The Impact of Government Interventions on COVID-19 Spread and Consumer Spending

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Abstract.
We examine the impact of government interventions on the spread of COVID-19 and consumer spending. We do this by first estimating models of COVID-19 spread, consumer spending, and social distancing in the United States during the early stages of the COVID-19 pandemic. Social distancing has a large effect on reducing COVID-19 spread, and is responsive to national and local case numbers. Non-mask government interventions reduce COVID-19 spread, while the effectiveness of mask mandates is much smaller and statistically insignificant. Mask mandates tend to increase social distancing, as do non-mask governmental restrictions as a whole. Social distancing hurts spending in the absence of a mask mandate, but has a negligible effect on spending if there is a mask mandate. Mask mandates have a direct effect of increasing spending in counties with high levels of social distancing, while reducing spending in counties with low levels of social distancing. We use these three estimated models to calculate the effect of mask mandates and other governmental interventions on COVID-19 cases, deaths and consumer spending. Implemented mask mandates decreased COVID-19 cases by a statistically insignificant 750,000 cases, saving 27,000 lives, over a 4-month period, but led to $150B of additional consumer spending. Other non-mask governmental interventions that were implemented reduced the number of COVID-19 cases by 34M, saving 1,230,000 lives, while reducing consumer spending by approximately $703B over our 4-month period of the study. Thus, these restrictions were cost effective as long as one values each saved life at $579,000 or more.

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1. Introduction

COVID-19 has been a disruptive force throughout the world. As of February 24, 2022, there have been 429M confirmed cases worldwide, and almost 78M confirmed cases in the US; Almost 6M people have died, including over 930,000 deaths in the US.[1] Furthermore, the pandemic has devastated the worldwide economy (International Monetary Fund 2020) and pressed the US economy into a recession (National Bureau of Economics Research 2020). While the impact of COVID-19 has been significant, there is uncertainty about how much masking policies and government Non-Pharmaceutical Interventions (closing public venues, closing non-essential venues, closing schools, imposing shelter-in-place restrictions, limiting the sizes of gatherings, and limiting religious gatherings – henceforth collectively referred to as NPIs) have affected the spread of COVID-19, social distancing, and the level of consumer spending.

We address these questions by first measuring the impact of social distancing, mask mandates, and NPIs on the spread of COVID-19. We show that social distancing reduces the spread of COVID-19, while mask mandates only have a statistically insignificant effect on reducing the spread of COVID-19. We also show that some NPI policies slow the spread of COVID-19.

We then examine the effects of mask mandates and NPIs on social distancing levels. Consistent with Seres et al. (2020) and Marchiori (2020), we find that mask mandates increase the level of social distancing, as do non-mask governmental NPIs as a whole. Further, social distancing increases as COVID-19 cases and growth rates increase nationally, but the impact of local cases is smaller.

[1] World Health Organization COVID-19 Dashboard, https://covid19.who.int. Accessed on February 24, 2022.

We also evaluate the impact of mask mandates and NPIs on spending. Our largest finding is that mask mandates can undo the negative impact of social distancing, but non-mask NPIs decrease consumer spending.

Finally, we compare the amount of COVID-19 spread and spending that would have occurred if (1) none of the counties had a mask mandate instead of the mask mandates that were actually implemented, and (2) none of the counties introduced NPIs instead of the NPIs that were actually imposed. We find that the mask mandates that were implemented saved a statistically insignificant 27,000 lives and increased consumer spending by $150B over the 4-month time period we study. Thus, mask mandates are likely both pro-health and pro-business. In the case of government NPIs, we see a tradeoff between lives saved and consumer spending. Over the 4-month time period of our study, the implemented NPIs saved 1,230,000 lives but reduced consumer spending by approximately $700B. The cost of each life saved was around $579,000, which was a worthwhile cost according to most estimates of values for lives.

The paper is organized as follows. Section 2 discusses the data we use for the analysis. Section 3 presents the model and estimation for the spread of COVID-19. Section 4 examines shifters of social distancing. Section 5 presents the model and estimation for consumer spending. Section 6 presents the counterfactual analysis of how contagion and spending are affected by the different interventions. Finally, Section 7 concludes.

2. Data

Our analysis covers a four-month period from April 1, 2020 – July 31, 2020. We begin our analysis on April 1 because by then most of the country was affected by COVID-19 and a large fraction of the county had already began social distancing. While one may want to contrast shopping or distancing behaviors before vs. after COVID-19 began, there was likely an unobservable structural break between the way people shopped and socially distanced before COVID-19 compared to what they did during the COVID-19 pandemic; we are unlikely to be able to capture this structural break within our model. We choose the end date for our analysis because our data on government NPIs end at this time.

Our data come from a number of sources. Our data on the number of daily confirmed cases for 3055 U.S. counties or country-equivalents come from the New York Times. Note that in this dataset the numbers are diagnosed cases on a given day. COVID-19 has an average incubation period of 5 days (Lauer et al. 2020; Li et al. 2020). We are also informed by local health officials that there was, on average, a 5-day gap between the onset of a patient's symptoms and the final diagnosis result during the timeframe we study. Accordingly, we assume the infection date of a case occurs 10 days before it is reported by the New York Times. Thus, we assume that the cases that were reported on April 11, 2020 actually occurred on April 1, 2020.

Our demographic data come from the Census Bureau's 2014-2018 American Community Survey. Our weather data come from the National Oceanic and Atmospheric Administration. These variables, as well as a full description of each variable, and the computer codes we use in this paper, can be found at this website: https://tinyurl.com/2z7k5r5x.

We supplement these public data with a few other data sources. Our social distancing data come from SafeGraph. SafeGraph collects cellphone GPS location data from a panel of cellphone users when a set of installed apps are used. While the data are proprietary, they are available free of charge to academics studying COVID-19 (https://www.safegraph.com/covid-19-

data-consortium). We create a social distancing index using a Principal Component Analysis (PCA) of four metrics: the percentage of residents staying home, the percentage of residents working full-time at their workplace, the percentage of residents working part-time at their workplace, and the median duration that residents stay home. The resulting first principal component of the PCA is negatively correlated with the percentage of people staying home and the duration that people stay home, and positively correlated with the two work metrics. To make sure the social distancing index is more numerically intuitive, we define the negative of this first principal component as the social distancing index so that a higher index corresponds to a greater level of social distancing.

Ultimately, the fitted social distancing index is SocialDistIndex = 0.53FractStayHome – 0.51FullTimeWork – 0.61PartTimeWork + 0.31StayHomeDuration, where the four right-hand-side variables have been demeaned, and stay-home duration is defined in terms of minutes.[2] These four variables are significantly correlated. In particular, the correlation between the percentage of residents staying home full-time and the stay-home duration is 0.39. The correlations between the percentage of residents staying home full-time and percentages of residents working full-time or part-time are -0.56 and -0.68, respectively. Intuitively, the index says that social distancing increases as more people stay at home, and people spend a greater percentage of their time at their homes, while social distancing decreases as people spend more time at work.

