The Impact of Social Distancing and Masking on COVID-19 Spread and Consumer Spending

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Abstract.
We examine the impact of Social Distancing and Masking on the spread of COVID-19 and on consumer spending. We first estimate models of COVID-19 spread and consumer spending. We find that social distancing has a large effect on reducing COVID-19 spread, while the evidence on mask mandates is mixed. We also find that social distancing reduces consumer spending, but that mask mandates increase consumer spending. Mask mandates also reduce social distancing, magnifying the positive effect on spending. Finally, we observe that social distancing varies significantly by political affiliation, with counties that had high vote shares for Trump in 2016 engaging in significantly less social distancing than counties that had low vote shares for Trump in 2016. We demonstrate that if the whole country had engaged in Trump-supporting levels of social distancing instead of non-Trump-supporting levels of social distancing, COVID-19 cases and deaths would be much higher, while consumer spending would only increase modestly.

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1. Introduction

COVID-19 has been a disruptive force throughout the world. There are over 43 million confirmed cases worldwide, and over 8.5 million confirmed cases in the US. Over 1 million people have died, including over 225,000 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 a debate about how much social distancing and masking policies have affected both the death rates and the level of consumer spending. We thus examine the role of these effects on both the spread of COVID-19 and the level of consumer spending.

In particular, we first measure the impact of social distancing and mask mandates. We show that social distancing affects the spread of COVID-19 and the level of consumer spending. We then show that social distancing is driven by both government orders and by the percentage of votes Trump received in 2016, reflecting different views towards the pandemic. Finally, we compare the level of social distancing that would have occurred, holding all else equal, if all counties had 10% of the electorate vote for Trump (henceforth "10% Trump") to the level of social distancing that would have occurred if 90% of the electorate in each county had voted for Trump (henceforth “90% Trump”).

We find that moving from levels of social distancing in 10% Trump counties to 90% Trump counties would result in a large shift in the number of people who get sick, ultimately leading to a difference in 91,428 deaths over 4 months. However, the impact of such a change on consumer

[1] World Health Organization COVID-19 Dashboard, https://covid19.who.int. Accessed on Oct. 29, 2020.

spending would be much smaller: Moving from 10% Trump levels of social distancing to 90% Trump levels of social distancing only increase consumer spending by 1.8 percentage points. We also find that mask mandates reduce the spread of COVID-19 by 0.8 percentage points, and further increase consumer spending by 5.4 percentage points.

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 presents the model and estimation for consumer spending. Section 5 examines shifters of social distancing. Section 6 presents the counterfactual analysis of how contagion and spending would be affected by different social distancing attitudes. Finally, Section 7 concludes.

2. Data

Our data come from a number of sources. Much of our data comes from public sources. Our data on the number of positive cases comes from the New York Times. These data contain confirmed cases for 2,953 U.S. counties or county-equivalents. Our demographic data comes from the Census Bureau's 2014-2018 American Community Survey. Our weather data comes from the National Oceanic and Atmospheric Administration. These variables, as well as a full description of the variables, can be found at this website: https://github.com/songyao21/covid_data_depot.

We supplement this 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 for free to academics studying COVID-19 (https://www.safegraph.com/covid-19-data-consortium). We measure social distancing as the first principle component of several metrics, including the percentage of residents staying home, the percentage of residents working full-time at their workplace, the percentage of residents working at their workplace part time, and the median duration of residents staying home. We take the negative of this first principle component as the social distancing index, which means that the higher the index is, the greater the social distancing (as one would intuitively interpret a social distancing variable). These cellphone GPS location data are supplied at the daily level for residents of each Census Block Group. We aggregate this variable to the county level by taking the weighted median, where the weights are the number of cellphones in the data at each Block Group. Some of our analysis is run at a weekly level. In that case, we average our measure across the corresponding 7 days.

We also use SafeGraph data on point of interest (POI) visits that report how many cellphone users in their data visit different businesses on each day. From this dataset, we use businesses that averaged over 50 visits a week from Dec. 30, 2019 to Feb. 2, 2020 to calculate whether a business was open after the pandemic. We assume that a business was open if it had over 40% of the weekly visits as it experienced from Dec. 30, 2019 to Feb. 2, 2020. To further reduce extreme cases, we also smooth the open status of stores such that we do not consider a store to be closed in a week if it is deemed to be open in the previous and following weeks. We use a minimum threshold of visits to determine whether a business is open because most businesses have a few visits even in periods where they were known to be closed; we attribute these visits as being from employees. Using the 40% threshold leads to a result where the bulk of openings correspond to known times of loosening of economic restrictions. We divide all businesses into 3 categories: essential, hybrid, and non-essential, and then examine the opening rate for each of these 3 categories. Legal definitions of essential businesses vary across jurisdictions. Instead, we classify each category of POI into these 3 categories based on our interpretations of what is essential as laid out in Jiang (2020). This classification is not always straightforward; thus, we present our complete classification in Online Appendix 1.

Our spending data are provided by https://tracktherecovery.org/. These data are made publicly available by Opportunity Insights, based at Harvard University, 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 Sunday iteration of this measure to give us aggregate weekly spending. The spending is aggregated at the state level, and is divided into different categories based on the Merchant Category Code (MCC) that the firm uses. The industries include accommodation and food service; arts, entertainment, and recreation; general merchandise stores and apparel and accessories; grocery and food store; health care and social assistance; and transportation and warehousing.[2] Each observation measures the seasonally adjusted change relative to the January 2020 index period for the corresponding industry.[3] For simplicity, we refer to this indexed data as the consumer spending recovery index.

Facial mask mandates data come from three sources. The first source of data is from Wright et al. (2020), who collect county-level facial mask mandate information. We further compile a

[2] Total spending for the entire economy is also included in the dataset

[3] This number is $\frac{\left(\frac{Spending(Date\ 2020)}{Spending(January\ 2020)}\right)}{\left(\frac{Spending(Date\ 2019)}{Spending(January\ 2019)}\right)} - 1$. See Chetty et al. (2020) for more details, including the method of handling holidays.

second dataset from online sources for state-level facial mask mandates.[4] For counties that never issued any mask mandates, we use their respective state level mandates as the county mask policies. A third source of mask mandate data is pertaining to state employee mask mandates, which are collected by Lyu and Wehby (2020).

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

Table 1: Summary Statistics

	mean	median	sd
social distancing index	0.546	0.521	0.969
local WOW % change in cases	0.400	0.000	2.175
national WOW % change in cases	0.106	-0.001	0.272
avg precipitation	3.446	0.167	8.125
avg temperature	19.435	21.255	7.120
open rate$_E$	0.958	0.980	0.089
open rate$_N$	0.729	0.912	0.371
open rate$_H$	0.946	0.976	0.136
median income	53082.755	51159.500	14523.368
frac white	0.833	0.892	0.158
frac black	0.092	0.026	0.142
frac asian	0.014	0.007	0.028
frac hispanic	0.094	0.043	0.135
frac public transit commuter	0.010	0.003	0.031
frac senior	0.122	0.120	0.032
frac youth	0.224	0.223	0.034
population density	293.439	53.096	1795.992
Trump vote share	0.626	0.653	0.154
consumer spending recovery index for total spending	-0.118	-0.096	0.104
consumer spending recovery index for accommodation & food service	-0.431	-0.424	0.146
consumer spending recovery index for arts, entertainment, & recreation	-0.590	-0.597	0.122
consumer spending recovery index for general merchandise stores & apparel and accessories	-0.152	-0.139	0.168
consumer spending recovery index for grocery & food store	0.133	0.131	0.072
consumer spending recovery index for health care & social assistance	-0.277	-0.244	0.199
consumer spending recovery index for transportation & warehousing	-0.564	-0.547	0.102

3. The Effect of Social Distancing and Masking on the Spread of COVID-19

When examining the impact of COVID intervention measures on the economy, it is important to compare these gains in the economy with losses in health. Thus, we estimate a model of COVID-19 spread as a function of social distancing and mask mandates.

[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.

Our estimation is based on a modified version of the 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). We modify this paper to allow the spread of COVID-19 to be less than proportionate to the number of infectious individuals. As shown in Liu et al. 2020, this functional form would be expected if people's networks are concentrated such that a person's friends or acquaintances are more likely to be friends or acquaintances with the person's other friends or acquaintances than with random people. Examples where this will happen is in workplaces, where a person's co-workers are also co-workers with each other, or at nursing homes, where the residents are all connected to each other more than with random outside individuals. As Liu et al. 2020 shows, such a form fits the data very well, even out of sample.

Our model is essentially the same as Liu et al. 2020. Thus, we only give a quick summary of this model, and leave most of the detailed explanations of the model and justification of the assumptions to that paper. Mathematically, we model that new infections, $y_{i,t}$, in a given county i on date t follow the following process:

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

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 case number of 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 8 days and 2 days before date t. Following recent literature (Nishiuram et al. 2020, Liu et al. 2020), we assume the disease has a 6-day incubation period, during which the infected individuals can further spread the disease. 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 incubation period has little impact on the estimation results; Liu et al. 2020 shows that using a 14-day incubation period (i.e., $Y_{i,t-2} - Y_{i,t-16}$) yields extremely similar simulated forecasts. The main difference between our model and a standard SIR model is the exponent, ω. In standard SIR models, ω is constrained to be 1, while we find that ω is 0.57. As noted above, we interpret this estimate as capturing the network concentration in a reduced-form manner.

We expect that 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, a social distancing index and indicator variables denoting the presence of a county level mask mandate to the public or to state employees.[5]

We estimate the case model by taking the logarithm of both sides of equation 1. Occasionally, $y_{i,t}$ are 0 for some counties on certain days. To assure $ln(y_{i,t})$ is well defined, we add 1 to each observation of daily county cases.[6] After rearranging, we have

$$\left[ln(y_{i,t} + 1) - ln(S_{i,t})\right] = \alpha_i + \beta_t + \mu X_{i,t} + \omega\ ln\left(Y_{i,t-2} - Y_{i,t-8}\right) + e_{i,t}. \tag{3}$$

One difficulty in estimating Equation 3 is that social distancing may be endogenous because it can be affected by the severity of the pandemic. To address the potential bias due to

[5] We include mask mandates but not other shelter-in-place mandates because the shelter-in-place mandates will not directly change the spread of COVID-19, but rather will have an effect only to the extent that they change social distancing. On the other hand, mask mandates change the spread of contagion conditional on the level of social distancing that occurs. Furthermore, we observe that social distancing and shelter-in-place mandates are often endogenous to the spread. That is, the timing of these actions is not random. We have a good instrument for social distancing, but not for the imposition of shelter-in-place orders.

[6] We only estimate the model using observations where there are positive infectious cases in the county, so we do not impose the addition of 1 to the right-hand side.

the endogeneity, we use an Instrumental Variable approach, where the amount of rain in county i on day t is an instrument for social distancing. This has been used by several papers studying social distancing (Qiu et al. 2020, Holtz et al. 2020, