates from March 31 through May 22, 2020. The authors find that mask mandates reduced the growth rate of cases, and that the mitigating effect increased with the number of days following the mandate's implementation. Our findings regarding mask mandates are broadly similar; however, we use a much longer time horizon. In another related paper on the impact of masks, Chernozhukov, Kasahara, and Schrimpf (2020) show that policies and information regarding transmission risk are important determinants for the numbers of COVID-19 cases and deaths. The authors also conduct counterfactuals examining the potential effect of a national mask mandate early in the pandemic and find that such a mandate would have been effective at limiting case growth in April and May. Relative to this analysis, we use a different estimation procedure and different counterfactuals, and we consider the effect of mask mandates and mobility restrictions on the COVID-19 case counts over a much longer time period. Moreover, mask wearing is not guaranteed even when mask mandates are in place, and therefore we supplement our mask mandate analysis with data on actual mask wearing and attitudes toward masks collected by Dynata for the *New York Times* in early July 2020. These data serve as a proxy for compliance with the mandates across locations. While there is some analysis examining the relationship between mask wearing and the COVID-19 case count (see, for example, Cheng et al. 2020, Dyke et al. 2020, IHME Forecasting Team 2020, Bundgaard et al. 2020), to our knowledge we are the first to combine data on mask mandates with data on mask use to gauge the effect of compliance on the effectiveness of those mandates. Analyses of the effects of mask mandates in other countries such as Germany (Mitze et al. 2020) and Canada (Karaivanov et al. 2020) also show significant reductions in case counts after mandates are introduced.

The remainder of this policy brief proceeds as follows. Section 2 discusses our data and provides an initial visualization of the relationship between mobility and the number of COVID-19 cases and deaths, as well as the impact of mask mandates on case counts across locations and over time. Section 3 presents the empirical specification we use for our formal analysis. Section 4 reports our empirical results, and Section 5 concludes.

2 Data and Initial Visual Analysis

As of November 15, 2020, there were about 11 million cumulative (reported) cases of COVID-19 in the United States and roughly 245,000 deaths. A key feature of the data is the noticeable increase in the case count in mid-June followed by a decline in late July and a rebound starting in mid-October, as shown in Figure 2.[2] Fortunately, the number of deaths did not increase proportionally, likely due to a younger age profile of new cases as well as greater availability of key medical devices and some improvements in therapeutics. While there is little data on mobility by age group, the increased share of cases among individuals younger than 40 in recent months, as shown in Figure 3, is likely the result of increased mobility among those age groups, especially during the summer months. Older individuals may also be more likely to wear masks, as the severity of the disease tends to increase with the age of the person who contracts it. As we discuss in the next subsection, there is relevant state-level variation in mobility and case/death counts. There is also variation in the timing of local (state-level) mask mandate implementation, the actual rules regarding mask wearing, and compliance with these mandates. We exploit all of this variation in our empirical analysis.

2.1 Data

Our data include information on the numbers of COVID-19 infections and deaths, as well as measures of mobility, mask mandates, and mask wearing.

COVID-19 Data. We obtain data on daily case and death counts from DataHub, which cleans and normalizes data from the Johns Hopkins University Center for Systems Science and Engineering.[3] Figure 4 shows that there is substantial variation in the daily numbers of

[2]The growth rate of cases (and deaths) is much lower than in late-March/early-April, a pattern that is typical of infectious diseases. See Atkeson and Zha (2020) for more details.

[3]https://datahub.io/core/covid-19.

new cases (averaged over a seven-day rolling window) across states and over time. The left panel further shows that after a period of convergence across states to lower levels of daily cases relative to population (case rates) in late May and early June, daily case rates across states diverged again in mid-June, when infection rates in some states surged. A third wave in new cases began in mid-October, with many states passing their previous peak levels of infection rates. In addition, while the growth rate of new cases (right panel) fell over time, as is typical of a pandemic, variation in the growth rate of new cases across states increased again during the summer.

Mobility. All of our measures come from anonymized cellphone ping data aggregated in different ways. The various measures fall into three categories: (1) indexes that track visits to landmarks or places of business, (2) indexes that measure time spent at home, and (3) indexes that quantify contacts between individuals. Information on contacts (or lack there of) potentially serves as a proxy for the degree of social distancing, while the visit data capture the extent to which individuals are moving around regardless of whether they make contact with others. These approaches for measuring mobility capture slightly different aspects of individuals' movements that could affect the COVID-19 case (and death) count somewhat differently. Therefore, we consider all three types in our analysis.

In particular, we focus on state-level mobility measures and use data from Safegraph (SG) on visits outside of the home and time spent at home, along with the Cuebiq contact index (CI) and the PlaceIQ device exposure index (DEX). The SG "visit" data capture the year-over-year change in the total number of visits to SG's network of points of interest. SG "time at home" measures the median percentage of time that cellphones within a census block group (CBG) stay at their "home" locations each day. We construct state-level time-at-home measures by taking a population-weighted average of the relevant CBG data.[4] The Cuebiq CI measures whether two or more cellular devices come within 50 feet of each other in a five-minute period.[5] Finally, the PlaceIQ DEX captures the number of devices that visit the same venue in the same day.[6]

Figure 5 depicts the state-level variation in the mobility measures (daily values averaged

[4]We cannot calculate year-over-year changes for SG time at home because of data vintage changes. See https://readme.safegraph.com/docs/social-distancing-metrics.

[5]Data on the year-over-year change in the CI are available, and we hand-collected them from the Cuebiq website: https://www.cuebiq.com/visitation-insights-contact-index/. Note that Cuebiq does not report data for Alaska or Hawaii.

[6]We cannot calculate year-over-year changes in the state-level DEX with the data available to us, and therefore we use the level of the index in our analysis.

over a seven-day rolling window). The wave of stay-at-home orders in March 2020 resulted in a substantial decline in mobility (and increased time at home), which was followed by a clear increase in mobility in most states starting in mid-April, when some of these orders were lifted. Dispersion in mobility across states also increased, especially for the Cuebiq CI. Despite the rebound in these measures, mobility remained below where it was before the pandemic in most states during our sample period.[7] In addition, the Cuebiq CI and to a lesser extent SG visits showed an increase in mobility beginning in early October that tapered off more recently. Overall, we believe that our chosen mobility measures provide a good summary of the information contained in the cellphone-based activity data.

Mask Mandates. Data on mandates come primarily from state public health websites. There are data on when a state's mandate was announced, the date it took effect, and the extent and coverage of the mandate. We verify the reported dates against various published sources, including www.masks4all.org, www.ballotpedia.org, and the appendix of Lyu and Wehby (2020). For our purposes, we record whether the mandate applies to the entire state (at the time it was issued by the governor's office) or just some localities or situations. The top panel of Figure 6 shows that most states currently have a state-wide mask mandate; however, there is substantial variation in when the mandates went into effect—ranging from mid- to late April in several northeastern states to early November, when Utah became the latest state to expand its mask wearing requirements in response to its surging infection rates. As of November 15, 2020, 15 states had only partial (not statewide) mask policies.

Mask Wearing. Data on mask-wearing behavior comes from a survey conducted by Dynata on behalf of the *New York Times* from July 2 through July 14, 2020. The survey garnered roughly 250,000 responses to the question, "How often do you wear a mask in public when you expect to be within six feet of another person?" The survey includes county- and state-level geographic identifiers for the respondents, and for our analysis, we calculated the proportion of people in a state who responded either "always" or "frequently" to this question. (We recognize, however, that mask wearing is likely correlated with other COVID-19 mitigation behaviors, such as maintaining adequate social distance.) While the survey was conducted only once, there is substantial state-level variation in reported mask wearing, as shown in the bottom panel of Figure 6.[8] Furthermore, there is meaningful variation in

[7]Exceptions include South Dakota during the Sturgis Motorcycle Rally in August, and Louisiana, Maine, Montana, South Dakota, and Wyoming, which saw mobility (based on the SG time-at-home measure) at pre-pandemic levels in early September.

[8]See Appendix A.2 for more information about the *New York Times* mask-wearing data.

mask wearing that is distinct from the variation in mask mandates. For example, while both Maine and Delaware instituted statewide mask mandates on May 1, Delaware had the fourth-highest rate of mask use in the *Times* survey, and Maine was in 26th place. In fact, the presence of mandates (measured as of the start of the survey) explains only half of the state-level variation in mask wearing. In turn, preexisting state-level characteristics, such as the proportion of votes in a state for the Republican party in the 2016 presidential election or beliefs about climate change, can explain more than 82 percent of the variation.[9] We therefore interpret our mask-wearing measure as a state-level proxy for overall compliance with mask-wearing mandates.[10]

2.2 Initial Visual Analysis: Mobility, Cases, and Deaths

Before employing more formal regression analysis to study the connection between mobility, face masks, and new COVID-19 cases/deaths, we use binned scatter plots to visualize their relationship.[11] In constructing these binned scatter plots, we control for the effects of time-invariant state characteristics on new cases/deaths (via state fixed effects) and for the typical S-shaped dynamic of epidemics (via epidemic-time fixed effects). The averages shown in these plots are also weighted by state population. For brevity, we show plots for two of our mobility measures, SG visits and the Cuebiq CI.[12] Negative values for lagged mobility on the x-axis indicate that mobility is lower than it was at the same time in 2019, with lower absolute numbers signaling more mobility.

Figure 7 first shows the relationship between new cases (per 100,000 population) and lagged mobility (over different lags). The plots depict an upward-sloping relationship for each mobility measure. That is, higher mobility in the past is associated with a greater number of new cases today (conditional on state and epidemic-time fixed effects). Consistent with the incubation period for the virus, mobility affects the number of new cases with a

[9]We measure climate change beliefs based on the proportion of people who responded affirmatively to the following question from the Yale Climate Opinion Survey: "Assuming global warming is happening, do you think it is caused mostly by human activities?" Voting data come from the MIT Election Lab Database. See the appendix for more details on these data.

[10]Previous studies that document the relationship between political beliefs and compliance with lockdown policies and mask mandates include Brzezinski et al. (2020), Milosh et al. (2020), and Welsch.

[11]Binned scatter plots show the average value of the variable on the y-axis for each x-axis value after first grouping the x-axis data into equally sized bins.

[12]Corresponding graphs for the two other mobility measures are shown in the Appendix A.4. Note that the correlation between time spent at home and cases is negative, as expected.

lag, with the relationship becoming somewhat stronger (steeper) at longer lags.[13]

Figure 8 repeats the exercise with the number of new deaths instead of new cases on the y-axis. We employ a longer lag structure to reflect our prior that mortality from the virus should take longer than it takes to become infected. The plots suggest that higher mobility in the past is associated with a greater number of deaths; as expected, this effect appears with a delay that is longer than the delay for new cases.

Finally, Figure 9 provides a first look at how the use of face masks may alter the relationship between mobility and the spread of COVID-19. In these plots, we depict new cases relative to mobility conditional on state-level mask mandates. Unlike in our previous plots, here we do not control for state or epidemic-time fixed effects. However, we focus on the latest wave of cases by restricting the sample to new cases/deaths from August 15, 2020, through November 5, 2020—admittedly, the relationship is the clearest during this time frame. The plots suggest that mask mandates limit the effect of mobility on the number of new COVID-19 cases, particularly when mobility is high. The mechanism behind this effect is likely an increase in mask wearing. That is, for a given level of mobility, there is a lower level of contagion when mask wearing is mandated.

3 Empirical Specification

To more formally analyze the relationship between mobility, masks, and COVID-19 cases/deaths, we begin by defining the growth rate of new infections or deaths as follows:

$$1 + r_{it} \equiv \frac{Y_{it}}{Y_{i,t-1}},$$

where Y_{it} is the cumulative number of COVID-19 cases (deaths) at time t in state i. For cases, r_{it} is the average number of newly infected people for each previously infected person, so this value largely reflects how quickly the virus is transmitting between people. For deaths, r_{it} also depends on the deadliness of the virus once a person is infected. If $r > 0$, cases (deaths) continue to grow. If $r = 0$, no new cases (deaths) occur.

In our initial analysis, we model log growth rates as an exponential function of state fixed effects, epidemic-time fixed effects, and mobility:

$$\ln(Y_{it}) - \ln(Y_{i,t-1}) = \ln(1 + r_{it}) = e^{\alpha_i + f(K_{it}) + \beta M_{i,t-1}},$$

[13]These relationships are robust to the exclusion of cases that occur in nursing homes.

which can be transformed into the following linear estimation equation:[14]

$$\ln\left[\ln(Y_{it}) - \ln(Y_{i,t-1})\right] = \alpha_i + f(K_{it}) + \beta M_{i,t-1} + \varepsilon_{it}. \tag{1}$$

In this setup, α_i is a state fixed effect that captures time-invariant differences across states that may affect the growth rate of new cases (deaths); $f(K_{it})$ captures the dynamics of the evolution of the pandemic, with $K_{it} = t - E_{i\tau}$ equaling the number of days since or before reaching an epidemic-related threshold at date τ, $E_{i\tau}$, which we allow to be state specific; M_{it} is a measure of mobility that is standardized to have mean 0 and standard deviation 1. We estimate K_{it} using epidemic-time fixed effects, given the typical S-shaped dynamics of epidemics, which measure the number of days in a given location since or before it recorded 5 deaths from the virus per 1 million inhabitants.

We adapt equation (1) slightly and estimate it using (overlapping) weekly growth rates of cases (deaths) to rule out day-of-week effects in testing and/or reporting. We analogously average mobility over the preceding seven days and include a lagged dependent variable to capture the persistent nature of local outbreaks of the virus.[15]

Our initial estimation equation takes the form:

$$\ln\left[\ln(Y_{it}) - \ln(Y_{i,t-7})\right] = \alpha_i + f(K_{it}) + \beta Lx.\overline{M}_{it} + \gamma L7.\ln\left[\ln(Y_{it}) - \ln(Y_{i,t-7})\right] + \varepsilon_{it}, \tag{2}$$

where we explore the relationship with cases for different lags of mobility (denoted by Lx with $x \in [7, 42]$) to capture the idea that changes in mobility might feed into measured cases with a delay since there is an incubation period before an individual tests positive for COVID-19. Correlations between mobility and cases for lags beyond 14 days might reflect community spread. Initially, we average mobility over seven days while varying the lag period, but our preferred specification for cases lags mobility seven days after averaging it over a 21-day period given that we find the effects of mobility diminish after 21 days. (For deaths, we lag mobility 14 days after averaging it over a 35-day period.)

Our estimates of equation (2) are weighted by state population, and the coefficient of interest is β, which measures how much one-standard-deviation higher mobility increases the log growth rate of COVID-19 cases (deaths).[16] We employ all four measures of mobility

[14]This specification is similar to the one used in Orea and Alvarez (2020) to study the effectiveness of Spain's lockdown in battling the spread of COVID-19.

[15]The addition of the lagged dependent variable also helps to improve the fit of the regression.

[16]Given the semi-log specification and the lagged dependent variable, the effect of mobility on the uncon-

for this analysis, primarily one at a time to avoid the issue of multicollinearity, although we present some estimates in which we include multiple mobility measures.