The SafeGraph data are supplied at the daily level for residents of each Census Block Group. We aggregate this index to the county level by taking the weighted median, where the

[2] See https://tinyurl.com/2z7k5r5x for more details.

weights are the number of cellphones in the data at each Census Block Group. We run some of our analysis at a weekly level. In that case, we average our measure across the corresponding 7 days from Tuesday to Monday.

Our spending data are provided by https://tracktherecovery.org/. These data are made publicly available by Opportunity Insights and have been collected from a number of sources. Chetty et al. (2020) provide a detailed summary of the variables in the dataset. We use the consumer spending data that come from consumer credit card and debit card purchases originally supplied by Affinity Solutions. The spending data are at the county-daily level for 1685 counties. These counties account for 87% of the population of the 3055 counties in our COVID-19 case data. This dataset is smoothed over 7-day periods, and we use the Tuesday iteration of this measure to track aggregate weekly spending. Each observation measures the seasonally adjusted change relative to the January 2020 index period,[3] which we refer to as the consumer spending recovery index.

Facial mask mandate data come from three sources. The first source is Wright et al. (2020), who collect county-level facial mask mandate information. We compile a second dataset from online sources for state-level facial mask mandates.[4] Third, we use data on employee mask mandates for businesses, which are collected by Lyu and Wehby (2020). We define the mask mandate to be 1 on any date where either the county or the state has a mask mandate (regardless of whether it is for the public or only for employees of businesses).

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[3] $\frac{\left(\frac{Spending(Date\ 2020)}{Spending(January\ 2020)}\right)}{\left(\frac{Spending(Date\ 2019)}{Spending(January\ 2019)}\right)} - 1$. See Chetty et al. (2020) for more details.

[4] See https://www.littler.com/publication-press/publication/facing-your-face-mask-duties-list-statewide-orders and https://www.cnn.com/2020/06/19/us/states-face-mask-coronavirus-trnd/index.html. Accessed on October 28, 2020.

Finally, we obtain other COVID-19 NPI policy data from the company Keystone Strategy, which contain exact dates of each NPI restriction in each county when the restriction was in effect.[5] We focus on 6 common restrictions: shelter-in-place orders, closing of public schools, closing of public venues, closing non-essential businesses, limiting large gatherings, and limiting religious gatherings.

We provide a summary of all variables used in our analyses in Table 1.

Table 1: Summary Statistics

	mean	sd	min	max
Temperature ($^\circ F$)	59.942	3.411	-3.847	97.396
Humidity (%)	67.619	15.494	0.409	100.000
Precipitation ($inch$)	0.100	0.157	0.000	1.010
Social distancing	0.630	1.010	-5.756	5.128
Mask mandates	0.500	0.500	0.000	1.000
Closing of public venues	0.571	0.495	0.000	1.000
Closing of non-essential businesses	0.524	0.499	0.000	1.000
Closing of schools	0.855	0.352	0.000	1.000
Shelter in place	0.443	0.497	0.000	1.000
Gathering size limits	0.754	0.431	0.000	1.000
Religious gathering limits	0.370	0.483	0.000	1.000
Local week-over-week growth rate in cases	0.200	3.979	-1.000	906.000
National week-over-week growth rate in cases	0.126	0.275	-0.139	1.395
Local cases in the past 7 days per 1000 people	0.523	1.214	0.000	115.385
National cases in the past 7 days per 1000 people	0.727	0.327	0.413	1.414
Consumer spending recovery index: total spending	-0.112	0.165	-1.370	0.724
Log(pop. density)	3.884	1.692	-1.313	11.183
Frac. of Black	0.093	0.146	0.000	0.874
Trump 2020 vote share	0.647	0.160	0.054	0.962

[5] See https://www.keystonestrategy.com/coronavirus-covid19-intervention-dataset-model/, accessed on May 15, 2021.

3. The Spread of COVID-19

We begin our analysis by estimating a model of COVID-19 spread as a function of social distancing, mask mandates, and other NPIs. Our estimation is based on a standard Susceptible-Infected-Recovered (SIR) model. The SIR model is widely used in predicting the contagion of infectious diseases (e.g., Adda 2016), including COVID-19 (Chinazzi et al. 2020, Kissler et al. 2020, Liu et al. 2020).

Mathematically, we consider that new infections, $y_{i,t}$, in a given county i on date t follow the following process:

$$y_{i,t} \;=\; R_{i,t}\, S_{i,t}\big(Y_{i,t-2} - Y_{i,t-8}\big) \tag{1}$$

where $R_{i,t}$ is the rate of infection and $S_{i,t}$ is the percentage of population in county i who have not contracted the disease. $Y_{i,t}$ represents the cumulative cases in county i by date t and, accordingly, the term of $Y_{i,t-2} - Y_{i,t-8}$ accounts for individuals who were infected between 7 days and 2 days before date t. Our assumption of a 6-day infectious period, during which the infected individuals can further spread the disease, follows the literature (Nishiuram et al. 2020). As a result, $Y_{i,t-2} - Y_{i,t-8}$ represents the infectious population who may directly cause infections on date t. The assumption of the length of the infectious period has little impact on the estimation results; Liu et al. (2020) shows that using a 14-day infectious period (i.e., $Y_{i,t-2} - Y_{i,t-16}$) vs. a 6-day infectious period yield extremely similar simulated forecasts.

The rate of spread of COVID-19 might change over locations and time. Thus, we model $R_{i,t}$ to vary with multiple factors:

$$R_{i,t} \;=\; exp\,(\,\alpha_i \;+\; \beta_t \;+\; \mu' X_{i,t} \;+\; e_{i,t}\,) \tag{2}$$

where α_i and β_t are county fixed effects and date fixed effects, respectively. $X_{i,t}$ includes average temperature, humidity, the social distancing index, an indicator variable denoting the presence of a mask mandate, a set of indicators for each NPI policy. Further, we include interactions between social distancing and the mask mandate, as well as allowing social distancing, mask mandates, and the NPIs to have heterogeneous effects based on the fraction of the population that is Black, the log of the population density, and the fraction of the population that voted for Trump in 2020.[6] The Black population has been disproportionately hit harder by COVID-19 than other racial groups (see, e.g., Chowkwanyun and Reed 2020). Population density is related to COVID-19 spread because the number of people one is exposed to varies across urban vs. rural areas. Similarly, population density could affect the impact of government interventions, both because the extent to which these interventions reduce contact is affected by baseline interaction rates, and because people in high population-density areas may self-distance more even in the absence of government orders since they perceive that they are getting more exposure to COVID-19. Finally, President Trump repeatedly mocked mask mandates and other governmental NPIs, perhaps in an attempt to keep the economy running. It is feasible, then, that supporters of Trump may respond differently to mask mandates or other governmental interventions based on their perception about the importance of these mandates. These different perceptions may also be shaped by the different media Trump supporters and Trump non-supporters watch (Simonov et al. 2020).

