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. Social distancing has a large effect on reducing COVID-19 spread, while mask mandates are most effective when combined with social distancing. Non-mask government interventions also reduce COVID-19 spread. Social distancing is more responsive to national case numbers than local case numbers. Mask mandates tend to increase social distancing, as do shelter-in-place orders. However, other governmental restrictions do not change social distancing much. Social distancing hurts spending in the absence of a mask mandate, but has no effect on spending if there is a mask mandate. Mask mandates have a direct effect of reducing spending in counties with low levels of social distancing. Non-mask governmental interventions as a whole do not have a large effect on consumer spending. 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 not only decreased COVID-19 cases by 1.2M, saving 45,000 lives, over a 4-month period, but added $99B of additional spending. The other governmental interventions that were implemented reduced the number of COVID-19 cases by nearly 15M, saving over 545,000 lives, while reducing consumer spending by nearly $170B over our 4-month period. Thus, these restrictions were cost effective as long as one values each saved life at $306,000 or more.

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1. Introduction

COVID-19 has been a disruptive force throughout the world. As of May 18, 2021, there have been over 163M confirmed cases worldwide, and over 32M confirmed cases in the US; Over 3.3M people have died, including over 580,000 deaths in the US.[1] Further, 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 reduce the spread of COVID-19 if they are accompanied by sufficient levels of social distancing. 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. We also show that shelter-in-place orders increase social distancing, while the other NPIs have very little impact on distancing. Further, social distancing increases as

[1] World Health Organization COVID-19 Dashboard, https://covid19.who.int. Accessed on May 18, 2021.

COVID-19 cases and growth rates increase nationally, but the impact of local cases is much smaller.

We also evaluate the impact of the COVID-19 restrictions on spending. Our largest finding is that mask mandates can undo the negative impact of social distancing. Overall, non-mask NPIs have only a small direct effect on total 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 also discuss what would have happened if the whole country had introduced mask mandates or NPIs.

We find that the mask mandates that were implemented saved 45,000 lives and increased consumer spending by $99B over the 4-month time period we study. Thus, mask mandates are both pro-health and pro-business. If mask mandates had been uniformly implemented, they would have saved an additional 22,000 lives and increased spending by an additional $145B. 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 over 545,000 lives but reduced consumer spending by almost $170B. The cost of each life saved was around $300,000, 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 country had already began social distancing. While one may want to contrast the shopping or distancing behavior before vs. after COVID-19 began, there was likely an unobservable structural break between the way people shopped and 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 2,953 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 is on average a 5-day gap between the onset of a patient's symptoms and the final diagnosis result. 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 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.[2] 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 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.

[2] The fitted social distancing index is $SocialDistIndex = 0.53 FractStayHome - 0.51 FullTimeWork - 0.61 PartTimeWork + 0.31 StayHomeDuration$, where the four right-hand-side variables have been demeaned, and stay-home duration is defined in terms of minutes. See https://tinyurl.com/2z7k5r5x for more details.

Our spending data are provided at the state level 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, which come from consumer credit card and debit card purchases originally supplied by Affinity Solutions. 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).

Finally, we obtain other COVID-19 NPI policy data from the company Keystone Strategy, which contain exact dates of each county starting restrictions.[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.

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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.

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

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	-0.125	0.104	-0.446	0.089
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

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 model 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 recent 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

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

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 because they perceive that they are getting more exposure to COVID-19. Finally, President Trump repeatedly mocked mask mandates and other governmental restrictions, 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 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 parameters from the SIR regression (which are 5 times larger than they would be if we used only reported cases). We use reported cases everywhere else in the paper: for the social distancing and spending analyses, and in the simulations in Section 6, we divide the number of cases we obtain 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. 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

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

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 use the average of the 9-15 day lagged social distancing levels, mask mandate levels, and NPI levels as instruments for these underlying variables.[7] The lagged variables are correlated with the contemporaneous levels of social distancing, mask mandates, and NPIs because people's distancing patterns and the government's policies tend to change slowly.[8] However, these lagged variables should not affect the rate of contagion, conditional on the number of infectious people and the date fixed effects. We choose the specific lagged periods because, on the one hand, given the infectious patients are captured by $(Y_{i,t-2} - Y_{i,t-8})$, lagged terms shorter than 8 days may be invalid instruments; on the other hand, further increasing the lags weakens the strength of the instruments.

Table 2 presents the estimation results. 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

[7] For the interaction terms, we use the lags of the social distancing, mask mandate, or NPI times the corresponding demographic values.

[8] The F-statistics of first-stage regressions appear in the online appendix. First-stage estimates are reported at https://tinyurl.com/2z7k5r5x.

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 ($^\circ F$)	−0.00003	Closing of public venues	-0.256^{***}
	(0.001)	×Log(pop. density)	(0.055)
Humidity (%)	0.003^{***}	Closing of public venues	2.419^{*}
	(0.0004)	×Frac. of Black	(1.239)
Social distancing	-0.345^{***}	Closing of public venues	-2.326^{***}
	(0.053)	×Trump 2020 vote share	(0.656)
Mask Mandates	0.080^{*}	Closing of non-essential businesses	0.386^{***}
	(0.041)	×Log(pop. density)	(0.061)
Social distancing×Mask mandates	-0.208^{***}	Closing of non-essential businesses	−1.616
	(0.038)	×Frac. of Black	(1.389)
Closing of public venues	−0.061	Closing of non-essential businesses	2.936^{***}
	(0.086)	×Trump 2020 vote share	(0.659)
Closing of non-essential businesses	−0.015	Closing of schools	−0.030
	(0.097)	×Log(pop. density)	(0.021)
Closing of schools	0.043	Closing of schools	-1.704^{***}
	(0.039)	×Frac. of Black	(0.450)
Shelter in place	-0.087^{*}	Closing of schools	−0.084
	(0.047)	×Trump 2020 vote share	(0.264)
Gathering size limits	-0.120^{***}	Shelter in place	0.084^{***}
	(0.041)	×Log(pop. density)	(0.030)
Religious gathering limits	0.031	Shelter in place	-2.581^{***}
	(0.057)	×Frac. of Black	(0.777)
Social distancing	-0.104^{***}	Shelter in place	0.606^{**}
×Log(pop. density)	(0.017)	×Trump 2020 vote share	(0.293)
Social distancing	-0.681^{***}	Gathering size limits	-0.067^{***}
×Frac. of Black	(0.256)	×Log(pop. density)	(0.023)
Social distancing	-0.550^{***}	Gathering size limits	-0.812^{*}
×Trump 2020 vote share	(0.213)	×Frac. of Black	(0.424)
Mask Mandates	0.043^{**}	Gathering size limits	−0.229
×Log(pop. density)	(0.019)	×Trump 2020 vote share	(0.273)
Mask Mandates	-1.888^{***}	Religious gathering limits	-0.094^{***}
×Frac. of Black	(0.478)	×Log(pop. density)	(0.027)
Mask Mandates	-1.011^{***}	Religious gathering limits	0.701
×Trump 2020 vote share	(0.246)	×Frac. of Black	(0.699)
		Religious gathering limits	-0.529^{*}
		×Trump 2020 vote share	(0.272)
Observations	372,710		
R^2	0.165		
County FE	YES		
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

interpret. We see 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., 0.08 – 0.208*0.63). The negative coefficient on the interaction between social distancing and the mask mandate shows that masking and social distancing are complements, not substitutes, which highlights the importance of social distancing even when mask mandates are in place. We also observe that mask mandates are most effective in areas with a greater Black population, higher Trump support, and greater population density.

We find that, on the whole, other government interventions (i.e., NPIs) reduce the spread of COVID-19, although only limits on gatherings and sheltering-in-place are statistically significant. A big part of the lack of statistical significance is likely due to the high correlation between these variables.[9] It is hard to find a general pattern with the interaction variables, except to note that most of the interaction terms with fraction Black, and the sum of these terms, are negative, indicating that these interventions are especially effective in areas with higher percentages of Black residents.

4. Determinants of Social Distancing

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

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

[9] The pairwise correlations between the 6 NPI policies range from 0.18 to 0.75, with a median correlation of 0.43.

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.[10] $m_{i,t}$ 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 results 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 average of the 9-15 day lags of these variables as instruments. The logic behind the validity of these instruments follows the same reasoning we laid out for the case model in Section 3.