To assess the role of mask mandates and mask use in the growth rate of new cases, we modify equation (2) as follows:

$$\ln\left[\ln(Y_{it}) - \ln(Y_{i,t-7})\right] = \alpha_i + f(K_{it}) + \beta Lx.\overline{M}_{it} + \eta Lx.\overline{F}_{it} + \gamma L7.\ln\left[\ln(Y_{it}) - \ln(Y_{i,t-7})\right] + \varepsilon_{it}, \tag{3}$$

where $\overline{F}_{it}$ measures whether a face-mask mandate is in place during the time period when mobility is measured. For example, if mobility is averaged over 21 days and a mask mandate is in place for 14 (21) [0] of those days, then $\overline{F}_{it}$ is 2/3 (1) [0].

For all of our empirical estimates of equations (2) and (3), we calculate standard errors using a Driscoll-Kraay approach that is robust to autocorrelation, heteroskedasticity, and cross-sectional correlation. Because our log-growth-rate specification drops state-day observations that have no new cases or case growth, we try an alternative specification in which the dependent variable is the seven-day rolling average of new cases relative to population instead of the log growth rate—the results are similar and not reported for brevity.[17]

Our empirical specifications (equations [2] and [3]) are parsimonious, as we abstract from other measures that have been implemented to contain the virus, such as business closures or limits on group gatherings. Most of these other measures are intended to encourage social distancing and limit mobility, and their effects are embedded in the mobility measures we consider. Our objective is to understand whether mask mandates, conditional on mobility, help to offset the effects of mobility on the spread of the virus.

4 Results

4.1 Mobility and COVID-19 Spread

Results from estimating equation (2) are presented in Table 1. Each panel is based on the mobility measure specified in the first row, and each column refers to a regression with a different lag of mobility (from 7 to 42 days) averaged over the preceding seven days. The mobility measures are standardized to facilitate the comparison of the estimated effects across measures. Overall, we find that increased mobility—more visits, more contacts, or

ditional mean (long-run) weekly growth rate of cases (deaths) is $(\exp(\beta) - 1)/(1 - \gamma)$.

[17] We also experimented with variants of the log transformation, such as adding 1 to the number of new cases or to the growth rate of cases itself, and the results remained similar to our main findings.

less time at home—is associated with a higher growth rate of cases.[18] The magnitude of the estimated effects is also quite similar across mobility measures, with slightly smaller effects for the PlaceIQ DEX. In addition, the effect of mobility on case growth seems to taper off for lags longer than 21 days. Going forward, we choose a specification for case growth that averages mobility over 21 days and lags this average by 7 days.

Analogous regressions for the growth rate of deaths from COVID-19 in Table 2 show a more delayed effect of mobility that persists at longer lags. This delayed impact of mobility on the growth rate of deaths relative to the growth rate of cases is expected given what we know about the disease. While some individuals succumb to COVID-19 rather quickly, others are initially helped by available medical interventions and therapeutics but take a turn for the worse weeks after becoming infected. Going forward, we use a specification for the growth rate of deaths where we average our mobility measures over 35 days and lag them 14 days.

In Table 3, we explore whether our mobility measures contain different information using regressions that include two mobility measures at a time. (Not all possible combinations are shown.) As one can intuit from our previous results, the mobility measures are highly correlated, and only one of the measures remains significant in most specifications.[19]

4.2 The Role of Face-Mask Mandates

We next explore whether mask mandates help to mitigate the effect of mobility on the spread of COVID-19. As noted earlier and shown in Figure 6, mask mandates have been implemented at different times and to different degrees across states throughout the pandemic. As of November 15, 2020, only one state, South Dakota, had no reported face-mask requirement, while 14 states had mask requirements specific to certain locations or businesses (partial mandates). All other states had mandates generally requiring face masks "everywhere in public where social distancing is not possible."

We find that mask mandates are negatively correlated with the growth rate of cases (deaths), based on estimates of equation (3) that also control for lagged mobility (see Ta-

[18] The number of observations is different across mobility measures because of differences in data availability. In particular, the Cuebiq CI data do not include Alaska or Hawaii, and the PlaceIQ DEX data are not as current.

[19] The results in column (6) are an exception, but the estimates are consistent with multicollinearity; the estimated effect for SG visits becomes significantly larger, while the estimated effect for the Cuebiq CI turns negative when the two measures are included together.

ble 4). This is true regardless of the mobility measure we use, although the estimated mandate effect is a bit larger (in absolute value) in regressions that control for contacts rather than visits.

To better understand the quantitative significance of our estimates, we run two counterfactual exercises. First, we predict the number of total cases the United States would have had on November 15 if mask mandates had been put in place in every state by May 15, 2020.[20] Figure 10 (left panel) depicts the evolution of actual and counterfactual cases under this scenario over time. Our most conservative estimates are those that use SG time at home as our mobility measure. Based on these estimates, the United States would have had 26.4 percent (about 3.06 million) fewer cases as of November 15—a meaningful difference. The analogous numbers for SG visits, PlaceIQ DEX, and Cuebiq CI are 29.8 percent, 34.3 percent, and 34.3 percent, respectively.[21] A later national mask mandate would have prevented fewer cases and consequently fewer deaths, but it still would have been beneficial. Indeed, we estimate that the case count as of November 15 would have been 3.4 percent lower (about 360,000 fewer cases) if every state had a mask mandate by August 15, 2020. These results demonstrate the beneficial nature of mask mandates and, implicitly, mask use, especially given that they are a very low-cost public health option for helping to control the spread of the virus.

Second, we predict the number of COVID-19 cases that the United States would have had if mobility in every state had remained fixed at the May 15 level rather than continuing to recover. In this alternative counterfactual, we find that infections on November 15 would have been 60.7 percent lower when we use the SG time-at-home measure, 66.2 percent lower using SG visits, 53.1 percent lower using the PlaceIQ DEX, and 46.5 percent lower using the Cuebiq CI. Figure 10 (right panel) depicts this scenario for SG time at home. These results highlight how much mobility contributes to the spread of COVID-19.

Restricting mobility to its near-lockdown levels of mid-May certainly would have been effective at reducing the number of COVID-19 cases, and ultimately the number of deaths from the disease. But the costs of this intervention would have been substantial in terms of the reduced economic activity. Mask mandates, if they had been implemented earlier and across all states, would have been about half as effective as lockdowns at reducing the number

[20] We detail our approach and calculations in Appendix A.3. For states that implemented their mandates earlier than May 15, we use the actual mandate dates.

[21] The percentage for PlaceIQ DEX is for November 11—the latest date possible given the data available to us. The percentage for fewer cases for November 15 would be slightly higher.

of COVID-19 infections (and deaths), but they are much less costly for the economy.[22] This speaks to an important challenge that policymakers face in determining how best to combat the COVID-19 public health crisis, especially given the recent resurgence in case counts.

4.3 Factors Determining the Effectiveness of Face-Mask Mandates

While our previous analysis shows that mask mandates are indeed important for controlling the spread of the virus, we further explore situations in which mask mandates potentially have an even greater impact. First, we check if the timing of mask mandates matters for their effectiveness using the following specification:

$$\begin{aligned}\ln\left[\ln(Y_{it})-\ln(Y_{i,t-7})\right] = \alpha_i + f(K_{it}) + \beta Lx.\overline{M}_{it} + \eta Lx.\overline{F}_{it} + \theta Lx.\overline{F}_{it} \times I_{it}^{early} \\ + \gamma L7.\ln\left[\ln(Y_{it})-\ln(Y_{i,t-7})\right] + \varepsilon_{it},\end{aligned} \tag{4}$$

where $I_{it}^{early} = 1$ when the mandate was in place within the first two months of a location reaching 5 deaths per 1 million inhabitants.[23] Recall that the persistence of cases/deaths already implies that an earlier mandate will have a larger effect on the number of cumulative cases/deaths at any given date. This specification estimates whether the earlier mandate has a differentially larger effect at each date beyond what is captured by this persistence.

Table 5 presents the results from estimating equation (4) and shows that mask mandates that were implemented early are far more strongly negatively correlated with the growth rate of deaths in all specifications. In contrast, we find no evidence that mask mandates implemented early on were more effective in reducing the growth rate of cases.[24]

Second, we explore whether mask mandates are more effective in states that have higher levels of mask compliance (based on the *New York Times* survey data) using the following

[22] The estimated effectiveness of mask mandates relative to reductions in mobility varies with the mobility measure and ranges from 30 percent as effective for SG time a home to 81 percent as effective for PlaceIQ DEX. The average relative effectiveness across our four estimates is roughly 52 percent.

[23] This timing cutoff was chosen based on a bimodal distribution of when mandates were put in place in terms of epidemiological time. Fourteen states had mask mandates in place early by this definition.

[24] While this result may appear at odds with our finding that lagged case count growth predicts death count growth, earlier mandates were enacted during times when states' medical systems were particularly overburdened. Hospital bed utilization rates over the week prior to the enactment of mask mandates averaged 76 percent for the states that enacted mask mandates early and 52 percent for states that enacted mandates later. When the rate of new infections slows down, more medical resources can be devoted to those already afflicted by the disease. Also, wearing masks early on might have helped reduce the viral loads of those infected by COVID-19.

specification:

$$
\begin{aligned}
\ln\left[\ln(Y_{it}) - \ln(Y_{i,t-7})\right] = \alpha_i + f(K_{it}) + \beta Lx.\overline{M}_{it} + \eta Lx.\overline{F}_{it} + \lambda Lx.\overline{F}_{it} \times C_i \\
+ \gamma L7.\ln\left[\ln(Y_{it}) - \ln(Y_{i,t-7})\right] + \varepsilon_{it},
\end{aligned}
\tag{5}
$$

where C_i denotes compliance as measured in the survey data. We first estimate this equation by ordinary least squares (OLS), as in our previous analysis. However, as mentioned earlier, we find that mask compliance is strongly driven by the characteristics of a state's population. We therefore also estimate a version of this specification by instrumenting (IV) mask compliance with preexisting state characteristics, such as demographics, education, population density, urbanization, political leaning, and beliefs about climate change.[25]

Tables 6 and 7 report estimates of equation (5) by OLS and IV, respectively. The results show that mask mandates are indeed more effective in states where mask compliance is high. This estimated effectiveness is somewhat stronger when we use preexisting state characteristics as instruments for mask-wearing compliance. We use these estimates to consider another counterfactual exercise in which we predict the number of total cases the United States would have had on November 15 if mask mandates had been put in place in every state by May 15 and compliance with mandates in every state was at least as high as the 90th percentile of the observed compliance distribution. We find that the cumulative number of cases on November 15 would have been 40.9 percent lower (about 4.75 million fewer cases) when we use the SG time-at-home measure, 41.4 percent lower using SG visits, 49.5 percent lower using the PlaceIQ DEX, and 54.1 percent lower using the Cuebiq CI. For the SG time-at-home measure that we focus on, a national mask mandate enacted on May 15 along with a high degree of compliance would have prevented close to two-thirds of the number of infections avoided by restricting time-at-home to the levels seen on May 15. Based on estimates using the contact-based mobility measures, a national mask mandate with a high degree of compliance is even more effective at reducing cases than policies that would have held mobility at its mid-May level.

Overall, this analysis shows that while on an a priori, scientific basis, face masks may be equally effective everywhere against the transmission of COVID-19, the success of mask mandates during this pandemic depends on when they were implemented and the degree of compliance with the mandate, which may be correlated with adherence to other related

[25]More precisely, we instrument the interaction term $Lx.\overline{F}_{it} \times C_i$ using interactions of the lagged mask mandate measure with these state characteristics.

government policies.

4.4 Robustness and Further Discussion

Changes in Testing: A potential concern with our parsimonious estimation approach is that our estimates of the effect of mobility and mask mandates on the spread of COVID-19 might be biased due to omitted factors such as changing testing capacity over time. However, we verify that our estimated mobility and mask-mandate effects barely change after we control for changes in testing rates across states (see Table 8, column 2 relative to column 1).[26]

Controlling for lagged case count growth in death count growth regressions: Overall, the effect of mobility on the death count operates through cases. In particular, we find that the estimated coefficients for mobility and mask mandates in our growth-rate-of-deaths regressions decline and become statistically insignificant when we add lagged case count growth as an additional control (see Table 8, column 4). However, mobility has an effect on death count growth distinct from its effect on lagged case count growth in states with populations more vulnerable to COVID-19. We reach this conclusion based on interacting our mobility measure with a state-level vulnerability index from the COVID-19 Healthcare Coalition; the interaction is significant even after we control for lagged case count growth.[27] This finding highlights that social distancing likely helps save more lives (on a relative basis) in more vulnerable populations. Similar interactions with mask mandates are not significant.

5 Concluding Thoughts and Policy Implications

We find a strong, positive correlation between (lagged) mobility and the growth rate of COVID-19 cases. Mobility is also related to the growth rate of deaths but with a longer lag, as individuals who contract the virus do not succumb immediately due to medical treatment and other factors. While we are not the first to document the link between mobility and COVID-19 cases and deaths, our estimation approach follows the best practices in the existing economics and epidemiological literatures, including controlling for epidemic-time fixed effects.

---

[26] Note that the estimates in column (1) of Table 8 have slightly fewer observations than the equivalent baseline estimates in Table 4 because we have restricted the sample to dates with valid testing data.

[27] See the data appendix for a description of this index.

The novel feature of our analysis is that it considers the role played by masks in conjunction with the relationship between mobility and COVID-19 spread. Specifically, we exploit substantial variation across US states in the timing of the implementation of mask mandates and show that these mandates are effective in reducing at least half of the effects of increased mobility on the growth rates of COVID-19 cases and deaths. We further find that the effectiveness of mask mandates is greater in states where the mandates were implemented early and in states where there is greater compliance (more mask wearing) with the regulations—more mask use may also be correlated with compliance with other COVID-19-related government policies that target social distancing. Our counterfactual exercises further illuminate the close connection between mobility and the virus as well as the partially offsetting effects of mask mandates. These counterfactual case counts are likely an underestimate of the true benefit of mask mandates, since our regression equation does not account for spillover effects across states from increased mask wearing and lower case counts.

Mobility increases the spread of COVID-19, but masks can help to mitigate the growth in case counts. Indeed, one need look no further than the shutdown of economic activity both domestically and in Europe in March and April to understand the link between mobility and the public health outcomes associated with COVID-19. In the spring, decisions were made to severely limit mobility in many locations in an effort to slow the spread of the virus and ease the burden on the health-care system. These restrictions entailed severe economic costs and highlighted the tradeoff between allowing the movement of individuals that is needed to facilitate economic activity and limiting the public health costs of the virus. After the sharp economic contraction in the spring, there has been much less appetite among state and local government officials for using containment policies to the same degree to battle the resurgence of the virus. Our analysis suggests that universal mask requirements and educational campaigns aimed at increasing compliance could be a helpful and effective alternative. In addition, while not addressed directly by our analysis, the provision of free or subsidized masks of the appropriate kind as well as guidance on proper mask use might be desirable.

Daniel Cooper *a senior economist and policy advisor in the research department at the Federal Reserve Bank of Boston. His email address is Daniel.Cooper@bos.frb.org.*

Vaishali Garga *is an economist in the research department at the Federal Reserve Bank of Boston. Her email address is Vaishali.Garga@bos.frb.org.*

María José Luengo-Prado *is a senior economist and policy advisor in the research department at the Federal Reserve Bank of Boston. Her email address is Maria.Luengo-Prado@bos.frb.org.*

Jenny Tang *is a senior economist in the research department at the Federal Reserve Bank of Boston. Her email address is Jenny.Tang@bos.frb.org.*

The views expressed herein are those of the authors and do not indicate concurrence by the Federal Reserve Bank of Boston, the principals of the Board of Governors, or the Federal Reserve System.

The authors thank Keith Barnatchez, Rachel Cummings, Nishan Jones, Justin Rohan, and Zorah Zafari for research assistance, and Giovanni Olivei for comments.

References

Atkeson, Karen Kopecky, Andrew, and Tao Zha. 2020. "Four Stylized Facts about COVID-19." Working Paper 27719. National Bureau of Economic Research.
Available at https://www.nber.org/papers/w27719.

Baqaee, David, Emmanuel Farhi, Michael Mina, and James H. Stock. "Policies for a Second Wave." *Brookings Papers on Economic Activity.*
Available at https://www.brookings.edu/bpea-articles/policies-for-a-second-wave/.

Brzezinski, Adam, Valentin Kecht, David Van Dijcke, and Austin L. Wright. 2020. "Belief in Science Influences Physical Distancing in Response to COVID-19 Lockdown Policies." Working Paper 2020-56. University of Chicago, Becker Friedman Institute for Economics.
Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3587990.

Bundgaard, Henning, Johan Skov Bundgaard, Daniel Emil Tadeusz Raaschou-Pedersen, Christian von Buchwald, Tobias Todsen, Jakob Boesgaard Norsk, Mia M. Pries-Heje, Christoffer Rasmus Vissing, Pernille B. Nielsen, Ulrik C. Winslw, Kamille Fogh, Rasmus Hasselbalch, Jonas H. Kristensen, Anna Ringgaard, Mikkel Porsborg Andersen, Nicole Bakkegrd Goecke, Ramona Trebbien, Kerstin Skovgaard, Thomas Benfield, Henrik Ullum, Christian Torp-Pedersen, and Kasper Iversen. 2020. "Effectiveness of Adding a Mask Recommendation to Other Public Health Measures to Prevent SARS-CoV-2 Infection in Danish Mask Wearers." *Annals of Internal Medicine.*
Available at https://pubmed.ncbi.nlm.nih.gov/33205991/.

Cheng, Vincent CC, Shuk-Ching Wong, Vivien WM Chuang, Simon YC So, Jonathan HK Chen, Siddharth Sridhar, Kelvin KW To, Jasper FW Chan, Ivan FN Hung, Pak-Leung Ho, et al. 2020. "The Role of Community-Wide Wearing of Face Mask for Control of Coronavirus Disease 2019 (COVID-19) Epidemic due to SARS-CoV-2." *Journal of Infection* 81(1): 107–114.
Available at https://pubmed.ncbi.nlm.nih.gov/32335167/.

Chernozhukov, Victor, Hiroyuki Kasahara, and Paul Schrimpf. 2020. "Causal Impact of Masks, Policies, Behavior on Early Covid-19 Pandemic in the U.S." *Journal of Econometrics* ISSN 0304-4076.
Available at http://www.sciencedirect.com/science/article/pii/S0304407620303468.

Couture, Victor, Jonathan I Dingel, Allison E Green, Jessie Handbury, and Kevin R Williams. 2020. "Measuring Movement and Social Contact with Smartphone Data: A Real-Time Application to COVID-19." Working Paper 27560. National Bureau of Economic Research.
Available at https://www.nber.org/papers/w27560.

Davydiuk, Tetiana, and Deeksha Gupta. 2020. "Income Inequality, Debt Burden and COVID-19." Working paper. Available at SSRN: https://ssrn.com/abstract=3641965.

Desmet, Klaus, and Romain Wacziarg. 2020. "Understanding the Spatial Variation in COVID-19 across the United States." Working Paper 27329. National Bureau of Economic Research.
Available at https://www.nber.org/papers/w27329.

Dyke, Miriam E. Van, Tia M. Rogers, Eric Pevzner, Catherine L. Satterwhite, Hina B. Shah, Wyatt J. Beckman, Farah Ahmed, D. Charles Hunt, and John Rule. 2020. "Trends in County-Level COVID-19. Incidence in Counties With and Without a Mask Mandate—Kansas, June 1–August 23, 2020." *Morbidity and Mortality Weekly Report* 69(47): 1777–1781.
Available at http://dx.doi.org/10.15585/mmwr.mm6947e2.

Giuliani, Diego, Maria Michela Dickson, and Giuseppe Espa. 2020. "Modelling and Predicting the Spatio-Temporal Spread of COVID-19 in Italy." *BMC Infectious Diseases* 20(700).
Available at https://doi.org/10.1186/s12879-020-05415-7.

IHME Forecasting Team. 2020. "Modeling COVID-19 Scenarios for the United States." *Nature Medicine*.
Available at https://www.nature.com/articles/s41591-020-1132-9.

Karaivanov, Alexander, Shih En Lu, Hitoshi Shigeoka, Cong Chen, and Stephanie Pamplona. 2020. "Face Masks, Public Policies and Slowing the Spread of COVID-19: Evidence from Canada." Working Paper 27891. National Bureau of Economic Research.
Available at https://www.nber.org/system/files/working_papers/w27891/w27891.pdf.

Kissler, Stephen M., Christine Tedijanto, Edward Goldstein, Yonatan H Grad, and Marc Lipsitch. 2020. "Projecting the Transmission Dynamics of SARS-CoV-2 through the Postpandemic Period." *Science* 860–868.
Available at https://science.sciencemag.org/content/368/6493/860.full.

Lyu, Wei, and George Wehby. 2020. "Community Use of Face Masks and COVID-19: Evidence From a Natural Experiment of State Mandates in the US." *Health Affairs* 39(8): 1419–1425.
Available at https://doi.org/10.1377/hlthaff.2020.00818.

Milosh, Maria, Marcus Painter, Konstantin Sonin, David Van Dijcke, and Austin L. Wright. 2020. "Unmasking Partisanship: Polarization Undermines Public Response to Collective Risk." Working Paper 2020-102. University of Chicago, Becker Friedman Institute for Economics.
Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3664779.

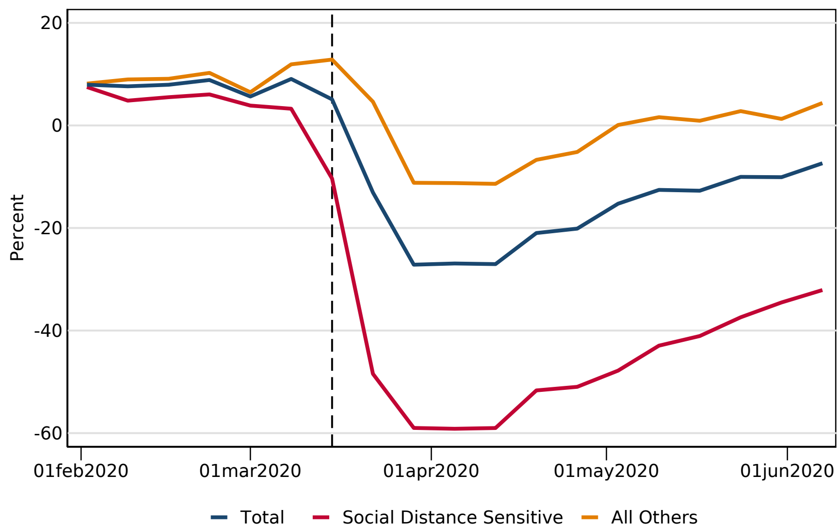
Mitze, Timo, Reinhold Kosfeld, Johannes Rode, and Klaus Walde. 2020. "Face Masks Considerably Reduce COVID-19 Cases in Germany: A Synthetic Control Method Approach." Working Paper 13319. National Bureau of Economic Research.
Available at http://ftp.iza.org/dp13319.pdf.

Orea, Luis, and Inmaculada C. Alvarez. 2020. "How Effective Has the Spanish Lockdown Been to Battle COVID-19? A Spatial Analysis of the Coronavirus Propagation across Provinces." Working Paper 2020/03. FEDEA.
Available at https://documentos.fedea.net/pubs/dt/2020/dt2020-03.pdf.

Welsch, David M. "Do Masks Reduce COVID-19 Deaths? A County-Level Analysis using IV." *Covid Economics* 57(13): 20–45.
Available at https://cepr.org/content/covid-economics.

Wilson, Daniel J. 2020. "Weather, Social Distancing, and the Spread of COVID-19." Working Paper 2020-23. Federal Reserve Bank of San Francisco.
Available at https://www.frbsf.org/economic-research/publications/working-papers/2020/23/.

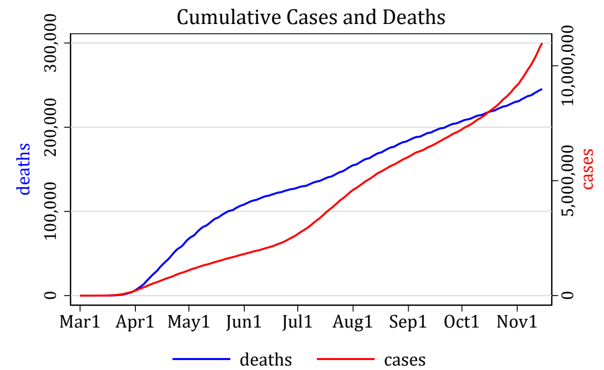
Figure 1. Credit and Debit Card Transaction Growth



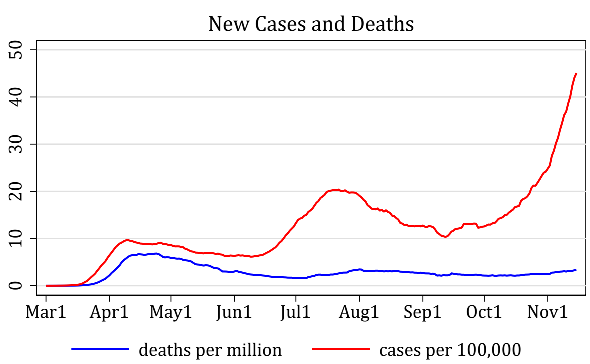
Source: Affinity Solutions.

Notes: Year-over-year growth of credit and debit card transactions.
Dashed line represents week when most school (and other) shutdowns occured.

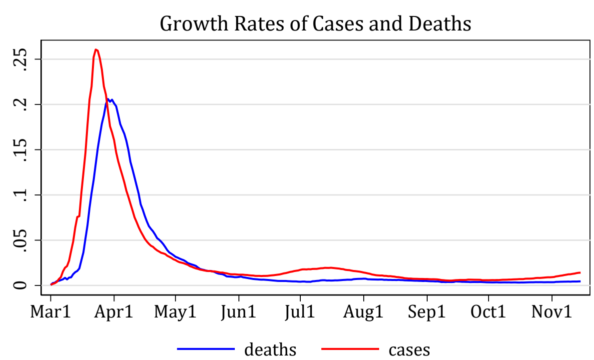
Figure 2. COVID-19 National Trends



Source: Data from the Johns Hopkins University Center for Systems Science and Engineering via DataHub (https://datahub.io/core/covid-19).

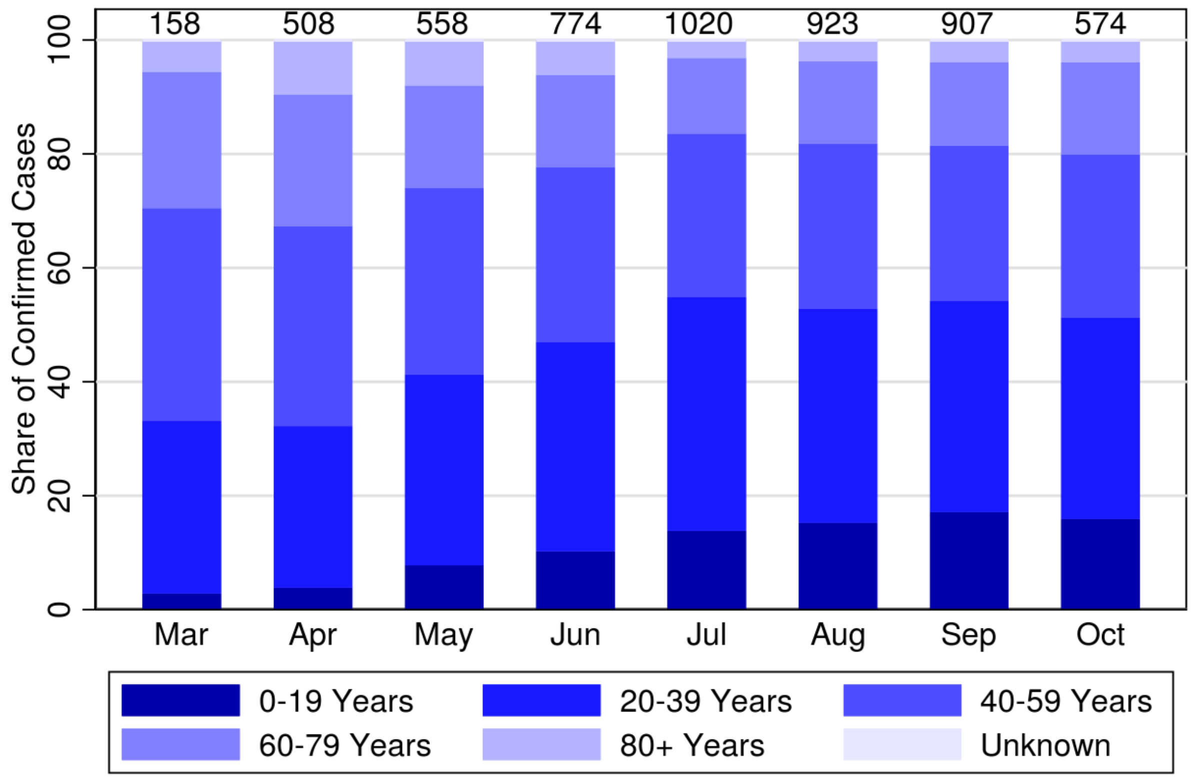


Source: Data from the Johns Hopkins University Center for Systems Science and Engineering via DataHub (https://datahub.io/core/covid-19).
Note: 7-day rolling averages of daily figures



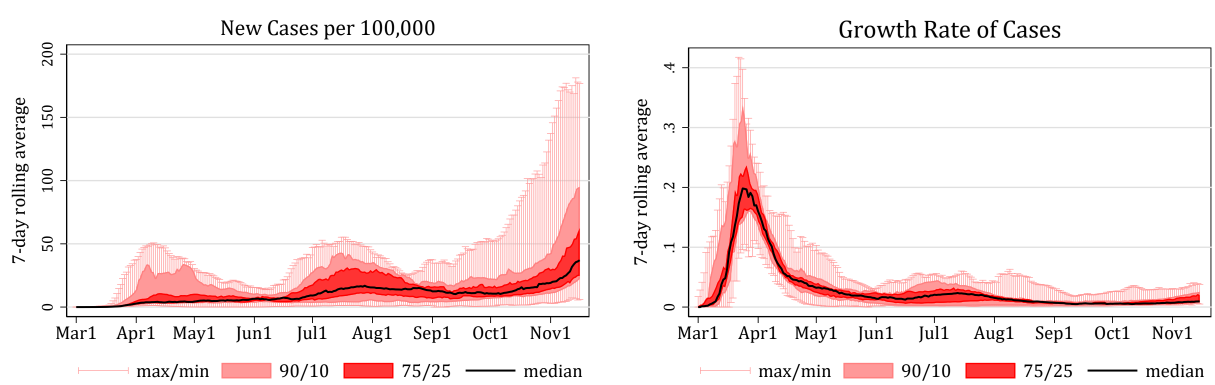
Source: Data from the Johns Hopkins University Center for Systems Science and Engineering via DataHub (https://datahub.io/core/covid-19).
Note: 7-day rolling averages of daily figures

Figure 3. Age Distribution of New COVID-19 Cases



Source: Centers for Disease Control and Prevention.
Note: Numbers at the top of the bars equal monthly total (in thousands) of new laboratory-confirmed cases.
The graph includes data through October 16, 2020.