Finally, we assume that the true number of cases is 5 times the number of diagnosed cases. We choose this scaling factor according to Phipps et al. (2020), which shows that the

[6] Acemoglu et al. (2020) and Gomes et al. (2020) show the importance of including heterogeneity in SIR models.

detection rate of COVID-19 was about 20% in the US by the end of August 2020. This assumption only affects $S_{i,t}$, the fraction of people in the county that have not yet had COVID-19 and are assumed to remain susceptible, and the scaling of the fixed-effects parameters from the SIR regression (which are 5 times larger than they would be if we used only reported cases).[7] We use reported cases everywhere else in the paper: for the social distancing and spending models. Also, we divide the number of cases obtained from the model by 5 before reporting the case numbers and before feeding these case numbers into the social distancing or spending models during the simulations in Section 6. Thus, the numbers in Section 6 are comparable to the reported numbers of cases and deaths.

We estimate the case model by taking the logarithm of both sides of equation 1, and rearranging. Occasionally, $y_{i,t}$ are 0 for some counties on certain dates. To assure $ln(y_{i,t})$ is well defined, we add 1 to each observation of daily county cases, as well as to the number of infectious individuals. After rearranging, we have

$$\left[ln\left(y_{i,t}+1\right)-ln\left(S_{i,t}\right)-\ ln\left(Y_{i,t-2}-Y_{i,t-8}+1\right)\right]=\ \alpha_i+\beta_t+\mu' X_{i,t}+e_{i,t}. \tag{3}$$

We call the left-hand side of this equation the log of the reproduction ratio.

Note that social distancing, mask mandates, or NPIs may be endogenous because they can be affected by the severity of the pandemic. To address such endogeneity, we use a two-staged least squares approach, where we instrument for the social distancing, mask mandates and other non-mask government NPIs with the interactions of week dummies and dummies indicating the party composition of the state government, which we define by 4 variables

[7] We consider a robustness check by setting the scaling factor between actual and reported cases as 10 or 1. These alternative assumptions have little impact on the magnitudes of other variables than the fixed effects.

indicating the party of the state's governor, as well as whether both houses of the legislature are also controlled by the same party.[8] These partisan outcomes were determined before the presence of COVID-19, and likely affect the policies that the government implemented. However, because we also include the county-level vote share for Trump in 2020 (which has a 98% correlation with the Trump vote share in 2016), the state-level partisan composition should not predict the local behavioral responses to the government policies conditional on the level of the local vote shares. As a second set of instrumental variables, we also use week dummies interacting with the vote share that Trump received in 2016 for the Designated Market Area (DMA) in which a given county sits, which should influence the slant of the media that all counties in that DMA receive but is orthogonal to each county's severity of the pandemic. In that sense, the vote share in a given DMA can be interpreted as a preference-externality-style instrumental variable (Waldfogel 2003, Thomas 2020, Li et al. 2020). We use the 2016 vote share for Trump to ensure that this instrument is not influenced by COVID or the government's response to COVID. However, the vote share for Trump in 2016 should be correlated with the media slant that people in that market receive. Note that there can be quite a variety in Trump's vote share across counties within each DMA, so the impact of political preferences on behavior is still identified. We also include instruments consisting of the interactions between county demographics (percentage Black, Trump 2020 vote share, and the log(population density) and both the dummies about which party controls the state government and the DMA Trump vote shares.[9]

[8] The 4 dummy variables are then: Democrat governor with Democrat legislature; Democrat governor with at least one legislative branch controlled by the GOP; GOP governor with at least one legislative branch controlled by the Democrats; GOP governor with GOP legislature. We thank an anonymous reviewer for this suggestion.

[9] The F-statistics of first-stage regressions appear in the appendix: See Table A1 for the SIR model, Table A2 for the Social Distancing model, and Table A3 for the Spending model. The corresponding IV-induced incremental R-squared of the first-stage regressions are reported at https://tinyurl.com/2z7k5r5x.

Table 2 presents the estimation results.[10] We note that we have demeaned each of the demographic variables (percent of Black residents, log population density, and Trump's vote share) in order to make the main effects on social distancing, mask mandates and NPIs easier to interpret. We observe that social distancing lowers the transmission rate substantially. It is harder to interpret the impact of masking, since the social distancing variable is not demeaned: if we add the coefficient for the mask mandate with the product of the interaction coefficient and the mean of social distancing (0.63), we find that, on average, masks slightly decrease the transmission rate (i.e., 0.062 – 0.076*0.63 = -0.014), although this effect is far from statistically significant. We also observe that mask mandates are most effective in areas with a higher level of Trump support, perhaps because many people in these areas might not mask except when they are required to do so.

We find that, on the whole, other government interventions (i.e., NPIs) reduce the spread of COVID-19. While several of the coefficients on individual non-mask NPIs are statistically significant, the lack of significance, or even positive coefficients, of the other NPIs may partially be due to the high correlation between these variables.[11] It is hard to observe a consistent pattern with the interaction effects.

[10] We asses goodness of instruments by reporting overidentification, underidentification and Kleibergen Paap weak instrument statistic (robust for heteroskedasticity) in each of the tables.
[11] The pairwise correlations between the 6 NPI policies range from 0.18 to 0.75, with a median correlation of 0.43.

Table 2: Standard SIR Model

	Dependent variable: Log(Reproduction Ratio)		
Independent Var.	Estimates/S.E.	Independent Var. Cont'd	Estimates/S.E. Cont'd
Temperature ($^\circ F$)	-0.002	Closing of public venues	-0.367***
	(0.001)	×Log(pop. density)	(0.054)
Humidity (%)	0.004***	Closing of public venues	0.524
	(0.001)	×Frac. of Black	(0.547)
Social distancing	-0.433***	Closing of public venues	-2.125***
	(0.090)	×Trump 2020 vote share	(0.584)
Mask Mandates	0.062	Closing of non-essential businesses	0.053
	(0.063)	×Log(pop. density)	(0.053)
Social distancing×Mask mandates	-0.076	Closing of non-essential businesses	4.238***
	(0.066)	×Frac. of Black	(0.883)
Closing of public venues	0.100	Closing of non-essential businesses	1.443**
	(0.081)	×Trump 2020 vote share	(0.688)
Closing of non-essential businesses	0.056	Closing of schools	-0.194***
	(0.099)	×Log(pop. density)	(0.048)
Closing of schools	-0.274***	Closing of schools	-1.595*
	(0.106)	×Frac. of Black	(0.962)
Shelter in place	-0.072	Closing of schools	0.662
	(0.081)	×Trump 2020 vote share	(0.569)
Gathering size limits	-0.271***	Shelter in place	0.009
	(0.093)	×Log(pop. density)	(0.039)
Religious gathering limits	-0.333***	Shelter in place	-0.863**
	(0.088)	×Frac. of Black	(0.359)
Social distancing	0.072***	Shelter in place	-0.243
×Log(pop. density)	(0.015)	×Trump 2020 vote share	(0.488)
Social distancing	0.120	Gathering size limits	0.047
×Frac. of Black	(0.169)	×Log(pop. density)	(0.052)
Social distancing	0.850***	Gathering size limits	-4.856***
×Trump 2020 vote share	(0.193)	×Frac. of Black	(1.014)
Mask Mandates	0.017	Gathering size limits	-1.058
×Log(pop. density)	(0.027)	×Trump 2020 vote share	(0.865)
Mask Mandates	0.614*	Religious gathering limits	0.329***
×Frac. of Black	(0.314)	×Log(pop. density)	(0.057)
Mask Mandates	-0.660**	Religious gathering limits	-3.167***
×Trump 2020 vote share	(0.307)	×Frac. of Black	(0.826)
		Religious gathering limits	0.107
		×Trump 2020 vote share	(0.593)
Observations	372,710	Overidentification statistic	720.095
R^2	0.16	Underidentification statistic	1442.731
County FE	YES	Kleibergen Paap weak instrument statistic	14.459
Date FE	YES		
Estimation period	4/1-7/31		