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

[10] We define local/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

changes with the progression of the pandemic. Column 2 shows the same estimation with date fixed effects. 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.

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	0.152^{***}	0.149^{***}
growth rate in cases	(0.0002)	(0.0002)	×Log(pop. density)	(0.041)	(0.039)
National week-over-week	0.083^{***}		Closing of public venues	-1.764^{**}	-1.533^{**}
growth rate in cases	(0.024)	(0.000)	×Frac. of Black	(0.831)	(0.722)
Local cases in the past 7 days	0.023^{***}	0.023^{***}	Closing of public venues	0.224	0.276
per 1000 people	(0.006)	(0.006)	×Trump 2020 vote share	(0.358)	(0.350)
National cases in the past 7 days	0.111^{***}		Closing of non-essential	-0.014	-0.007
per 1000 people	(0.028)	(0.000)	businesses×Log(pop. density)	(0.042)	(0.040)
Precipitation (*inch*)	0.068^{***}	0.069^{***}	Closing of non-essential	1.982^{**}	1.654^{*}
	(0.002)	(0.002)	businesses×Frac. of Black	(0.979)	(0.855)
Temperature ($^\circ F$)	-0.002^{***}	-0.003^{***}	Closing of non-essential	0.407	0.337
	(0.0004)	(0.0004)	businesses×Trump 2020 vote share	(0.338)	(0.333)
Mask mandates	0.057^{**}	0.046^{**}	Closing of schools	0.028^{**}	0.028^{**}
	(0.024)	(0.021)	×Log(pop. density)	(0.012)	(0.012)
Closing of public venues	-0.025	0.001	Closing of schools	0.215	0.103
	(0.048)	(0.043)	×Frac. of Black	(0.279)	(0.248)
Closing of non-essential businesses	0.058	0.029	Closing of schools	0.203	0.181
	(0.065)	(0.057)	×Trump 2020 vote share	(0.131)	(0.131)
Closing of schools	-0.015	-0.020	Shelter in place	0.020	0.026
	(0.021)	(0.019)	×Log(pop. density)	(0.024)	(0.022)
Shelter in place	0.127^{***}	0.108^{***}	Shelter in place	0.682	0.448
	(0.030)	(0.026)	×Frac. of Black	(0.629)	(0.539)
Gathering size limits	0.005	0.012	Shelter in place	-0.529^{***}	-0.493^{***}
	(0.023)	(0.021)	×Trump 2020 vote share	(0.179)	(0.171)
Religious gathering limits	-0.027	-0.011	Gathering size limits	-0.039^{***}	-0.042^{***}
	(0.034)	(0.031)	×Log(pop. density)	(0.014)	(0.013)
Mask mandates	-0.050^{***}	-0.048^{***}	Gathering size limits	-0.586^{**}	-0.475^{*}
×Log(pop. density)	(0.015)	(0.014)	×Frac. of Black	(0.270)	(0.242)
Mask mandates	0.710^{*}	0.541^{*}	Gathering size limits	-0.531^{***}	-0.517^{***}
×Frac. of Black	(0.375)	(0.317)	×Trump 2020 vote share	(0.152)	(0.151)
Mask mandates	-0.507^{***}	-0.518^{***}	Religious gathering limits	-0.021	-0.025
×Trump 2020 vote share	(0.096)	(0.094)	×Log(pop. density)	(0.016)	(0.016)
			Religious gathering limits	-0.355	-0.146
			×Frac. of Black	(0.440)	(0.396)
			Religious gathering limits	-0.243	-0.250^{*}
			×Trump 2020 vote share	(0.151)	(0.149)
Observations	372,710	372,710			
R^2	0.808	0.828			
County FE	YES	YES			
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

We find that social distancing increases when cases of COVID-19 are high and increasing, but this is driven by national cases more than local cases, likely reflecting the attention COVID-19 receives in the press. Mask mandates and shelter-in-place orders also both increase social distancing. The main effects on the other governmental interventions are minimal. 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). Mask mandates are especially effective at increasing social distancing among Black residents, while Trump-supporting areas socially distance less in the presence of mask mandates, perhaps as a protest counterreaction. Finally, mask mandates have less of an effect on social distancing in high population density areas.