Figure 4. State-Level Variation in COVID-19 Cases



Source: Data from the Johns Hopkins University Center for Systems Science and Engineering via DataHub (https://datahub.io/core/covid-19).

Source: Data from the Johns Hopkins University Center for Systems Scienc and Engineering via DataHub (https://datahub.io/core/covid-19).

Figure 5. State-Level Variation in Mobility

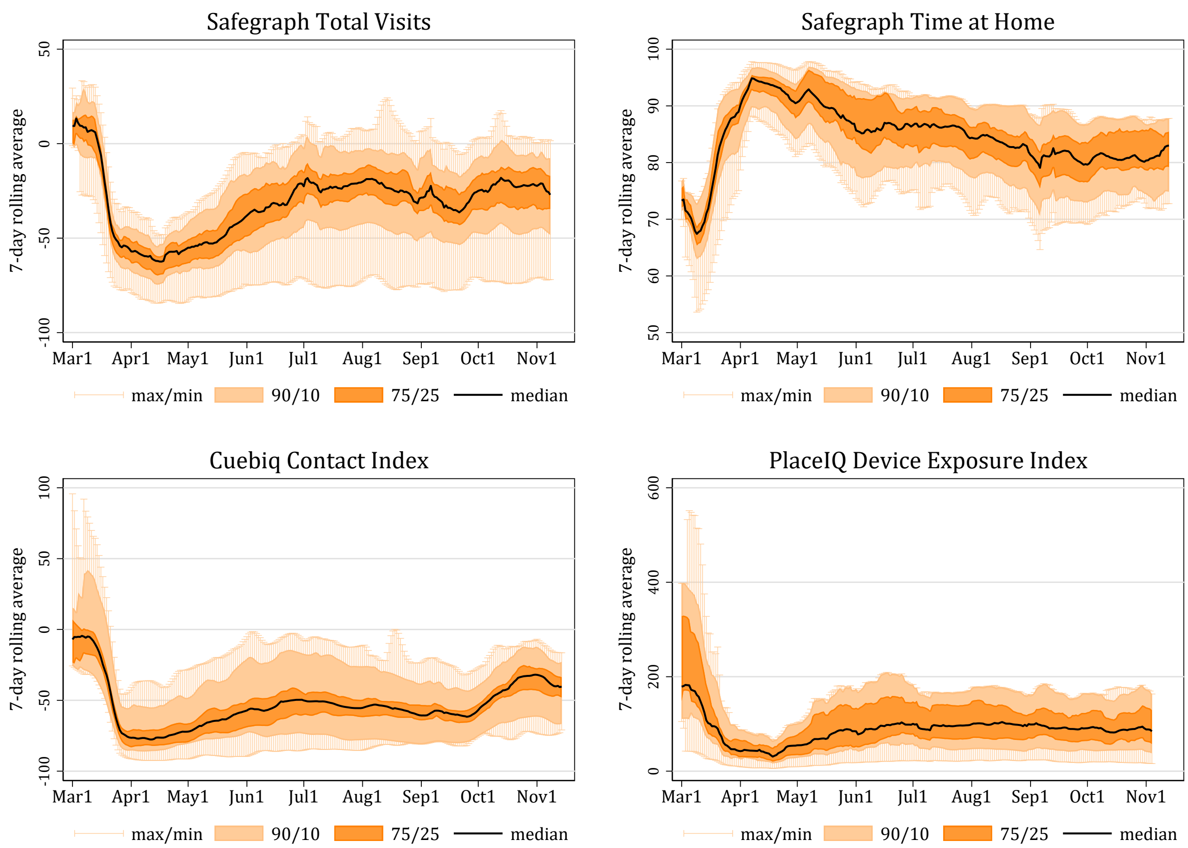
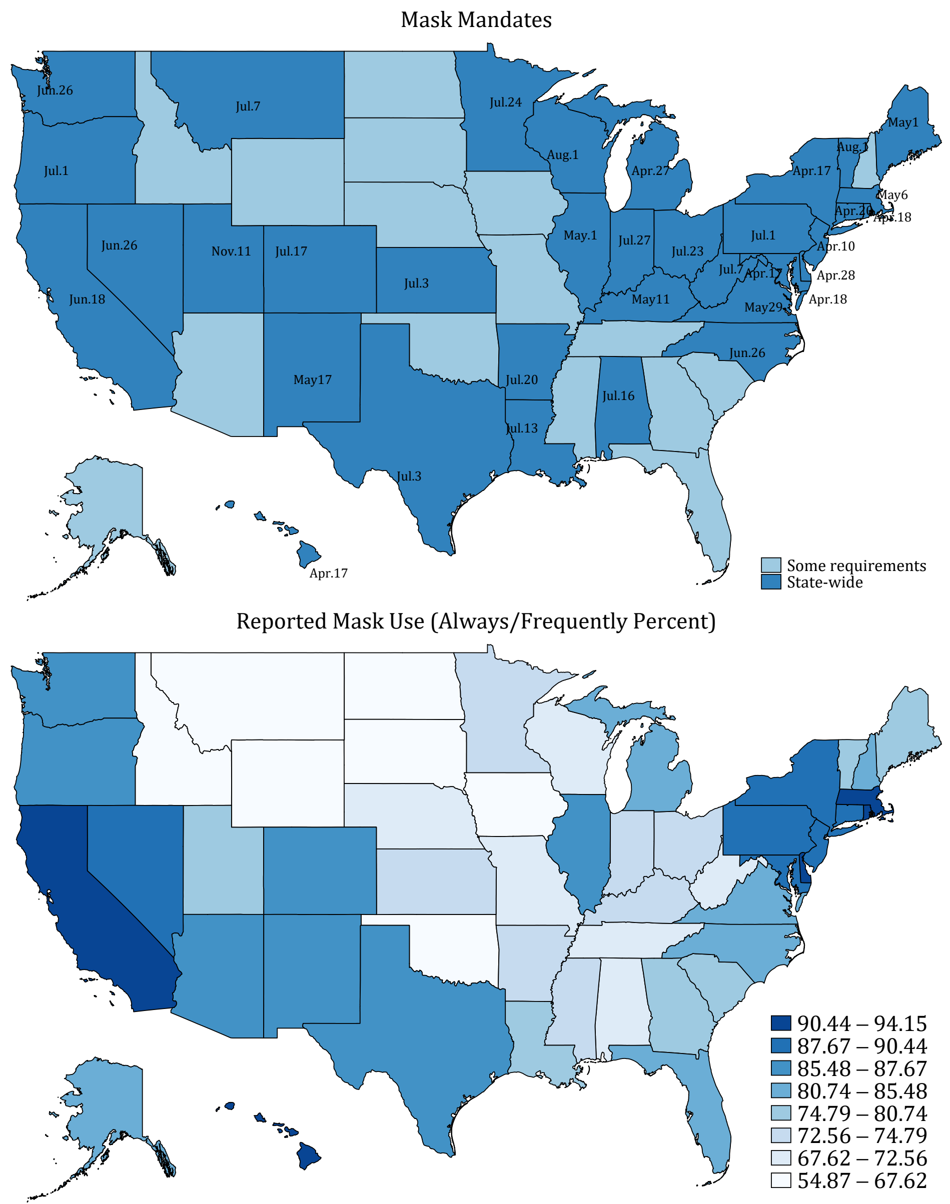
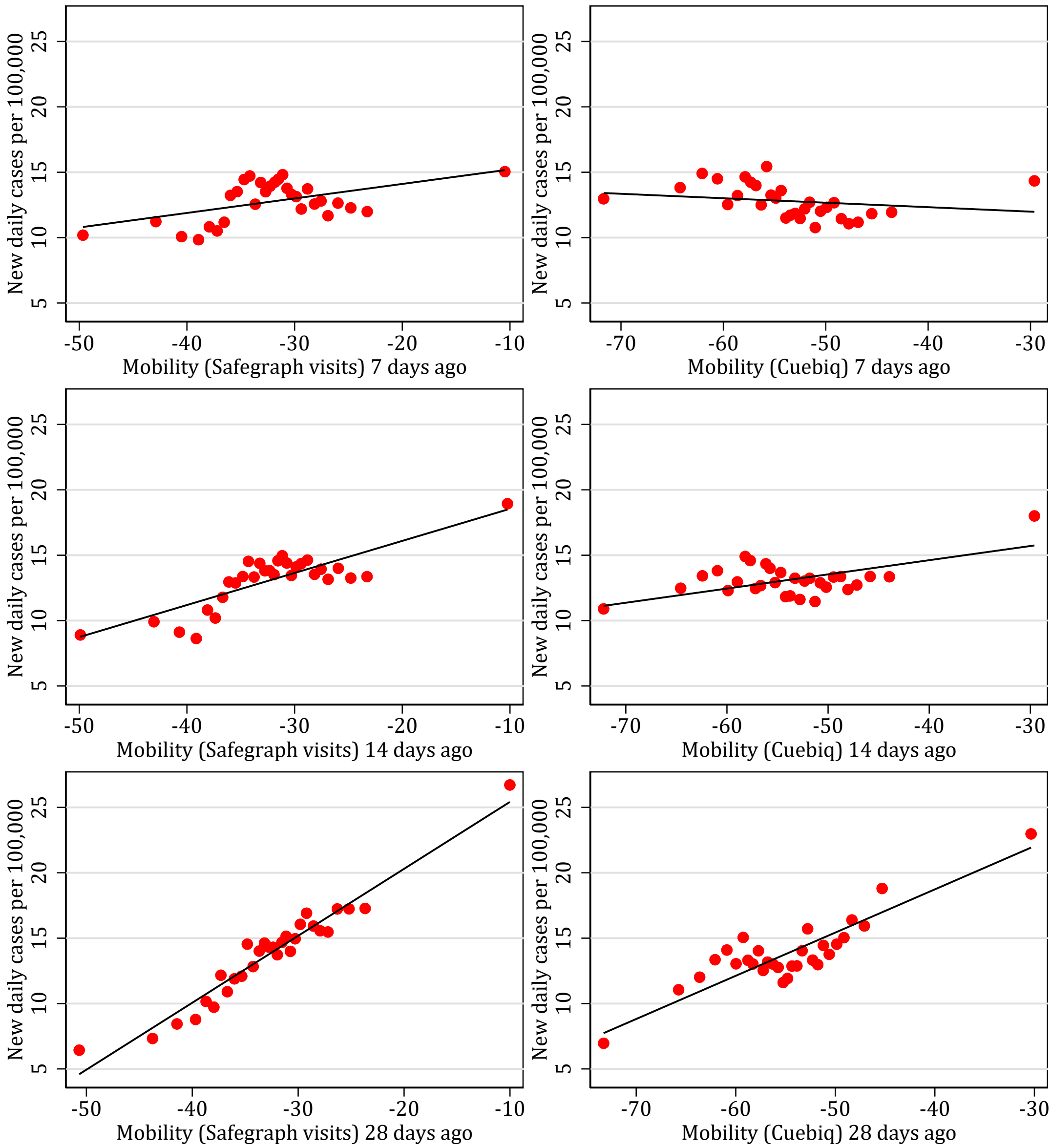


Figure 6. State-Level Variation in Mask Requirements and Mask Use



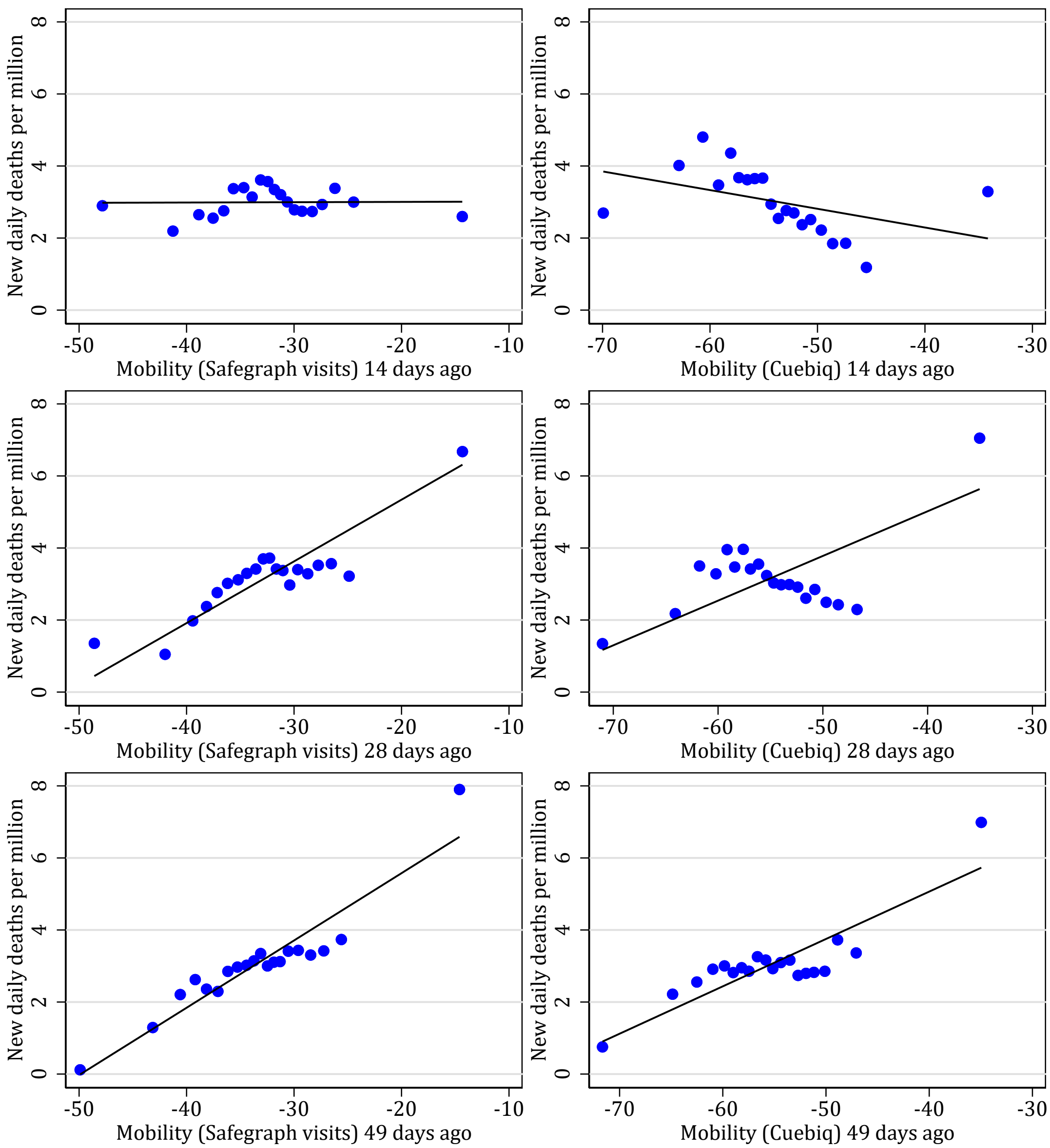
Notes: Data on mandates from the websites of the different states as of November 1, 2020. Data on mask use from a survey conducted by Dynata on behalf of the *New York Times* from July 2 through July 14, 2020.

Figure 7. State-Level Relationship between Lagged Mobility and Cases



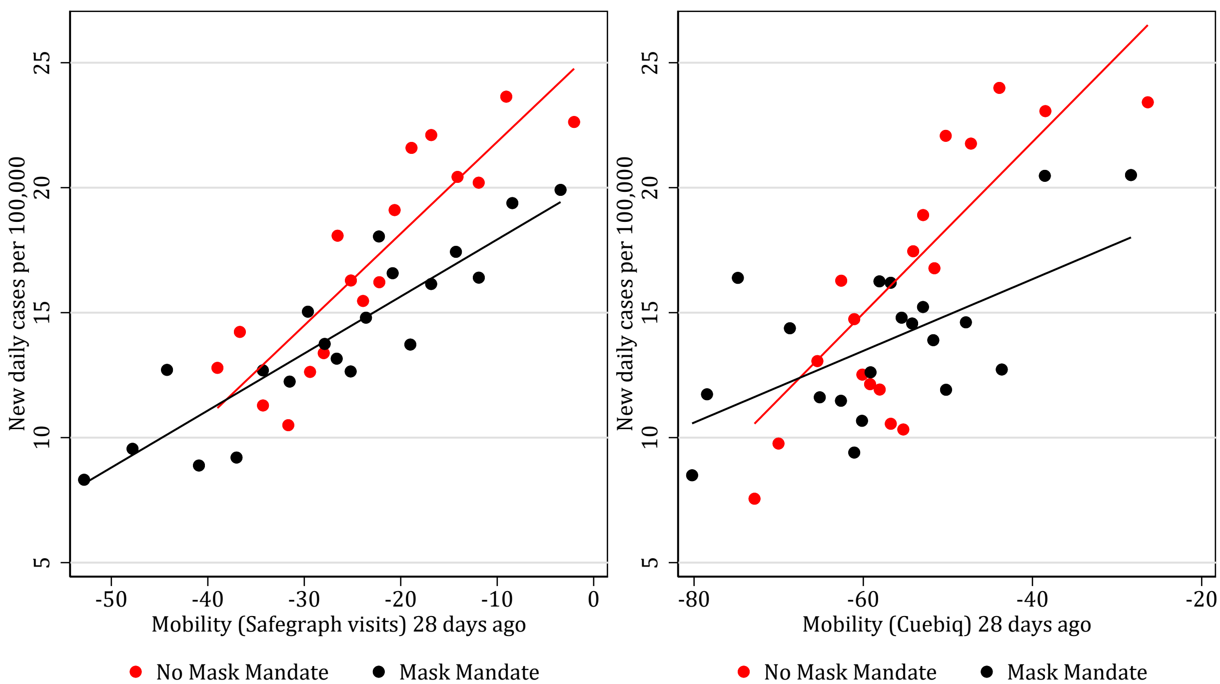
Notes: Cases and mobility are averaged over a 7-day period. Binned scatter plots controlling for state fixed effects and epidemic-time fixed effects (time relative to reaching 5 deaths per 1 million).

Figure 8. State-Level Relationship between Lagged Mobility and Deaths



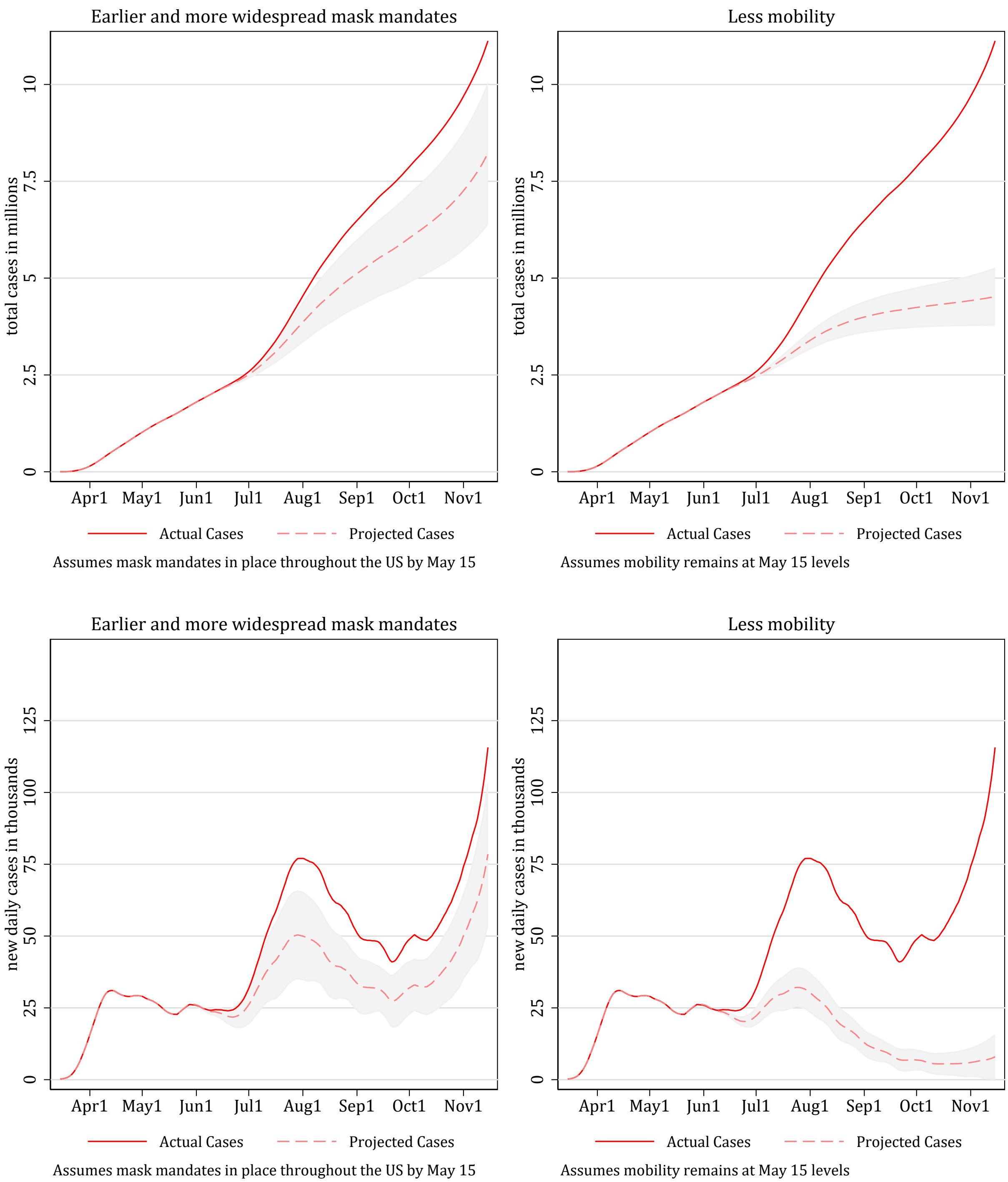
Notes: Deaths and mobility are averaged over a 7-day period. Binned scatter plots controlling for state fixed effects and epidemic-time fixed effects (time relative to reaching 5 deaths per 1 million).

Figure 9. Mobility, Cases, and Mask Mandates



Notes: Cases and mobility are averaged over a 7-day period. Cases from August 15 through November 5. Mask Mandate must be in place when mobility is measured. Binned scatter plots without controls.

Figure 10. Counterfactuals: Mask Mandates versus Restricting Mobility



Notes: Counterfactuals in these figures use the SafeGraph time at home measure of mobility. The top panels present total cases, while the bottom panels depict a 7-day rolling average of new daily cases. Two-standard-deviation error bands depicted for the projections.

Table 1. Mobility and Cases, Log-Growth-Rate Specification

	(1)	(2)	(3)	(4)	(5)	(6)
Lags in days	7	14	21	28	35	42
SG, visits	0.15***	0.15***	0.12***	0.07	0.02	0.05
	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)	(0.04)
L7.LHS	0.87***	0.86***	0.86***	0.86***	0.87***	0.86***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Adj. R-squared.	0.78	0.78	0.78	0.79	0.78	0.77
Obs.	12207	12207	12097	11811	11461	11104
SG, home time	–0.18***	–0.15***	–0.09*	–0.07	–0.04	–0.06*
	(0.03)	(0.04)	(0.05)	(0.06)	(0.06)	(0.03)
L7.LHS	0.87***	0.85***	0.86***	0.86***	0.87***	0.85***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Adj. R-squared.	0.78	0.78	0.78	0.79	0.78	0.77
Obs.	12207	12207	12097	11811	11461	11104
PlaceIQ, DEX	0.14***	0.14***	0.10***	0.06*	0.02	0.00
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
L7.LHS	0.88***	0.87***	0.86***	0.87***	0.87***	0.87***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Adj. R-squared.	0.78	0.78	0.78	0.78	0.78	0.77
Obs.	12003	12207	12097	11811	11461	11104
Cuebiq, CI	0.16***	0.15***	0.10***	0.04	0.03	0.04
	(0.02)	(0.03)	(0.03)	(0.06)	(0.05)	(0.03)
L7.LHS	0.87***	0.85***	0.85***	0.86***	0.86***	0.85***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Adj. R-squared.	0.77	0.77	0.77	0.77	0.77	0.76
Obs.	11733	11733	11624	11347	11011	10668
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Epidemic time FE	Yes	Yes	Yes	Yes	Yes	Yes
Pop. weights	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimation equation: $\ln[\ln(Y_{it}) - \ln(Y_{i,t-7})] = \alpha_i + f(K_{it}) + \beta Lx.\overline{M}_{it} + \gamma L7.\ln[\ln(Y_{it}) - \ln(Y_{i,t-7})] + \varepsilon_{it}$, where Y_{it} denotes COVID-19 cases in state i at date t, measured in days. α_i and $f(K_{it})$ denote state fixed effects and epidemic-time fixed effects, respectively. Epidemic time is time relative to a state reaching 5 deaths per 1 million inhabitants. M denotes mobility, and L is the lag operator. Mobility measures are averaged over 7 days on a rolling basis. Each panel presents results for the mobility measure indicated. Columns vary by the lag (Lx) of the mobility measure. All mobility measures are standardized for easier interpretation of the coefficients. Regressions are weighted by state population. Driscoll-Kraay standard errors. The sample includes all available dates through November 15, 2020.

Table 2. Mobility and Deaths, Log-Growth-Rate Specification

	(1)	(2)	(3)	(4)	(5)	(6)
Lags in days	7	14	21	28	35	42
SG, visits	0.03	0.12**	0.17***	0.18***	0.15***	0.20***
	(0.06)	(0.05)	(0.03)	(0.03)	(0.04)	(0.05)
L7.LHS	0.75***	0.75***	0.74***	0.73***	0.72***	0.70***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
Adj. R-squared.	0.55	0.56	0.56	0.56	0.55	0.54
Obs.	11078	11078	11069	11027	10867	10585
SG, home time	0.01	–0.09	–0.14**	–0.15***	–0.14***	–0.16***
	(0.11)	(0.07)	(0.05)	(0.03)	(0.05)	(0.05)
L7.LHS	0.75***	0.75***	0.74***	0.73***	0.73***	0.71***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
Adj. R-squared.	0.55	0.56	0.56	0.56	0.55	0.54
Obs.	11078	11078	11069	11027	10867	10585
PlaceIQ, DEX	–0.04	0.04	0.10**	0.11***	0.09***	0.08**
	(0.08)	(0.07)	(0.05)	(0.04)	(0.03)	(0.03)
L7.LHS	0.75***	0.75***	0.75***	0.74***	0.73***	0.72***
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Adj. R-squared.	0.55	0.55	0.56	0.56	0.55	0.53
Obs.	10878	11078	11069	11027	10867	10585
Cuebiq, CI	–0.01	0.05	0.09**	0.07***	0.10***	0.12***
	(0.06)	(0.06)	(0.04)	(0.02)	(0.03)	(0.04)
L7.LHS	0.76***	0.76***	0.76***	0.75***	0.74***	0.73***
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
Adj. R-squared.	0.57	0.57	0.57	0.57	0.57	0.55
Obs.	10791	10791	10782	10740	10580	10302
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Epidemic time FE	Yes	Yes	Yes	Yes	Yes	Yes
Pop. weights	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimation equation: $\ln[\ln(Y_{it}) - \ln(Y_{i,t-7})] = \alpha_i + f(K_{it}) + \beta Lx.\overline{M}_{it} + \gamma L7.\ln[\ln(Y_{it}) - \ln(Y_{i,t-7})] + \varepsilon_{it}$, where Y_{it} denotes COVID-19 deaths in state i at date t, measured in days. α_i and $f(K_{it})$ denote state fixed effects and epidemic-time fixed effects, respectively. Epidemic time is time relative to a state reaching 5 deaths per 1 million inhabitants. M denotes mobility, and L is the lag operator. Mobility measures are averaged over 7 days on a rolling basis. Each panel presents results for the mobility measure indicated. Columns vary by the lag (Lx) of the mobility measure. All mobility measures are standardized for easier interpretation of the coefficients. Regressions are weighted by state population. Driscoll-Kraay standard errors. The sample includes all available dates through November 15, 2020.