Note: Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

4. Determinants of Social Distancing

We next estimate the following model to understand how government interventions affect social distancing:

$$d_{i,t} = \alpha_i + \beta_{dow(t)} + \rho_{w(t)} + \delta\, q_{i,t} + \varphi\, p_t + \mu\, m_{i,t} + \theta\, c_{i,t} + \lambda' X_{i,t} + \zeta_{i,t} \qquad (4)$$

where $d_{i,t}$ is the social distancing index of county i on date t, as defined in section 2. α_i, $\beta_{dow(t)}$ and $\rho_{w(t)}$ are county, day-of-the-week and week fixed effects, respectively. $q_{i,t}$ and p_t represent the county and national confirmed cases per 1000 people in the past seven days and week-over-week growth rate in the number of confirmed cases, respectively.[12] $m_{i,t}$ is the average temperature (in Fahrenheit), $c_{i,t}$ is the average precipitation (in inches), $X_{i,t}$ consists of a string of binary indicator variables of COVID-19 related public orders: the mask mandates and other NPIs, as well as interactions between these variables and the fraction of the population that is Black, the log of the population density, and the share of the vote Trump received in 2020.

Some readers may wonder why we use day-of-the-week fixed effects and week fixed effects instead of date fixed effects. We do this so that we can measure how national case numbers, which are constant across locations on any date, affect social distancing. We also show that using date fixed effects does not change the other estimates.

Because mask mandates and NPIs may be correlated with the same factors that affect social distancing, we run two-staged least squares using the same state-level party control status of the government and DMA-level voter preference instruments that we used in Section 3. The logic behind these instruments is also equivalent to the logic laid out in Section 3.

[12] We define local or national week-over-week growth rate in the confirmed cases as:
(total confirmed cases in the past 1-7 days)/(total confirmed cases in the past 8-14 days+1)-1

The results are in Table 3. Column 1 presents our preferred specification, with day-of-the-week and week fixed effects rather than date fixed effects, which allows us to estimate the impact of both national and local COVID-19 cases on social distancing. This is especially important for the counterfactual analysis in Section 6, where we want to account for how social distancing changes with the progression of the pandemic. Column 2 shows the same estimation with date fixed effects but having the national case numbers dropped from the regression. We observe that using the day-of-the-week and week fixed effects instead of date fixed effects does not change any of the estimated parameters in a meaningful way.

We find that social distancing increases when cases of COVID-19 are high and increasing. The coefficient is much larger for national cases, likely reflecting the attention COVID-19 receives in the press. That said, there is a lot more variation in local breakouts, and when there is a strong local breakout of cases, this will lead to substantially more social distancing.[13] Mask mandates increase social distancing, and the non-mask government NPIs as a whole also increase distancing. The positive impact of mask mandates on social distancing likely come from the masks serving as a reminder to increase distancing, consistent with Seres et al. (2020) and Marchiori (2020). Trump-supporting areas socially distance less in the presence of mask mandates, perhaps as a protest counter-reaction.

[13] While we believe that the estimates reflect the real tradeoff of local vs. national cases, it is also the case that there is more measurement error (in percentage terms) in local cases. Thus, we cannot rule out that some of this difference in the estimates is due to attenuation bias.

Table 3: Social Distancing Model

	Dependent variable: Social Distancing				
Independent Var.	(1) Estimates/S.E.	(2) Estimates/S.E.	Independent Var. Cont'd	(1) Estimates/S.E. Cont'd	(2) Estimates/S.E. Cont'd
Local week-over-week	-0.0001	0.0001	Closing of public venues	0.084***	0.085***
growth rate in cases	-0.0002	(0.0002)	×Log(pop. density)	(0.031)	(0.031)
National week-over-week	0.074***		Closing of public venues	0.655**	0.636**
growth rate in cases	(0.009)		×Frac. of Black	(0.270)	(0.269)
Local cases in the past 7 days	0.022***	0.022***	Closing of public venues	0.169	0.172
per 1000 people	(0.005)	(0.005)	×Trump 2020 vote share	(0.317)	(0.314)
National cases in the past 7 days	0.105***		Closing of non-essential	0.005	0.007
per 1000 people	(0.024)		businesses×Log(pop. density)	(0.029)	(0.029)
Precipitation ($inch$)	0.067***	0.068***	Closing of non-essential	1.062**	1.038**
	(0.002)	(0.002)	businesses×Frac. of Black	(0.415)	(0.416)
Temperature ($^\circ F$)	-0.003***	-0.004***	Closing of non-essential	0.346	0.277
	-0.0002	(0.0005)	businesses×Trump 2020 vote share	(0.346)	(0.348)
Mask mandates	0.089***	0.089***	Closing of schools	0.105***	0.109***
	(0.019)	(0.018)	×Log(pop. density)	(0.028)	(0.028)
Closing of public venues	0.026	0.031	Closing of schools	0.140	0.188
	(0.042)	(0.041)	×Frac. of Black	(0.574)	(0.578)
Closing of non-essential	-0.121**	-0.127**	Closing of schools	-1.876***	-1.837***
businesses	(0.058)	(0.058)	×Trump 2020 vote share	(0.413)	(0.412)
Closing of schools	0.280***	0.287***	Shelter in place	0.072***	0.073***
	(0.061)	(0.061)	×Log(pop. density)	(0.024)	(0.024)
Shelter in place	0.366***	0.367***	Shelter in place	-0.593***	-0.538***
	(0.043)	(0.043)	×Frac. of Black	(0.178)	(0.177)
Gathering size limits	-0.166***	-0.171***	Shelter in place	0.124	0.220
	(0.051)	(0.050)	×Trump 2020 vote share	(0.289)	(0.289)
Religious gathering limits	0.065	0.068	Gathering size limits	-0.047	-0.050
	(0.045)	(0.045)	×Log(pop. density)	(0.033)	(0.033)
Mask mandates	-0.010	-0.009	Gathering size limits	-0.746	-0.731
×Log(pop. density)	(0.010)	(0.010)	×Frac. of Black	(0.536)	(0.531)
Mask mandates	-0.043	-0.038	Gathering size limits	2.021***	2.014***
×Frac. of Black	(0.123)	(0.124)	×Trump 2020 vote share	(0.563)	(0.556)
Mask mandates	-0.211*	-0.197*	Religious gathering limits	0.004	-0.002
×Trump 2020 vote share	(0.111)	(0.110)	×Log(pop. density)	(0.024)	(0.024)
			Religious gathering limits	-1.862***	-1.857***
			×Frac. of Black	(0.380)	(0.380)
			Religious gathering limits	-0.174	-0.202
			×Trump 2020 vote share	(0.266)	(0.264)
Observations	372,710	372,710	Overidentification statistic	1644.631	1640.408
R^2	0.79	0.81	Underidentification statistic	1545.917	1538.885
County FE	YES	YES	Kleibergen Paap weak instrument statistic	26.916	28.103
Day-of-week FE	YES	NO			
Week FE	YES	NO			
Date FE	NO	YES			
Estimation period	4/1-7/31	4/1-7/31			

Note: Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

5. Determinants of Consumer Spending

In this section, we investigate how social distancing and government interventions affect consumer spending. For this analysis, our data are provided in a format where the dependent variables are smoothed over 7 days, as described in Chetty et al. (2020). Given this smoothing, we estimate the model at the weekly level, with weeks defined as Tuesday through Monday:

$$s_{i,\tau} = a + \omega' X_{i,\tau} + \epsilon_{i,\tau} \quad (5)$$

where $s_{i,\tau}$ is the consumer spending recovery index at county i on week τ, as defined in Section 2. a is a constant term. $X_{i,\tau}$ consists of social distancing, amounts of precipitation, average temperature, the fraction of the population that is Black, the log of population density, Trump's 2020 vote shares, and indicator variables for mask mandates and the other NPIs, as well as demographic interactions with social distancing, mask mandates and the NPIs, where the demographic variables have been demeaned.[14]

Social distancing and government interventions can be correlated with the error of the spending regression. Thus, we instrument for social distancing and these government interventions using the party controlling the state government and DMA Trump vote share, as in the previous sections.

Table 4 presents the estimation results. Social distancing significantly reduces spending: a one standard-deviation increase in the social distancing measure (1.01, see Table 1) leads to a 9.7% decrease in spending. Mask mandates increase spending in areas where people practice high levels of social distancing, but decrease spending in areas that have low levels of social

[14] We do not include county or week fixed effects because spending is already expressed as a percentage of the county's pre-COVID-19 benchmark spending, and it is also already seasonally adjusted by comparing the spending to those in the same week one-year prior.

Table 4: Spending Model

	Dependent variable:		
	Total spending		
Independent Var.	Estimates/S.E.	Independent Var. Cont'd	Estimates/S.E. Cont'd
Precipitation ($inch$)	-0.003	Closing of public venues	-0.050***
	(0.006)	×Log(pop. density)	(0.015)
Temperature ($°F$)	0.001**	Closing of public venues	-0.114
	(0.0003)	×Frac. of Black	(0.129)
Log(pop. density)	-0.002	Closing of public venues	-0.306**
	(0.012)	×Trump 2020 vote share	(0.139)
Frac. of Black	0.110	Closing of non-essential businesses	0.008
	(0.197)	×Log(pop. density)	(0.012)
Trump 2020 vote share	-0.481***	Closing of non-essential businesses	0.331**
	(0.138)	×Frac. of Black	(0.161)
Social distancing	-0.096***	Closing of non-essential businesses	-0.083
	(0.008)	×Trump 2020 vote share	(0.155)
Mask mandates	0.017	Closing of schools	-0.030*
	(0.012)	×Log(pop. density)	(0.017)
Social distancing×Mask mandates	0.072***	Closing of schools	-0.075
	(0.010)	×Frac. of Black	(0.226)
Closing of public venues	0.036*	Closing of schools	0.375***
	(0.020)	×Trump 2020 vote share	(0.137)
Closing of non-essential businesses	-0.070***	Shelter in place	0.001
	(0.023)	×Log(pop. density)	(0.009)
Closing of schools	0.004	Shelter in place	-0.019
	(0.019)	×Frac. of Black	(0.080)
Shelter in place	-0.009	Shelter in place	0.198*
	(0.014)	×Trump 2020 vote share	(0.120)
Gathering size limits	-0.070***	Gathering size limits	0.048**
	(0.020)	×Log(pop. density)	(0.021)
Religious gathering limits	0.047**	Gathering size limits	-0.058
	(0.019)	×Frac. of Black	(0.150)
Social distancing	0.006	Gathering size limits	0.199
×Log(pop. density)	(0.005)	×Trump 2020 vote share	(0.204)
Social distancing	-0.026	Religious gathering limits	0.037***
×Frac. of Black	(0.053)	×Log(pop. density)	(0.012)
Social distancing	0.017	Religious gathering limits	-0.202**
×Trump 2020 vote share	(0.047)	×Frac. of Black	(0.091)
Mask mandates	-0.011	Religious gathering limits	0.250*
×Log(pop. density)	(0.007)	×Trump 2020 vote share	(0.142)
Mask mandates	0.069	Constant	-0.045
×Frac. of Black	(0.076)		(0.028)
Mask mandates	0.098		
×Trump 2020 vote share	(0.077)		
Observations	28,645	Overidentification statistic	1068.845
R^2	0.08	Underidentification statistic	977.226
Estimation period	4/1-7/31	Kleibergen Paap weak instrument statistic	11.745

Note: Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

distancing. The interaction terms between mask mandates and demographics are not statistically significant. Table 4 also shows that, in aggregate, non-mask NPIs depress spending.

6. The Effect of Government Interventions on Disease Spread and Spending

We now analyze the impact of (1) mask mandates, (2) all non-mask governmental interventions (NPIs) have on COVID-19 spread, deaths, and spending over the period of April 1 – July 31, 2020. Since there is feedback between the case model and the social distance model, we run the simulations for each date by first predicting the social distancing levels for each county using the actual observed values for each variable in X, except for changing either the masking or the other governmental NPIs (and their interaction terms) for the corresponding experiments. We also substitute the actual number of cases and percent changes in cases in the social distancing model with the predicted cases from the previous days. Once we have the date's social distancing levels, we then predict that date's COVID-19 cases, using the observed X variables except for the social distancing level, where we substitute in the predicted social distancing level, and for the relevant mask mandates and other governmental NPIs (and their interaction terms) variables, where we set the relevant policy.[15] Once we complete these calculations for a specific date, we move to simulating the social distancing and cases for the next date. After the whole sequence of cases and social distancing levels are simulated, we then calculate the spending levels using the observed data, except that we substitute the forecasted social distancing levels, the forecasted

[15] Extracting the cases from the fitted log of the reproduction ratio (equation 3) also involves accounting for the past cases. For this, we use the predicted cases from the previous days.

case levels, and the relevant mask mandates or governmental NPIs, in the place of the corresponding actual values.

We calculate the changes in consumer spending in actual dollar amounts instead of as an index. We do this by multiplying the spending from the 2020 monthly national personal consumer expenditure (PCE) by the ratio of the weighted average monthly consumer spending recovery index under each hypothetical scenario to the actual recovery index.[16, 17]

Because there is uncertainty in each of the model parameters, we obtain our mean results and confidence intervals by running 200 sets of simulations, where each simulation is based on a draw of coefficients from a multivariate normal distribution with the mean of the point estimates of the coefficients, and the variance-covariance matrix being the clustered variance-covariance matrix estimated empirically from each model.

The Effects of Mask Mandates

We show in Sections 3 and 4 that mask mandates increase the amount of social distancing and statistically insignificantly decrease the rate of COVID-19 spread. In Section 5 we find that mask mandates offset the negative effect of social distancing on consumer spending. We put these results together, and account for the feedback loop between cases and social distancing through our simulations. To carry these out, we first compare the cases and consumer spending under the original X values to those where we set the mask mandate variables (and the corresponding interaction terms) to 0. In both scenarios, we keep the non-mask government NPIs equal to their

[16] The National Personal Consumer Expenditure (PCE) is published monthly by the Federal Reserve Bank of St. Louis, see https://fred.stlouisfed.org/series/PCE (Accessed March 22, 2021).
[17] We report more details on converting index to dollars of spending in the appendix.

actual values. Setting the mask mandate variables to 0 represents our forecast of what would have happened if no mask mandates had been imposed. We find that, over our 4-month study period, the mask mandates that were imposed reduced the number of COVID-19 diagnosed cases by 751,000 (95% Confidence Interval (CI) = –510,000 to 1,758,000), saving 27,000 lives (CI = –19,000 to 64,000).[18] While the impact of mask mandates on cases is statistically insignificant, the point estimate on the cases reflects an approximately 20% reduction in cases. Interestingly, we estimate that the implemented mask mandates increased spending by $150B (CI = $85B to $225B), which reflects a change of about 3-4% of the actual consumer spending. If mask mandates had been imposed on the rest of the country, this would have saved a statistically insignificant 37,000 additional lives (CI = –10,000 to 101,000), but could have prevented approximately a third of the loss of consumer spending that was actually experienced during our study period, boosting the spending by an additional $183B (CI = $151B – $219B).[19]

The Imposition of Governmental Restrictions

We next examine the impact of a suite of non-mask governmental NPIs: closing of public venues, closing of non-essential businesses, closing schools, imposing shelter-in-place orders, and limiting public and religious gatherings. We impose all of these restrictions because the correlation

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[18] We assume that 3.657% of confirmed cases lead to death. This is calculated by taking the cumulative number of confirmed COVID-19 cases on July 31, 2020, and comparing that to the total number of COVID-19 deaths on August 13, 2020. The 13-day delay between diagnosis to death is based on this article: https://wwwnc.cdc.gov/eid/article/26/6/20-0320_article, accessed March 16, 2021.

[19] The total consumer spending during our study period was $4,460B, which was about $570B below the level of spending that we would have expected in the absence of a COVID-19 pandemic. This expected level of spending is calculated as $\sum_{t=April,\ldots July} \frac{2019\, Total\ Consumer\ Spending}{2018\, Total\ Consumer\ Spending} \cdot 2019\, Consumer\ Spending\ for\ month\ t$. The first term captures the expected growth rate, and the second term captures the seasonality and previous-year's level of spending.

between these restrictions is high, making it hard to accurately tease apart the effect of each specific order. In all of these simulations, the mask mandates are assumed to be at the levels that are observed in the data.

Our model finds that these restrictions were very successful at reducing the spread of COVID-19 – much more than masks: Comparing the number of diagnosed cases that would be forecasted when all variables (except cases and social distancing, as described above) are at their actual levels to the forecasts when these 6 NPI were not imposed anywhere shows that the NPIs that were imposed reduced COVID-19 cases by 34M (CI = 27M – 40M), corresponding with 1,230,000 lives saved (CI = 977,000 – 1,473,000). To get a sense of how large this effect is, this effect size reflects a 90% decrease in the number of cases that we forecast would have occurred if the NPIs were not implemented. However, these restrictions came at a cost of $703B to the economy (CI = $313B – $1,082B), reflecting an almost 15% reduction of spending compared to what we forecast spending would have been in the absence of these restrictions. In total, the impact of the NPIs on lives saved and spending corresponds to a cost of $579,000 per life saved (CI = $231K – $944K).[20, 21]

It is helpful to benchmark our cost per life saved against economic estimates of the value of a human life. The government's value of a life is $7.4-11.6M,[22] implying that it was strongly

[20] This ratio is calculated for each set of parameter draws, and then we take the average. It is not a ratio of the averages.

[21] We also replicate our simulations using the sub-sample estimates (i.e., using only the 1685 counties in the spending data), as reported in Tables A4 and A5. Our sub-sample estimates yield a cost of $456K per life saved (CI = $435K - $1008K), which is statistically indistinguishable from the $579K per life saved using the full-sample estimates.

[22] The Environmental Protection Agency uses $7.4M (https://www.epa.gov/environmental-economics/mortality-risk-valuation#whatvalue, accessed June 3, 2021). The Department of Transportation uses $11.6M (https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis, accessed June 3, 2021).

worth imposing these NPIs. Some readers may object that older people are more likely to die from COVID-19, so the average value of lost lives might be lower. Hall et al. (2020) find that each year of a lost life is valued at $100,000-$400,000. Using the ratio of years of deaths from COVID-19 in the U.S., as reported in Mitra et al. 2020 (Table 3, assuming a lifespan of 80 years), we see that each COVID-19 death represents a loss of approximately 7 years, implying a valuation of $700,000 - $2,800,000 per death. Thus, the imposition of these NPIs was cost effective, even if the cost per life saved is at the high end of our confidence interval.

7. Conclusion

Given the contentious views many politicians and citizens had towards mask mandates and other governmental restrictions that were imposed to stem the spread of COVID-19, it is important to understand the extent to which these interventions reduced the spread of COVID-19, as well as their effects on consumer spending. We show that social distancing and governmental NPIs reduced the spread of COVID-19. Mask mandates may also reduce the spread of COVID, but they are good at expanding spending in areas that exhibit higher social distancing. Because the areas that have higher social distancing also are the areas where there is more spending (e.g., bigger cities), the net effect of mask mandates on spending is strongly positive, as we observe in the simulations.

The other governmental restrictions we examine are more effective at stopping the spread of COVID-19 than masks, but come with a reduced level of consumer spending. Thus, we evaluate the cost of each life that is saved in terms of lost consumer spending, finding that these NPIs were a very cost-effective way to save lives.

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Appendix

Converting County-weekly level Predicted Consumer Spending Recovery Index to Actual Dollars

Given that the predicted response of our spending model is consumer spending recovery index, and that we are interested in converting such indices to actual dollar amount in the counterfactual studies, we implement the following steps to achieve the goal.

We first get the iteratively predicted county-level social distancing and case measures for each day and for all counties. We then take the average of the 7 daily social distancing indices across the week.

Once we get the predicted county-weekly indices, we then seek to convert them to actual dollars for easier interpretation. Since we only have national-monthly Personal Consumption Expenditures (PCE) in 2020, and our predicted indices are at the county-weekly level, we further do the following transformation. We first aggregate county-weekly indices to state-weekly indices, weighting by 2019 county-level GDP.[23] We then average the predicted and actual state-weekly indices in each month for each state so that we have a proxy for the predicted and actual state-monthly recovery index. Based on how the recovery index is defined in Chetty et al. (2020), we derive the state-monthly ratio between predicted and actual indices by calculating the following:

$$County\ Monthly\ Ratio = \frac{Predicted\ County\ Monthly\ Index + 1}{Actual\ County\ Monthly\ Index + 1}$$

[23] We choose to use 2019 county-level GDP as opposed to 2019 county-level PCE for weighting because county-level PCE is not publicly available.

Finally, we get the national-monthly ratio by weighting the state-monthly ratio obtained above with 2019 state-level GDP.[24] The idea is that a 1% recovery in a large state (reflected by pre-COVID GDP) has a larger effect on national PCE spending in 2020 than a 1% recover in a small state. After calculating the national-monthly ratio, we get the predicted national-monthly PCE as:

*Predicted National Monthly PCE = Predicted National Monthly Ratio*Actual National Monthly PCE in 2020*,

where Predicted National Monthly Ratio is the weighted sum of all state-monthly ratios defined above, and Actual National Monthly PCE is obtained from the Bureau of Economic Analysis.

First-Stage Regression F-statistics

In this appendix, we report the first-stage F-statistics of each endogenous variable in regressions reported in the paper. The IV-induced improvements of R-squared in those first-stage regressions can be accessed at https://tinyurl.com/2z7k5r5x.

[24] We find a 99% correlation between state-level PCE and state-level GDP, which adds support to our choice of county-level GDP for weighting.

Table A1: Case Model First Stage F-Stats

Endogenous Variable	First-stage F-Stats
Social distancing	109.06
Mask mandates	275.413
Social distancing × Mask mandates	126.425
Closing of public venues	256.197
Closing of non-essential businesses	262.73
Closing of schools	205.442
Shelter in place	373.826
Gathering size limits	270.058
Religious Gathering size limits	221.855
Social distancing × Log(pop. density)	581.37
Social distancing × Frac. of Black	398.932
Social distancing × Trump 2020 vote share	643.111
Mask mandates × Log(pop. density)	1533.44
Mask mandates × Frac. of Black	3109.757
Mask mandates × Trump 2020 vote share	1708.102
Closing of public venues × Log(pop. density)	1454.952
Closing of public venues × Frac. of Black	1449.005
Closing of public venues × Trump 2020 vote share	1685.226
Closing of non-essential businesses × Log(pop. density)	1714.373
Closing of non-essential businesses × Frac. of Black	1127.801
Closing of non-essential businesses × Trump 2020 vote share	1742.812
Closing of schools × Log(pop. density)	750.381
Closing of schools × Frac. of Black	320.165
Closing of schools × Trump 2020 vote share	629.136
Shelter in place × Log(pop. density)	1632.565
Shelter in place × Frac. of Black	2859.996
Shelter in place × Trump 2020 vote share	1732.073
Gathering size limits × Log(pop. density)	493.765
Gathering size limits × Frac. of Black	773.89
Gathering size limits × Trump 2020 vote share	546.98
Religious Gathering size limits × Log(pop. density)	830.352
Religious Gathering size limits × Frac. of Black	783.21
Religious Gathering size limits × Trump 2020 vote share	868.485

Table A2: Social Distancing Model First Stage F-Stats

Endogenous Variable	First-stage F-Stats
Mask mandates	271.756
Closing of public venues	255.091
Closing of non-essential businesses	261.130
Closing of schools	205.529
Shelter in place	367.430
Gathering size limits	268.670
Religious Gathering size limits	221.897
Mask mandates × Log(pop. density)	1536.259
Mask mandates × Frac. of Black	3108.395
Mask mandates × Trump 2020 vote share	1705.222
Closing of public venues × Log(pop. density)	1459.751
Closing of public venues × Frac. of Black	1446.534
Closing of public venues × Trump 2020 vote share	1686.548
Closing of non-essential businesses × Log(pop. density)	1721.644
Closing of non-essential businesses × Frac. of Black	1128.846
Closing of non-essential businesses × Trump 2020 vote share	1741.174
Closing of schools × Log(pop. density)	752.001
Closing of schools × Frac. of Black	319.264
Closing of schools × Trump 2020 vote share	630.084
Shelter in place × Log(pop. density)	1628.465
Shelter in place × Frac. of Black	2863.858
Shelter in place × Trump 2020 vote share	1725.579
Gathering size limits × Log(pop. density)	494.543
Gathering size limits × Frac. of Black	770.143
Gathering size limits × Trump 2020 vote share	546.280
Religious Gathering size limits × Log(pop. density)	830.704
Religious Gathering size limits × Frac. of Black	778.998
Religious Gathering size limits × Trump 2020 vote share	869.542

Table A3: Spending Model First Stage F-Stats

Endogenous Variable	First-stage F-Stat
Social distancing	77.411
Mask mandates	55.859
Social distancing×Mask mandates	37.953
Closing of public venues	34.484
Closing of non-essential businesses	32.700
Closing of schools	16.934
Shelter in place	46.272
Gathering size limits	19.943
Religious Gathering size limits	33.091
Social distancing×Log(pop. density)	147.642
Social distancing×Frac. of Black	96.083
Social distancing×Trump 2020 vote share	160.634
Mask mandates×Log(pop. density)	80.063
Mask mandates×Frac. of Black	99.505
Mask mandates×Trump 2020 vote share	85.137
Closing of public venues×Log(pop. density)	46.505
Closing of public venues×Frac. of Black	49.234
Closing of non-essential businesses×Trump 2020 vote share	61.078
Closing of non-essential businesses×Log(pop. density)	49.713
Closing of non-essential businesses×Frac. of Black	41.499
Closing of non-essential businesses×Trump 2020 vote share	60.028
Closing of schools×Log(pop. density)	21.856
Closing of schools×Frac. of Black	16.396
Closing of schools×Trump 2020 vote share	26.451
Shelter in place×Log(pop. density)	59.241
Shelter in place×Frac. of Black	115.630
Shelter in place×Trump 2020 vote share	68.177
Gathering size limits×Log(pop. density)	16.164
Gathering size limits×Frac. of Black	38.323
Gathering size limits×Trump 2020 vote share	18.392
Religious Gathering size limits×Log(pop. density)	33.119
Religious Gathering size limits×Frac. of Black	69.558
Religious Gathering size limits×Trump 2020 vote share	42.820

Robustness Check: Sub Sample vs. Full Sample for Case and Social Distancing Estimations

We report our estimations using both sub sample and full sample in Tables A4 and A5. We observe qualitatively similar results. Our simulations using the sub-sample estimates also yield statistically indistinguishable results: The sub-sample estimates yields a cost of $456K per life saved (CI = $435K - $1008K), vs. the full sample (as reported in the main paper) estimate of $579 per life saved.