5. Determinants of Consumer Spending

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

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

where $s_{i,\tau}$ is the consumer spending recovery index at state i on week τ.[11] 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

[11] This index is $\frac{\left(\frac{Spending(Date\ 2020)}{Spending(January\ 2020)}\right)}{\left(\frac{Spending(Date\ 2019)}{Spending(January\ 2019)}\right)} - 1$.

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.[12]

It is possible that social distancing or government interventions could be correlated with the error of the spending regression. Thus, we instrument for social distancing and these government interventions using the average of the 9-15 day lags of these variables, as in the previous sections.

Table 4 presents the estimation results. Social distancing reduces spending by a significant amount: a one standard-deviation increase in the social distancing measure leads to an 8% decrease in spending. Mask mandates have a small negative effect, but the significant interaction term between social distancing and masking implies that mask mandates substantially offset the negative effect of social distancing on spending. This finding can perhaps rationalize the U.S. Chamber of Commerce's support of mask mandates.[13] However, the benefit of mask mandates is generally smaller in areas with higher population densities, which is likely due to people's heighten concern about exposure in those areas even with mask mandates.

[12] We do not include state or week fixed effects because sales are already expressed as a percentage of the state's pre-COVID-19 benchmark sales, and they are already seasonally adjusted by comparing the sales to those in the same week one-year prior.

[13] https://www.uschamber.com/press-release/us-chamber-of-commerce-strongly-supports-president-biden-s-masks-mandate-applauds, accessed March 18, 2021.

Table 4: Spending Model

	Dependent variable: Total spending		
Independent Var.	Estimates/S.E.	Independent Var. Cont'd	Estimates/S.E. Cont'd
Precipitation (*inch*)	0.001	Closing of public venues	−0.102
	(0.018)	×Log(pop. density)	(0.073)
Temperature ($^\circ F$)	0.003***	Closing of public venues	1.005
	(0.001)	×Frac. of Black	(0.698)
Log(pop. density)	0.054**	Closing of public venues	−0.648
	(0.025)	×Trump 2020 vote share	(0.608)
Frac. of Black	−0.258	Closing of non-essential businesses	0.105
	(0.359)	×Log(pop. density)	(0.073)
Trump 2020 vote share	0.006	Closing of non-essential businesses	−1.103
	(0.265)	×Frac. of Black	(0.677)
Social distancing	−0.081***	Closing of non-essential businesses	0.584
	(0.022)	×Trump 2020 vote share	(0.721)
Mask mandates	−0.065*	Closing of schools	−0.008
	(0.039)	×Log(pop. density)	(0.025)
Social distancing×Mask mandates	0.091***	Closing of schools	−0.089
	(0.027)	×Frac. of Black	(0.314)
Closing of public venues	−0.067**	Closing of schools	−0.024
	(0.030)	×Trump 2020 vote share	(0.234)
Closing of non-essential businesses	0.057*	Shelter in place	0.027
	(0.030)	×Log(pop. density)	(0.026)
Closing of schools	0.0005	Shelter in place	−0.185
	(0.018)	×Frac. of Black	(0.361)
Shelter in place	0.028	Shelter in place	0.413
	(0.025)	×Trump 2020 vote share	(0.267)
Gathering size limits	−0.033*	Gathering size limits	0.008
	(0.018)	×Log(pop. density)	(0.018)
Religious gathering limits	0.019	Gathering size limits	0.110
	(0.026)	×Frac. of Black	(0.162)
Social distancing	−0.016	Gathering size limits	0.326*
×Log(pop. density)	(0.012)	×Trump 2020 vote share	(0.186)
Social distancing	−0.088	Religious gathering limits	−0.030*
×Frac. of Black	(0.164)	×Log(pop. density)	(0.018)
Social distancing	−0.239	Religious gathering limits	0.474*
×Trump 2020 vote share	(0.205)	×Frac. of Black	(0.279)
Mask mandates	−0.052***	Religious gathering limits	0.250
×Log(pop. density)	(0.016)	×Trump 2020 vote share	(0.189)
Mask mandates	0.305	Constant	−0.220***
×Frac. of Black	(0.236)		(0.084)
Mask mandates	−0.258		
×Trump 2020 vote share	(0.242)		
Observations	850		
R^2	0.558		
Estimation period	4/1-7/31		

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

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 X, except for changing either the masking or 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. 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 in place of the actual ones, and we change the relevant mask mandates or governmental NPIs, as needed.

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.[14, 15]

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 Section 3 that mask mandates increase the amount of social distancing and 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. Ultimately, we find that mask mandates are a win-win policy, both reducing the rates of COVID-19 and stimulating the economy (although this later effect is not statistically significant).

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. 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 1.2M (95%

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[14] 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).

[15] We report more details on converting index to dollars of spending in the online appendix.

Confidence Interval (CI) = 0.1M – 2.6M), saving 45,000 lives (CI = 3,000 – 94,000),[16] while increasing spending by $99B (CI = -$31B – $236B). If mask mandates had been imposed on the rest of the country, this would have saved a statistically insignificant 22,000 additional lives (CI = -10,000 – 46,000), but could have prevented approximately a quarter of the loss of consumer spending that was actually experienced during our study period, boosting the spending by an additional $145B (CI = $80B – $215B).[17]

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 between these restrictions is high, making it hard to accurately tease apart the effect of each specific order.

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 NPI were not imposed anywhere shows that the NPIs

[16] 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.

[17] 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.

that were imposed reduced COVID-19 cases by 15M (CI = 12M – 18M), corresponding with 550,000 lives saved (CI = 440,000 – 670,000). However, these restrictions came at a cost of $170B to the economy, although this estimate is not statistically significant (CI = -$102B – $472B). This corresponds to a cost of $306,000 per life saved (CI = -$206K – $858K).[18, 19]

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,[20] implying that it was strongly 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.[21]

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

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[18] This ratio is calculated for each set of parameter draws and then taking the average. It is not a ratio of the averages.
[19] Because so many locations imposed NPIs during our study period, imposing the full set of NPIs on areas that did not adopt them would only have reduced cases by 540,000 cases, corresponding to 20,000 lives. The change in spending would be a statistically insignificant *increase* of $32B (-$67B – $132B).
[20] 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).
[21] Because the 95% confidence interval for the effect of mask mandates on spending includes scenarios where spending decreases, the cost per life saved in our confidence interval for masks can be as high as $2M.

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, mask mandates and governmental NPIs reduce the spread of COVID-19. Mask mandates are also pro-business, offsetting the negative effect of social distancing on consumer spending. 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 cost-effective way to save lives.

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Online Appendix

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

Given that case and social distancing models are run at the county level, while our spending models are at the state level (due to data constraints), we implement the following steps to coordinate these three parts in all counterfactual studies.

We first get the iteratively predicted county-level social distancing and case measures for each day. Once we have done that, we aggregate the social distancing and case measures at the state-daily level, weighting each county's value by the county's population. This gives total state-level cases and the weighted average of the social distancing index, where the weekly average social distancing index is the average of the 7 daily social distancing indices across the week.

Once we get the predicted state-weekly indices, we then seek to convert them to actual dollars for easier interpretation. Since we only have national-monthly Personal Consumption Expenditures (PCE), and our indices are at the state-weekly level, we further do the following transformation. We first 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:

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

Finally, we get the national-monthly ratio by weighting the state-monthly ratio obtained above with actual state-level total PCE in calendar year 2018, which is the latest state-level PCE data available when we conduct our analyses. The idea is that a 1% recovery in a large state has a larger effect on national PCE spending than a 1% recover in a small state. For example, if

California's PCE was a billion, and national PCE was b billion in 2018, then California's weight would be a/b. 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*,

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. Detailed estimates of these regressions can be accessed at https://tinyurl.com/2z7k5r5x.

Table A1: Case Model First Stage F-Stats

Endogenous Variable	First-stage F-Stats
Social distancing	287.925
Mask mandates	1449.869
Social distancing×Mask mandates	508.162
Closing of public venues	2041.594
Closing of non-essential businesses	1202.877
Closing of schools	3737.609
Shelter in place	1220.559
Gathering size limits	1523.640
Religious gathering limits	4089.275
Social distancing×Log(pop. density)	380.271
Social distancing×Frac. of Black	403.318
Social distancing×Trump 2020 vote share	559.170
Mask mandates×Log(pop. density)	2701.828
Mask mandates×Frac. of Black	3344.971
Mask mandates×Trump 2020 vote share	3886.494
Closing of public venues×Log(pop. density)	2587.372
Closing of public venues×Frac. of Black	2060.373
Closing of public venues×Trump 2020 vote share	2739.251
Closing of non-essential businesses×Log(pop. density)	1635.079
Closing of non-essential businesses×Frac. of Black	2180.963
Closing of non-essential businesses×Trump 2020 vote share	1596.314
Closing of schools×Log(pop. density)	3272.773
Closing of schools×Frac. of Black	9845.893
Closing of schools×Trump 2020 vote share	4730.118
Shelter in place×Log(pop. density)	1067.357
Shelter in place×Frac. of Black	472.315
Shelter in place×Trump 2020 vote share	1005.210
Gathering size limits×Log(pop. density)	448.145
Gathering size limits×Frac. of Black	1750.506
Gathering size limits×Trump 2020 vote share	772.705
Religious gathering limits×Log(pop. density)	1139.754
Religious gathering limits×Frac. of Black	1772.597
Religious gathering limits×Trump 2020 vote share	1458.850

Table A2: Social Distancing Model First Stage F-Stats

Endogenous Variable	First-stage F-Stats
Mask mandates	1481.544
Closing of public venues	2082.028
Closing of non-essential businesses	1408.005
Closing of schools	4543.343
Shelter in place	1375.568
Gathering size limits	1744.411
Religious gathering limits	4796.144
Mask mandates×Log(pop. density)	2542.941
Mask mandates×Frac. of Black	7328.789
Mask mandates×Trump 2020 vote share	4182.987
Closing of public venues×Log(pop. density)	2886.228
Closing of public venues×Frac. of Black	3629.117
Closing of public venues×Trump 2020 vote share	3339.313
Closing of non-essential businesses×Log(pop. density)	1842.193
Closing of non-essential businesses×Frac. of Black	3666.127
Closing of non-essential businesses×Trump 2020 vote share	2360.614
Closing of schools×Log(pop. density)	3634.585
Closing of schools×Frac. of Black	12484.958
Closing of schools×Trump 2020 vote share	5284.651
Shelter in place×Log(pop. density)	1318.420
Shelter in place×Frac. of Black	818.470
Shelter in place×Trump 2020 vote share	1272.809
Gathering size limits×Log(pop. density)	474.237
Gathering size limits×Frac. of Black	1875.524
Gathering size limits×Trump 2020 vote share	863.290
Religious gathering limits×Log(pop. density)	1346.750
Religious gathering limits×Frac. of Black	2508.426
Religious gathering limits×Trump 2020 vote share	1895.335

Table A3: Spending Model First Stage F-Stats

Endogenous Variable	First-stage F-Stat
Social distancing	52.250
Mask mandates	358.800
Social distancing × Mask mandates	219.67
Closing of public venues	88.260
Closing of non-essential businesses	59.120
Closing of schools	466.090
Shelter in place	143.940
Gathering size limits	1031.800
Religious gathering limits	219.580
Social distancing × Log(pop. density)	3132.620
Social distancing × Frac. of Black	2126.370
Social distancing × Trump 2020 vote share	744.300
Mask mandates × Log(pop. density)	427.590
Mask mandates × Frac. of Black	1014.010
Mask mandates × Trump 2020 vote share	786.880
Closing of public venues × Log(pop. density)	1098.210
Closing of public venues × Frac. of Black	1766.210
Closing of public venues × Trump 2020 vote share	2032.510
Closing of non-essential businesses × Log(pop. density)	361.090
Closing of non-essential businesses × Frac. of Black	1766.210
Closing of non-essential businesses × Trump 2020 vote share	576.550
Closing of schools × Log(pop. density)	7998.340
Closing of schools × Frac. of Black	998.720
Closing of schools × Trump 2020 vote share	3038.080
Shelter in place × Log(pop. density)	963.740
Shelter in place × Frac. of Black	811.840
Shelter in place × Trump 2020 vote share	657.150
Gathering size limits × Log(pop. density)	1968.120
Gathering size limits × Frac. of Black	3358.690
Gathering size limits × Trump 2020 vote share	2352.210
Religious gathering limits × Log(pop. density)	1111.030
Religious gathering limits × Frac. of Black	1242.990
Religious gathering limits × Trump 2020 vote share	1566.740