Table 3. Mobility, Cases, and Deaths: Combining Mobility Measures

	(1)	(2)	(3)	(4)	(5)	(6)
	Cases			Deaths		
Lag SG, visits	0.06	0.13***	0.17***	0.12	0.27***	0.40***
	(0.05)	(0.05)	(0.06)	(0.10)	(0.06)	(0.06)
Lag SG, home time	–0.16***			–0.18*		
	(0.05)			(0.10)		
Lag PlaceIQ, DEX		0.07**			–0.01	
		(0.03)			(0.05)	
Lag Cuebiq, CI			0.06			–0.16***
			(0.05)			(0.06)
Lag LHS	0.85***	0.85***	0.83***	0.73***	0.73***	0.71***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Adj. R-squared.	0.79	0.78	0.78	0.57	0.57	0.59
Obs	12207	12003	11733	11078	11078	10791
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Epidemic time FE	Yes	Yes	Yes	Yes	Yes	Yes
Pop. weights	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimation equation: $\ln[\ln(Y_{it}) - \ln(Y_{i,t-7})] = \alpha_i + f(K_{it}) + \beta Lx.\overline{M}_{it} + \gamma L7.\ln[\ln(Y_{it}) - \ln(Y_{i,t-7})] + \varepsilon_{it}$, where Y_{it} denotes COVID-19 cases/deaths in state i at date t, measured in days. α_i and $f(K_{it})$ denote state fixed effects and epidemic-time fixed effects, respectively. Epidemic time is time relative to a state reaching 5 deaths per 1 million inhabitants. M denotes mobility, and L is the lag operator. We include two mobility measures at a time. The mobility measures for the case (death) regressions are averaged over 21 (35) days and lagged 7 (14) days. All mobility measures are standardized for easier interpretation of the coefficients. Regressions are weighted by state population. Driscoll-Kraay standard errors. The sample includes all available dates through November 15, 2020.

Table 4. Mobility, Mask Mandates, Cases and Deaths

	Visits	Home Time	PlaceIQ	Cuebiq	Visits	Home Time	PlaceIQ	Cuebiq
	Cases				Deaths			
Lag Mobility	0.17***	–0.20***	0.14***	0.17***	0.24***	–0.26***	0.12***	0.12***
	(0.05)	(0.05)	(0.04)	(0.03)	(0.05)	(0.05)	(0.05)	(0.04)
Mask Mandate	–0.07**	–0.06**	–0.09***	–0.09***	–0.07	–0.06	–0.11**	–0.12**
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Lag LHS	0.85***	0.84***	0.86***	0.85***	0.72***	0.73***	0.74***	0.75***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Adj. R-squared.	0.78	0.79	0.78	0.77	0.57	0.57	0.56	0.58
Obs	12207	12207	12003	11733	11078	11078	11078	10791
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Epidemic time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pop. weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimation equation: $\ln[\ln(Y_{it}) - \ln(Y_{i,t-7})] = \alpha_i + f(K_{it}) + \beta Lx.\overline{M}_{it} + \eta Lx.\overline{F}_{it} + \gamma L7.\ln[\ln(Y_{it}) - \ln(Y_{i,t-7})] + \varepsilon_{it}$, where Y_{it} denotes COVID-19 cases/deaths in state i at date t, measured in days. α_i and $f(K_{it})$ denote state fixed effects and epidemic-time fixed effects, respectively. Epidemic time is time relative to a state reaching 5 deaths per 1 million inhabitants. M denotes mobility, and L is the lag operator. $\overline{F}_{it}$ measures whether a face mask mandate is in place during the time period when mobility is measured. The mobility measures for the case (death) regressions are averaged over 21 (35) days and lagged 7 (14) days. All mobility measures are standardized for easier interpretation of the coefficients. Mask mandates match the corresponding mobility averaging and lag (a lag of 7 days for cases and 14 days for deaths, averaged over 21 and 35 days, respectively). Regressions are weighted by state population. Driscoll-Kraay standard errors. The sample includes all available dates through November 15, 2020.

Table 5. Mobility, Mask Mandate Timing, Cases and Deaths

	Cases				Deaths			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Visits	Home Time	PlaceIQ	Cuebiq	Visits	Home Time	PlaceIQ	Cuebiq
Lag Mobility	0.17***	–0.20***	0.14***	0.17***	0.20***	–0.21***	0.09**	0.11**
	(0.05)	(0.05)	(0.04)	(0.02)	(0.05)	(0.05)	(0.04)	(0.04)
Mask Mandate	–0.07**	–0.06**	–0.08***	–0.06*	0.04	0.03	0.01	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
Early Mandate	–0.02	–0.02	–0.04	–0.11*	–0.35***	–0.33***	–0.39***	–0.45***
× Mask Mandate	(0.04)	(0.05)	(0.05)	(0.06)	(0.08)	(0.09)	(0.08)	(0.10)
Lag LHS	0.85***	0.84***	0.85***	0.84***	0.70***	0.70***	0.71***	0.70***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Adj. R-squared.	0.78	0.79	0.78	0.78	0.57	0.57	0.57	0.59
Obs.	12207	12207	12003	11733	11078	11078	11078	10791
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Epidemic time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pop. weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimation equation: $\ln[\ln(Y_{it}) - \ln(Y_{i,t-7})] = \alpha_i + f(K_{it}) + \beta Lx.\overline{M}_{it} + \eta Lx.\overline{F}_{it} + \theta Lx.\overline{F}_{it} \times I_{it}^{early} + \gamma L7.\ln[\ln(Y_{it}) - \ln(Y_{i,t-7})] + \varepsilon_{it}$, where Y_{it} denotes COVID-19 cases/deaths in state i at date t, measured in days. α_i and $f(K_{it})$ denote state fixed effects and epidemic-time fixed effects, respectively. Epidemic time is time relative to a state reaching 5 deaths per 1 million inhabitants. M denotes mobility, and L is the lag operator. $\overline{F}_{it}$ measures whether a face mask mandate is in place during the time period when mobility is measured. $I_{it}^{early} = 1$ when the mandate was in place within the first 2 months of a location reaching 5 deaths per 1 million inhabitants. The mobility measures for case (death) regressions are averaged over 21 (35) days and lagged 7 (14) days. All mobility measures are standardized for easier interpretation of the coefficients. Mask mandates match the corresponding mobility averaging and lag (a lag of 7 days for cases and 14 days for deaths, averaged over 21 and 35 days, respectively). Regressions are weighted by state population. Driscoll-Kraay standard errors. The sample includes all available dates through November 15, 2020.

Table 6. Mobility, Mask Mandates, Mask Compliance, Cases and Deaths (OLS)

	Cases				Deaths			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Visits	Home Time	PlaceIQ	Cuebiq	Visits	Home Time	PlaceIQ	Cuebiq
Lag Mobility	0.17***	–0.19***	0.14***	0.17***	0.19***	–0.22***	0.10**	0.10**
	(0.05)	(0.05)	(0.04)	(0.03)	(0.05)	(0.05)	(0.04)	(0.05)
Mask Mandate	–0.07**	–0.06**	–0.08***	–0.08**	–0.05	–0.04	–0.07	–0.07*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)
Mask Mandate	–0.03	–0.04	–0.06**	–0.09**	–0.16***	–0.16***	–0.20***	–0.23***
× Compliance	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)	(0.02)	(0.03)
Lag LHS	0.84***	0.84***	0.85***	0.83***	0.71***	0.71***	0.71***	0.71***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Adj. R-squared.	0.79	0.79	0.78	0.78	0.57	0.57	0.57	0.59
Obs.	12207	12207	12003	11733	11078	11078	11078	10791
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Epidemic time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pop. weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimation equation: $\ln[\ln(Y_{it}) - \ln(Y_{i,t-7})] = \alpha_i + f(K_{it}) + \beta Lx.\overline{M}_{it} + \eta Lx.\overline{F}_{it} + \lambda Lx.\overline{F}_{it} \times C_i + \gamma L7.\ln[\ln(Y_{it}) - \ln(Y_{i,t-7})] + \varepsilon_{it}$, where Y_{it} denotes COVID-19 cases/deaths in state i at date t, measured in days. α_i and $f(K_{it})$ denote state fixed effects and epidemic-time fixed effects, respectively. Epidemic time is time relative to a state reaching 5 deaths per 1 million inhabitants. M denotes mobility, and L is the lag operator. $\overline{F}_{it}$ measures whether a face mask mandate is in place during the time period when mobility is measured. C_i denotes mask wearing compliance as measured in survey data. The mobility measures for case (death) regressions are averaged over 21 (35) days and lagged 7 (14) days. All mobility measures and mask compliance are standardized for easier interpretation of the coefficients. Mask mandates match the corresponding mobility averaging and lag (a lag of 7 days for cases and 14 days for deaths, averaged over 21 and 35 days, respectively). Regressions are weighted by state population. Driscoll-Kraay standard errors. The sample includes all available dates through November 15, 2020.

Table 7. Mobility, Mask Mandates, Mask Compliance, Cases and Deaths (IV)

	Cases				Deaths			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Visits	Home Time	PlaceIQ	Cuebiq	Visits	Home Time	PlaceIQ	Cuebiq
Lag Mobility	0.17***	–0.20***	0.14***	0.17***	0.19***	–0.22***	0.10**	0.09*
	(0.05)	(0.05)	(0.04)	(0.03)	(0.05)	(0.05)	(0.04)	(0.05)
Mask Mandate	–0.07**	–0.06**	–0.08***	–0.08**	–0.04	–0.03	–0.07	–0.07
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
Mask Mandate	–0.02	–0.04	–0.05*	–0.10**	–0.17***	–0.17***	–0.21***	–0.28***
× Compliance	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Lag LHS	0.84***	0.83***	0.85***	0.82***	0.70***	0.70***	0.71***	0.71***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Adj. R-squared.	0.78	0.79	0.78	0.78	0.57	0.57	0.56	0.58
Obs.	11901	11901	11901	11439	10778	10778	10778	10503
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Epidemic time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pop. weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimation equation: $\ln[\ln(Y_{it}) - \ln(Y_{i,t-7})] = \alpha_i + f(K_{it}) + \beta Lx.\overline{M}_{it} + \eta Lx.\overline{F}_{it} + \lambda Lx.\overline{F}_{it} \times C_i + \gamma L7.\ln[\ln(Y_{it}) - \ln(Y_{i,t-7})] + \varepsilon_{it}$, where Y_{it} denotes COVID-19 cases/deaths in state i at date t, measured in days. α_i and $f(K_{it})$ denote state fixed effects and epidemic-time fixed effects, respectively. Epidemic time is time relative to a state reaching 5 deaths per 1 million inhabitants. M denotes mobility, and L is the lag operator. $\overline{F}_{it}$ measures whether a face mask mandate is in place during the time period when mobility is measured. C_i denotes mask wearing compliance as measured in survey data. The mobility measures for case (death) regressions are averaged over 21 (35) days and lagged 7 (14) days. All mobility measures and mask compliance are standardized for easier interpretation of the coefficients. Mask mandates match the corresponding mobility averaging and lag (a lag of 7 days for cases and 14 days for deaths, averaged over 21 and 35 days, respectively). Regressions are weighted by state population. Driscoll-Kraay standard errors. The sample includes all available dates through November 15, 2020.

Table 8. Mobility, Face Masks, and COVID-19 Spread: Robustness

	(1)	(2)	(3)	(4)	(5)
	Cases		Deaths		
SG, visits	0.17***	0.18***	0.21***	0.07	0.06
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Mask Mandate	–0.07**	–0.07**	–0.05	–0.03	–0.04
	(0.03)	(0.03)	(0.04)	(0.06)	(0.06)
Test rate chg.		0.04***			
		(0.01)			
Lag Case Growth				0.23**	0.24**
				(0.11)	(0.10)
Mobility × Vulnerability					0.11***
					(0.03)
Adj. R-squared.	0.78	0.79	0.54	0.56	0.57
Obs.	12196	12196	10622	10622	10622
SG, home time	–0.20***	–0.21***	–0.22***	–0.05	–0.07
	(0.05)	(0.05)	(0.05)	(0.08)	(0.08)
Mask Mandate	–0.06**	–0.06**	–0.05	–0.04	–0.05
	(0.03)	(0.03)	(0.04)	(0.05)	(0.05)
Test rate chg.		0.04***			
		(0.02)			
Lag Case Growth				0.23*	0.23*
				(0.12)	(0.12)
Mobility × Vulnerability					–0.06**
					(0.03)
Adj. R-squared.	0.79	0.79	0.54	0.56	0.56
Obs.	12196	12196	10622	10622	10622
Place IQ, DEX	0.14***	0.15***	0.08	–0.06	–0.07
	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)
Mask Mandate	–0.09***	–0.09***	–0.09**	–0.06	–0.05
	(0.03)	(0.03)	(0.04)	(0.06)	(0.07)
Test rate chg.		0.04**			
		(0.01)			
Lag Case Growth				0.25**	0.27**
				(0.11)	(0.11)
Mobility × Vulnerability					0.16***
					(0.04)
Adj. R-squared.	0.78	0.78	0.54	0.56	0.57
Obs.	11992	11992	10622	10622	10622
Cuebiq, CI	0.17***	0.17***	0.10**	–0.04	–0.06
	(0.03)	(0.02)	(0.05)	(0.06)	(0.07)
Mask Mandate	–0.09***	–0.10***	–0.09**	–0.06	–0.07
	(0.03)	(0.03)	(0.05)	(0.06)	(0.06)
Test rate chg.		0.07***			
		(0.02)			
Lag Case Growth				0.23**	0.24**
				(0.11)	(0.11)
Mobility × Vulnerability					0.12*
					(0.07)
Adj. R-squared.	0.77	0.78	0.56	0.58	0.58
Obs.	11722	11722	10344	10344	10344

Notes: Estimates of equation (3) with a few additional controls. The dependent variable in these regressions is the weekly growth rate of cases/deaths. The mobility measures for the case (death) regressions are averaged over 21 (35) days and lagged 7 (14) days. All mobility measures are standardized for easier interpretation of the coefficients. Mask mandates match the corresponding mobility averaging and lag. Test rate chg. measures the change in the test rate over the last 7 days. Lag Case Growth is the growth rate of cases over the last 28 days lagged 7 days. Vulnerability is an index from the COVID-19 Health Coalition, standarized. Regressions are weighted by state population, and include state and epidemic-time fixed effects, and the 7-day lag of the dependent variable. Driscoll-Kraay standard errors. The sample includes all available dates through November 15, 2020.

A Appendix

A.1 Description of Mobility Measures

SafeGraph Total Visits

These data measure foot traffic to 6 million points of interest and are aggregated by category (for example, airports, supermarkets), by brands (for example, Costco, McDonalds), or location. The data come from smart phones that have their location turned on. Unlike other sources, SafeGraph provides data from 2019 to help contextualize 2020 data. Given the availability of 2019 data, we can calculate year-over-year differences in mobility as opposed to changes relative to an arbitrary reference period.

SafeGraph Time at Home

The data are generated using a panel of GPS pings from anonymous mobile devices. Safegraph determines the common nighttime location of each mobile device over a six-week period. It calls this location the device's "home." Safegraph then calculates the median percentage of time observed devices are "home" during a given day at the census-block-group (CBG) level. In our state-level regressions, we use the population-weighted average of the CBG medians. We do not calculate year-over-year changes in time at home because Safegraph warns against it, due to different vintages of the data at various points in time.

PlaceIQ/GitHub Data

PlaceIQ data, based on work by Couture et al. (2020), track smartphone device pings by location and day at a given venue. The data are used to compute a device exposure index, or "DEX." The daily DEX of device i is the number of distinct devices that visit any place (commercial venue) that i visits on the same day. (The DEX index is adjusted to address the sample selection problem due to some devices lack of movement from sheltering in place behavior.) There are index data for some demographic breakdowns: income quartiles, quartiles of college education shares, and race.

Cuebiq Contact Index

The Cuebiq Contact Index (CCI) measures if two or more devices come within 50 feet of each other for at least five minutes. The CCI allows researchers to compare device-level contacts to pre-COVID-19 contact and mobility trends. We use year-over-year changes in the CCI in our regressions.

A.2 Other Data Sources

New York Times Mask Use Survey

Mask-use data come from a partnership between the *New York Times* and the global data and survey firm Dynata. From July 2 through July 14, 2020, Dynata asked 250,000 survey participants about their mask use. Specifically, each participant was asked "How often do you wear a mask in public when you expect to be within six feet of another person?" Possible answers were "always," "frequently," "sometimes," "rarely," and "often."

The *New York Times* transformed the raw survey responses into county-level estimates by weighting the responses by age and gender, and approximating survey respondents' locations from their reported Zip codes. Initial estimates were made at the census-tract level, where a weighted average was taken of the 200 nearest responses; a greater weight went to closer responses. These tract-level estimates were then collapsed to the county level using each tract's population as a weight. We collapsed these county-level responses to the state level, weighting by county population.

State-Level Characteristics Used as Instruments of Mask Compliance

We use several variables from the following sources as instruments.

State-level population shares from the American Community Survey:

- The estimated share of a state's population that is 50 to 69 years old (inclusive).
- The estimated share of a state's population that identifies as Black.
- The estimated share of individuals with a bachelor's degree among the subset of the population that is 25 years old or older.
- The estimated share of individuals who commute using public transit.

Demographic controls from the Census Bureau:

- State's population density (people per square mile), 2019.
- Percentage of the state's population living in urban areas, obtained from the 2010 census.

We also consider the state-level shares of votes cast for the Republican party in the 2016 presidential election. These shares are based on data obtained from the MIT Election Lab Database, which provides vote counts at the county level that we aggregate up to the state level.

Lastly, we also use climate change beliefs from the Yale Climate Opinion Survey. We focus on responses to one particular question: "Assuming global warming is happening, do you think it is caused mostly by human activities?" Yale derives county-level responses from the raw survey data using a multilevel regression model with post-stratification. We collapse these estimates to the state level using county population data as weights.

The COVID-19 Healthcare Coalition Vulnerability Index

The vulnerability index measures a given community's (at the ZCTA level) vulnerability to adverse COVID-19 outcomes. Three different kinds of data are used to compute this index: medical risk factors, social risk factors, and health-care resource risk factors. Medical risk factors identify which communities have high numbers of individuals who fall into categories that make them more likely to be hospitalized or die from COVID-19. The medical risk factors that are included are the percentages of individuals who are age 65 or older, have asthma, are American Indian or Alaskan native (non-Hispanic), have cancer, have COPD, have diabetes, have kidney disease, who smoke, and also the number of residents in nursing homes. A community's social risk factors are based on individuals access to quality health care, a lack of which puts them at greater risk of adverse COVID-19 outcomes. The social risk factors that are included are the percentages of individuals who are uninsured, have income that is below 200 percent of the federal poverty level, are homeless, and are migrants. Health-care resource risk factors tell us about the capability of hospitals in each community to respond to COVID-19 outbreaks. The health-care resource risk factors that are included are hospital bed count per capita, ICU beds per capita, and distance to hospitals. The data come from a range of sources, including the Centers for Disease Control and Prevention, the American Academy of Family Physicians, the Department of Housing and Urban Development, and the Census Bureau, and they are aggregated from the ZCTA level to the state level by the COVID-19 Healthcare Coalition.

A.3 Counterfactual Exercises

National Mask Mandate

The regression equation we estimate is:

$$\ln\left(\ln Y_{i,t}-\ln Y_{i,t-7}\right)=\alpha_i+\gamma_{i,e_t}+\lambda\ln\left(\ln Y_{i,t-7}-\ln Y_{i,t-14}\right)+\delta Mandate_{i,t-7}+\beta Mobility_{i,t-7}+error_{i,t},$$

where $Mandate_{i,t-7}$ is the mandate variable that enters in the regression and is a moving average of past mandate indicators.

Suppose a national mask mandate goes into effect at date T. Then, the counterfactual mandate variable is different as of date $T+7$: $\widehat{Mandate}_{i,t-7}\geq Mandate_{i,t-7}$ for all i and for $t\geq T+7$.

For the first seven days, the RHS variables are all predetermined and are the initial conditions of the projection.

$$\begin{aligned}
\ln\left(\ln Y_{i,T}\widehat{-}\ln Y_{i,T-7}\right) &= \alpha_i+\gamma_{i,e_T}+\lambda\ln\left(\ln Y_{i,T-7}-\ln Y_{i,T-14}\right)+\delta\widehat{Mandate}_{i,T-7}+\beta Mobility_{i,T-7}+error_{i,T}\\
\ln\left(\ln Y_{i,T+1}\widehat{-}\ln Y_{i,T-6}\right) &= \alpha_i+\gamma_{i,e_{T+1}}+\lambda\ln\left(\ln Y_{i,T-6}-\ln Y_{i,T-13}\right)+\delta\widehat{Mandate}_{i,T-6}+\beta Mobility_{i,T-6}+error_{i,T+1}\\
&\dots\\
\ln\left(\ln Y_{i,T+6}\widehat{-}\ln Y_{i,T-1}\right) &= \alpha_i+\gamma_{i,e_{T+6}}+\lambda\ln\left(\ln Y_{i,T-1}-\ln Y_{i,T-8}\right)+\delta\widehat{Mandate}_{i,T-1}+\beta Mobility_{i,T-1}+error_{i,T+6}
\end{aligned}$$

Starting with the predicted value for $\ln\left(\ln Y_{i,T+7}\widehat{-}\ln Y_{i,T}\right)$, the RHS value for lagged cases now comes from the first projected value.

$$\begin{aligned}
\ln\left(\ln Y_{i,T+7}\widehat{-}\ln Y_{i,T}\right) &= \alpha_i+\gamma_{i,e_{T+7}}+\lambda\ln\left(\ln Y_{i,T}\widehat{-}\ln Y_{i,T-7}\right)+\delta\widehat{Mandate}_{i,T}+\beta Mobility_{i,T}+error_{i,T+7}\\
&\dots\\
\ln\left(\ln Y_{i,T+k}\widehat{-}\ln Y_{i,T+k-7}\right) &= \alpha_i+\gamma_{i,e_{T+k}}+\lambda\ln\left(\ln Y_{i,T+k-7}\widehat{-}\ln Y_{i,T+k-14}\right)+\delta\widehat{Mandate}_{i,T+k-7}+\beta Mobility_{i,T+k-7}\\
&+ error_{i,T+k}
\end{aligned}$$

We can iterate forward in time to get the projected values of the dependent variable based on these equations.

Define $dep_{i,t}\equiv\ln\left(\ln Y_{i,t}-\ln Y_{i,t-7}\right)$. Given $\widehat{dep_{i,t}}$ computed in the preceding steps, we can compute $\widehat{Y}_{i,t}$ as:

$$\widehat{Y}_{i,t}=\exp\left(\exp\left(\widehat{dep_{i,t-7}}\right)\right)\widehat{Y_{i,t-7}}. \tag{6}$$

For dates $t=T,\ldots,T+6$, $\widehat{Y_{i,t-7}}=Y_{i,t-7}$. Thereafter, we can iterate forward to compute the projected total cases for $t\geq T+7$.

Note that we can express the difference between projected and actual total cases linearly as only a function of the coefficients, the residuals, and the mandates:

$$\widehat{dep}_{i,t} - dep_{i,t} \;=\; \lambda\left(\widehat{dep}_{i,t-7} - dep_{i,t-7}\right) + \delta\left(\widehat{Mandate}_{i,t-7} - Mandate_{i,t-7}\right),$$

where $\widehat{dep}_{i,t-7} - dep_{i,t-7} \equiv 0$ for $t = T, \ldots, T+6$.

For computing the standard errors of the projected totals, we use the delta method. Let $\hat{\Omega}$ be the variance-covariance matrix of the coefficient vector X. Then,

$$Var\left(\widehat{Y}_{i,t}\right) = G'_{i,t}\hat{\Omega}G_{i,t},$$

where $G_{i,t}$ is the gradient of $\widehat{Y}_{i,t}$ w.r.t. the coefficients. We can write each term within $G_{i,t}$ analytically using the expression

$$\widehat{Y}_{i,t} = \widehat{Y}_{i,t-7}\exp\left(\exp\left(\widehat{dep}_{i,t}\right)\right).$$

For any single coefficient x, we have the recursion

$$\begin{aligned}\frac{\partial \widehat{Y}_{i,t}}{\partial x} \;&=\; \frac{\partial \hat{Y}_{i,t-7}}{\partial x}\exp\left(\exp\left(\widehat{dep}_{i,t}\right)\right) \\ &\quad + \underbrace{\widehat{Y}_{i,t}\exp\left(\exp\left(\widehat{dep}_{i,t}\right)\right)}_{\widehat{Y}_{i,t-7}}\exp\left(\widehat{dep}_{i,t}\right)\frac{\partial \widehat{dep}_{i,t}}{\partial x},\end{aligned}$$

with the initial values for $t = T, \ldots, T+6$:

$$\frac{\partial \widehat{Y}_{i,t}}{\partial x} = Y_{i,t-7}\exp\left(\widehat{dep}_{i,t}\right)\frac{\partial \widehat{dep}_{i,t}}{\partial x}.$$

Note that $\frac{\partial \widehat{dep}_{i,t}}{\partial x}$ will be nonzero only for the coefficient λ and the coefficient of the independent variable that we are doing a counterfactual on (here, δ) because we can write

$$\frac{\partial \widehat{dep}_{i,t}}{\partial x} = \frac{\partial}{\partial x}\left(\widehat{dep}_{i,t} - dep_{i,t} + dep_{i,t}\right) = \frac{\partial}{\partial x}\left(\widehat{dep}_{i,t} - dep_{i,t}\right),$$

where we have from above that $\widehat{dep}_{i,t} - dep_{i,t}$ can be expressed as a function only of actual data, λ, and the coefficient on the relevant variable in the counterfactual.

In the case of the mask mandate, we have the recursions

$$\begin{aligned}
\frac{\partial \widehat{dep}_{i,t}}{\partial \lambda} &= \lambda \frac{\partial \widehat{dep}_{i,t-7}}{\partial \lambda} + \widehat{dep}_{i,t-7} - dep_{i,t-7} \\
\frac{\partial \widehat{dep}_{i,t}}{\partial \delta} &= \lambda \frac{\partial \widehat{dep}_{i,t-7}}{\partial \delta} + \widehat{Mandate}_{i,t-7} - Mandate_{i,t-7},
\end{aligned}$$

with the initial values for $t = T, \ldots, T+6$:

$$\begin{aligned}
\frac{\partial \widehat{dep}_{i,t}}{\partial \lambda} &= 0 \\
\frac{\partial \widehat{dep}_{i,t}}{\partial \delta} &= \widehat{Mandate}_{i,t-7} - Mandate_{i,t-7}.
\end{aligned}$$

Putting this all together:

$$\begin{aligned}
G_{i,t} &= \exp\left(\exp\left(\widehat{dep}_{i,t}\right)\right) G_{i,t-7} + \widehat{Y}_{i,t-7} exp\left(\widehat{dep}_{i,t}\right) D_{i,t} \\
D_{i,t} &= \lambda D_{i,t-7} + \begin{bmatrix} \widehat{dep}_{i,t-7} - dep_{i,t-7} \\ \widehat{Mandate}_{i,t-7} - Mandate_{i,t-7} \end{bmatrix} \\
& \text{where } D_{i,t} \equiv \begin{bmatrix} \frac{\partial \widehat{dep}_{i,t}}{\partial \lambda} \\ \frac{\partial \widehat{dep}_{i,t}}{\partial \delta} \end{bmatrix},
\end{aligned}$$

with the initial values for $t = T, \ldots, T+6$:

$$\begin{aligned}
G_{i,t} &= \widehat{Y}_{i,t-7} \exp\left(\widehat{dep}_{i,t}\right) D_{i,t}, \\
D_{i,t} &= \begin{bmatrix} 0 \\ \widehat{Mandate}_{i,t-7} - Mandate_{i,t-7} \end{bmatrix}.
\end{aligned}$$

Mobility Restriction

The mobility counterfactual that we consider is one in which, starting at a chosen date T, mobility in all states is fixed at its respective level as of date T. The computation of projected total cases under this mobility counterfactual is analogous to the national mask mandate counterfactual. The only difference is that in computing the projected value of the dependent variable, we work off of a $\widehat{Mobility}_{i,t-7}$ matrix, which keeps mobility for all states fixed at its respective levels at date T, while the mask mandates remain at their data values.

The standard errors can also be computed analogously as follows:

$$
\begin{aligned}
G_{i,t} &= \exp\left(\exp\left(\widehat{dep}_{i,t}\right)\right) G_{i,t-7} + \widehat{Y}_{i,t-7} exp\left(\widehat{dep}_{i,t}\right) D_{i,t} \\
D_{i,t} &= \lambda D_{i,t-7} + \begin{bmatrix} \widehat{dep}_{i,t-7} - dep_{i,t-7} \\ \widehat{Mobility}_{i,t-7} - Mobility_{i,t-7} \end{bmatrix} \\
& \quad \text{where } D_{i,t} \equiv \begin{bmatrix} \frac{\partial \widehat{dep}_{i,t}}{\partial \lambda} \\ \frac{\partial \widehat{dep}_{i,t}}{\partial \beta} \end{bmatrix},
\end{aligned}
$$

with the initial values for $t = T, \ldots, T+6$:

$$
\begin{aligned}
G_{i,t} &= \widehat{Y}_{i,t-7} \exp\left(\widehat{dep}_{i,t}\right) D_{i,t}, \\
D_{i,t} &= \begin{bmatrix} 0 \\ \widehat{Mobility}_{i,t-7} - Mobility_{i,t-7} \end{bmatrix}.
\end{aligned}
$$

National Mask Mandate with Higher Compliance

The regression equation we estimate is:

$$
\begin{aligned}
\ln\left(\ln Y_{i,t} - \ln Y_{i,t-7}\right) &= \alpha_i + \gamma_{i,e_t} + \lambda \ln\left(\ln Y_{i,t-7} - \ln Y_{i,t-14}\right) + \delta Mandate_{i,t-7} + \beta Mobility_{i,t-7} \\
&+ \eta Mandate_{i,t-7} \times Compliance_i + error_{i,t},
\end{aligned}
$$

Suppose a national mask mandate goes into effect at date T and compliance is set to a higher value from date T as well. Then, the counterfactual mandate variable is different as of date $T+7: \widehat{Mandate}_{i,t-7} \geq Mandate_{i,t-7}$ for all i and for $t \geq T+7$ while the $\widehat{Compliance}_i$ variable is different as of date T.

As before, for the first seven days, the RHS variables are all predetermined and are the initial conditions of the projection. Starting with the predicted value for $\widehat{\ln\left(\ln Y_{i,T+7} - \ln Y_{i,T}\right)}$, the RHS value for lagged cases from period $T+7$ comes from the first projected value. We can iterate forward in time to get the projected values of the dependent variable for all future periods.

As before, we can express the difference between projected and actual total cases linearly as only a function of the coefficients, the residuals, the mandates, and compliance:

$$\begin{aligned}\widehat{dep}_{i,t} - dep_{i,t} &= \lambda\left(\widehat{dep}_{i,t-7} - dep_{i,t-7}\right) + \delta\left(\widehat{Mandate}_{i,t-7} - Mandate_{i,t-7}\right) \\ &+ \eta\left(\widehat{Mandate}_{i,t-7} \times \widehat{Compliance}_i - Mandate_{i,t-7} \times Compliance_i\right),\end{aligned}$$

where $\widehat{dep}_{i,t-7} - dep_{i,t-7} \equiv \eta Mandate_{i,t-7}\left(\widehat{Compliance}_i - Compliance_i\right)$ for $t = T, \ldots, T+6$.

For computing the standard errors of the projected totals, we use the delta method. Let $\hat{\Omega}$ be the variance-covariance matrix of the coefficient vector X. Then,

$$Var\left(\widehat{Y}_{i,t}\right) = G'_{i,t}\hat{\Omega}G_{i,t},$$

where $G_{i,t}$ is the gradient of $\widehat{Y}_{i,t}$ w.r.t. the coefficients. We can write each term within $G_{i,t}$ analytically using the expression

$$\widehat{Y}_{i,t} = \widehat{Y}_{i,t-7}\exp\left(\exp\left(\widehat{dep}_{i,t}\right)\right).$$

For any single coefficient x, we have the recursion

$$\begin{aligned}\frac{\partial\widehat{Y}_{i,t}}{\partial x} &= \frac{\partial\hat{Y}_{i,t-7}}{\partial x}\exp\left(\exp\left(\widehat{dep}_{i,t}\right)\right) \\ &+ \underbrace{\widehat{Y}_{i,t}\exp\left(\exp\left(\widehat{dep}_{i,t}\right)\right)}_{\widehat{Y}_{i,t-7}}\exp\left(\widehat{dep}_{i,t}\right)\frac{\partial\widehat{dep}_{i,t}}{\partial x},\end{aligned}$$

with the initial values for $t = T, \ldots, T+6$:

$$\frac{\partial\widehat{Y}_{i,t}}{\partial x} = Y_{i,t-7}\exp\left(\widehat{dep}_{i,t}\right)\frac{\partial\widehat{dep}_{i,t}}{\partial x}.$$

Note that $\frac{\partial\widehat{dep}_{i,t}}{\partial x}$ will be nonzero only for the coefficient λ and the coefficient of the independent variable that we are doing a counterfactual on (here, δ and η) because we can write

$$\frac{\partial\widehat{dep}_{i,t}}{\partial x} = \frac{\partial}{\partial x}\left(\widehat{dep}_{i,t} - dep_{i,t} + dep_{i,t}\right) = \frac{\partial}{\partial x}\left(\widehat{dep}_{i,t} - dep_{i,t}\right),$$

where we have from above that $\widehat{dep}_{i,t} - dep_{i,t}$ can be expressed as a function only of actual data, λ, and the coefficient on the relevant variable(s) in the counterfactual.

In the current case of a national mask mandate and higher compliance, we have the recursions

$$\begin{aligned}
\frac{\partial \widehat{dep}_{i,t}}{\partial \lambda} &= \lambda \frac{\partial \widehat{dep}_{i,t-7}}{\partial \lambda} + \widehat{dep}_{i,t-7} - dep_{i,t-7} \\
\frac{\partial \widehat{dep}_{i,t}}{\partial \delta} &= \lambda \frac{\partial \widehat{dep}_{i,t-7}}{\partial \delta} + \widehat{Mandate}_{i,t-7} - Mandate_{i,t-7} \\
\frac{\partial \widehat{dep}_{i,t}}{\partial \eta} &= \lambda \frac{\partial \widehat{dep}_{i,t-7}}{\partial \eta} + \widehat{Mandate}_{i,t-7} \times \widehat{Compliance}_i - Mandate_{i,t-7} \times Compliance_i.
\end{aligned}$$

with the initial values for $t = T, \ldots, T+6$:

$$\begin{aligned}
\frac{\partial \widehat{dep}_{i,t}}{\partial \lambda} &= 0 \\
\frac{\partial \widehat{dep}_{i,t}}{\partial \delta} &= \widehat{Mandate}_{i,t-7} - Mandate_{i,t-7} \\
\frac{\partial \widehat{dep}_{i,t}}{\partial \eta} &= \widehat{Mandate}_{i,t-7} \times \widehat{Compliance}_i - Mandate_{i,t-7} \times Compliance_i.
\end{aligned}$$

Putting this all together:

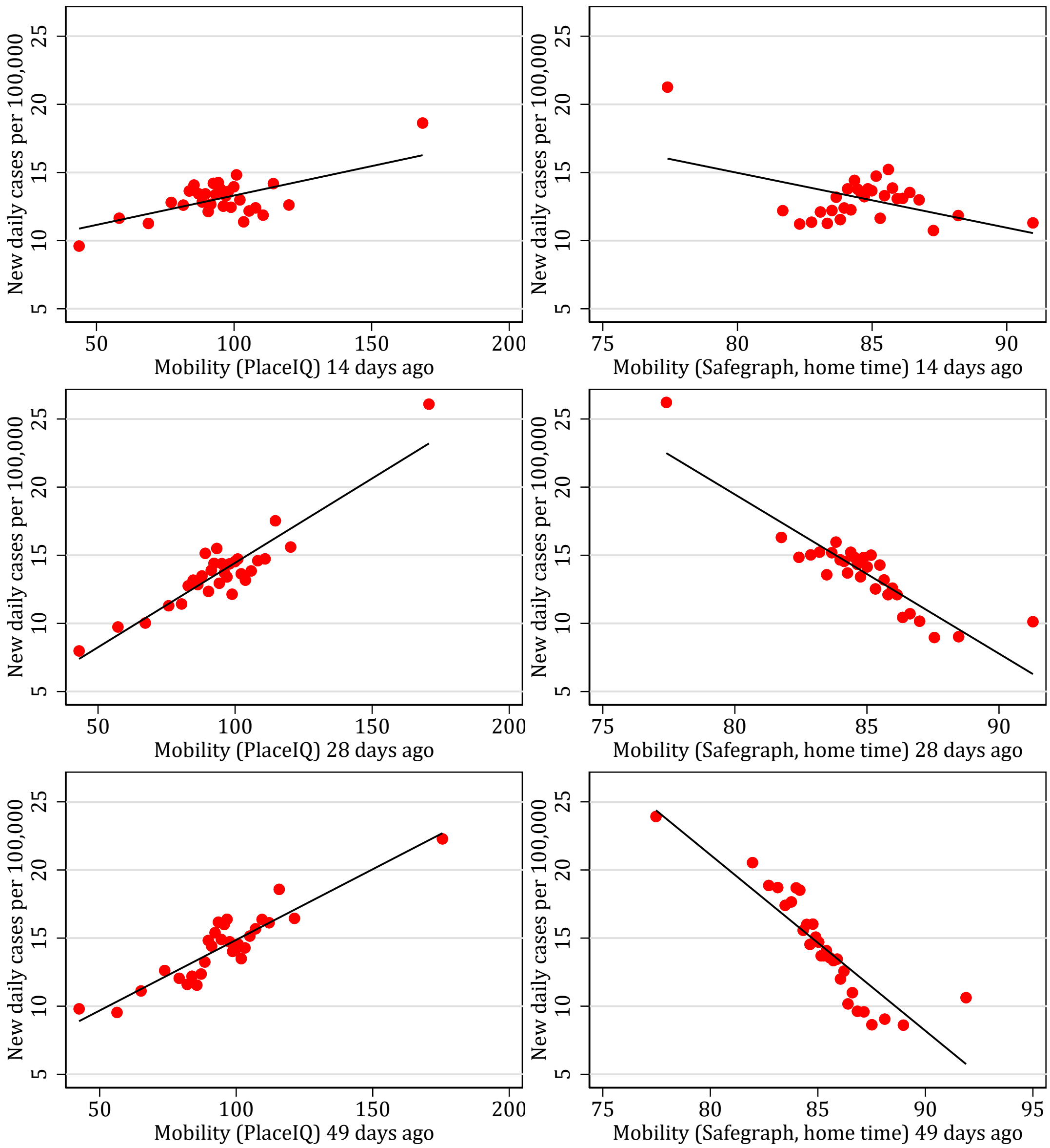
$$\begin{aligned}
G_{i,t} &= \exp\left(\exp\left(\widehat{dep}_{i,t}\right)\right) G_{i,t-7} + \widehat{Y}_{i,t-7} exp\left(\widehat{dep}_{i,t}\right) D_{i,t} \\
D_{i,t} &= \lambda D_{i,t-7} + \begin{bmatrix} \widehat{dep}_{i,t-7} - dep_{i,t-7} \\ \widehat{Mandate}_{i,t-7} - Mandate_{i,t-7} \end{bmatrix} \\
&\quad \text{where } D_{i,t} \equiv \begin{bmatrix} \frac{\partial \widehat{dep}_{i,t}}{\partial \lambda} \\ \frac{\partial \widehat{dep}_{i,t}}{\partial \delta} \\ \frac{\partial \widehat{dep}_{i,t}}{\partial \eta} \end{bmatrix},
\end{aligned}$$

with the initial values for $t = T, \ldots, T+6$:

$$\begin{aligned}
G_{i,t} &= \widehat{Y}_{i,t-7} \exp\left(\widehat{dep}_{i,t}\right) D_{i,t}, \\
D_{i,t} &= \begin{bmatrix} 0 \\ \widehat{Mandate}_{i,t-7} - Mandate_{i,t-7} \\ \widehat{Mandate}_{i,t-7} \times \widehat{Compliance}_i - Mandate_{i,t-7} \times Compliance_i \end{bmatrix}.
\end{aligned}$$

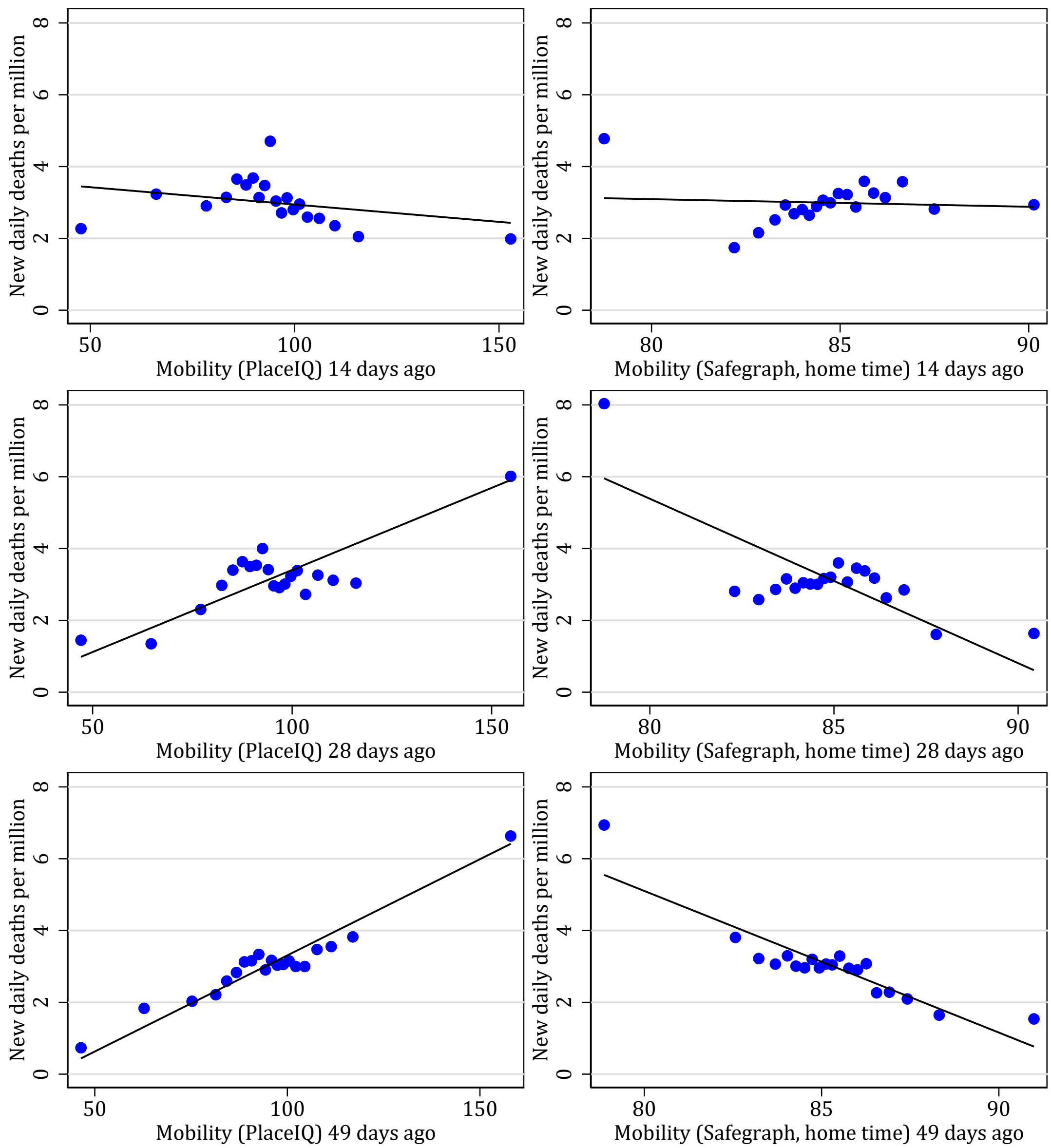
A.4 Additional Figures

Figure A.1. State-Level Relationship between Lagged Mobility and Cases



Notes: Cases and mobility are averaged over a 7-day period. Binned scatter plots controlling for state fixed effects and epidemic-time fixed effects (time relative to reaching 5 deaths per 1 million in a state).

Figure A.2. State-Level Relationship between Lagged Mobility and Deaths



Notes: Deaths and mobility are averaged over a 7-day period. Binned scatter plots controlling for state fixed effects and epidemic-time fixed effects (time relative to reaching 5 deaths per 1 million in as state).