Table A4: Standard SIR Model Sub vs. Full Sample

	Dependent variable: Log(Reproduction Ratio)				
Independent Var.	(1) Estimates/S.E.	(2) Estimates/S.E.	Independent Var. Cont'd	(1) Estimates/S.E. Cont'd	(2) Estimates/S.E. Cont'd
Temperature ($^\circ F$)	-0.002	-0.002	Closing of public venues	-0.342***	-0.367***
	(0.002)	(0.001)	×Log(pop. density)	(0.081)	(0.054)
Humidity (%)	0.004***	0.004***	Closing of public venues	0.874	0.524
	(0.001)	(0.001)	×Frac. of Black	(0.684)	(0.547)
Social distancing	-0.205*	-0.433***	Closing of public venues	-1.539*	-2.125***
	(0.110)	(0.090)	×Trump 2020 vote share	(0.821)	(0.584)
Mask Mandates	0.134	0.062	Closing of non-essential businesses	-0.002	0.053
	(0.082)	(0.063)	×Log(pop. density)	(0.076)	(0.053)
Social distancing×Mask mandates	-0.168**	-0.076	Closing of non-essential businesses	1.096	4.238***
	(0.081)	(0.066)	×Frac. of Black	(0.951)	(0.883)
Closing of public venues	0.049	0.100	Closing of non-essential businesses	0.394	1.443**
	(0.119)	(0.081)	×Trump 2020 vote share	(0.946)	(0.688)
Closing of non-essential businesses	-0.161	0.056	Closing of schools	-0.323***	-0.194***
	(0.146)	(0.099)	×Log(pop. density)	(0.098)	(0.048)
Closing of schools	-0.214	-0.274***	Closing of schools	-1.564	-1.595*
	(0.162)	(0.106)	×Frac. of Black	(1.513)	(0.962)
Shelter in place	0.227**	-0.072	Closing of schools	2.329**	0.662
	(0.107)	(0.081)	×Trump 2020 vote share	(0.974)	(0.569)
Gathering size limits	-0.057	-0.271***	Shelter in place	-0.030	0.009
	(0.146)	(0.093)	×Log(pop. density)	(0.054)	(0.039)
Religious gathering limits	-0.337***	-0.333***	Shelter in place	-0.674	-0.863**
	(0.128)	(0.088)	×Frac. of Black	(0.508)	(0.359)
Social distancing	0.052**	0.072***	Shelter in place	0.590	-0.243
×Log(pop. density)	(0.023)	(0.015)	×Trump 2020 vote share	(0.626)	(0.488)
Social distancing	0.395*	0.120	Gathering size limits	0.047	0.047
×Frac. of Black	(0.236)	(0.169)	×Log(pop. density)	(0.114)	(0.052)
Social distancing	0.284	0.850***	Gathering size limits	-3.486***	-4.856***
×Trump 2020 vote share	(0.245)	(0.193)	×Frac. of Black	(1.061)	(1.014)
Mask Mandates	0.019	0.017	Gathering size limits	-2.108	-1.058
×Log(pop. density)	(0.041)	(0.027)	×Trump 2020 vote share	(1.465)	(0.865)
Mask Mandates	0.670	0.614*	Religious gathering limits	0.350***	0.329***
×Frac. of Black	(0.438)	(0.314)	×Log(pop. density)	(0.085)	(0.057)
Mask Mandates	-0.831**	-0.660**	Religious gathering limits	-1.387*	-3.167***
×Trump 2020 vote share	(0.373)	(0.307)	×Frac. of Black	(0.819)	(0.826)
			Religious gathering limits	-0.225	0.107
			×Trump 2020 vote share	(0.844)	(0.593)
Observations	205,570	372,710	Overidentification statistic	492.327	720.095
R^2	0.10	0.16	Underidentification statistic	543.698	1442.731
County FE	YES	YES	Kleibergen Paap weak instrument statistic	2.838	14.459
Date FE	YES	YES			
Estimation period	4/1-7/31	4/1-7/31			

Note: Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table A5: Social Distancing Model Sub vs. Full Sample

	Dependent variable:				
	Social Distancing				
	(1)	(2)		(1)	(2)
Independent Var.	Estimates/S.E.	Estimates/S.E.	Independent Var. Cont'd	Estimates/S.E. Cont'd	Estimates/S.E. Cont'd
Local week-over-week	-0.0004**	-0.0001	Closing of public venues	0.083**	0.084***
growth rate in cases	-0.0002	-0.0002	×Log(pop. density)	(0.039)	(0.031)
National week-over-week	0.089***	0.074***	Closing of public venues	0.525	0.655**
growth rate in cases	(0.009)	(0.009)	×Frac. of Black	(0.382)	(0.270)
Local cases in the past 7 days	0.039***	0.022***	Closing of public venues	0.145	0.169
per 1000 people	(0.005)	(0.005)	×Trump 2020 vote share	(0.387)	(0.317)
National cases in the past 7 days	0.175***	0.105***	Closing of non-essential	0.029	0.005
per 1000 people	(0.028)	(0.024)	businesses×Log(pop. density)	(0.036)	(0.029)
Precipitation ($inch$)	0.075***	0.067***	Closing of non-essential	0.989**	1.062**
	(0.003)	(0.002)	businesses×Frac. of Black	(0.454)	(0.415)
Temperature ($^\circ F$)	-0.002***	-0.003***	Closing of non-essential	0.693	0.346
	(0.001)	-0.0002	businesses×Trump 2020 vote share	(0.465)	(0.346)
Mask mandates	0.097***	0.089***	Closing of schools	0.125**	0.105***
	(0.026)	(0.019)	×Log(pop. density)	(0.050)	(0.028)
Closing of public venues	0.001	0.026	Closing of schools	0.762	0.140
	(0.058)	(0.042)	×Frac. of Black	(0.971)	(0.574)
Closing of non-essential	-0.103	-0.121**	Closing of schools	-2.562***	-1.876***
businesses	(0.069)	(0.058)	×Trump 2020 vote share	(0.571)	(0.413)
Closing of schools	0.163*	0.280***	Shelter in place	0.052*	0.072***
	(0.090)	(0.061)	×Log(pop. density)	(0.031)	(0.024)
Shelter in place	0.314***	0.366***	Shelter in place	-0.777***	-0.593***
	(0.054)	(0.043)	×Frac. of Black	(0.222)	(0.178)
Gathering size limits	0.139	-0.166***	Shelter in place	-0.185	0.124
	(0.086)	(0.051)	×Trump 2020 vote share	(0.325)	(0.289)
Religious gathering limits	-0.114	0.065	Gathering size limits	-0.078	-0.047
	(0.073)	(0.045)	×Log(pop. density)	(0.059)	(0.033)
Mask mandates	-0.007	-0.010	Gathering size limits	-0.725	-0.746
×Log(pop. density)	(0.013)	(0.010)	×Frac. of Black	(0.619)	(0.536)
Mask mandates	0.056	-0.043	Gathering size limits	2.410**	2.021***
×Frac. of Black	(0.192)	(0.123)	×Trump 2020 vote share	(0.942)	(0.563)
Mask mandates	-0.241*	-0.211*	Religious gathering limits	0.024	0.004
×Trump 2020 vote share	(0.139)	(0.111)	×Log(pop. density)	(0.041)	(0.024)
			Religious gathering limits	-1.661***	-1.862***
			×Frac. of Black	(0.452)	(0.380)
			Religious gathering limits	-0.155	-0.174
			×Trump 2020 vote share	(0.346)	(0.266)
Observations	205,570	372,710	Overidentification statistic	1146.592	1644.631
R^2	0.84	0.79	Underidentification statistic	925.24	1545.917
County FE	YES	YES	Kleibergen Paap weak instrument statistic	7.736	26.916
Day-of-week FE	YES	YES			
Week FE	YES	YES			
Estimation period	4/1-7/31	4/1-7/31			

Note: Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01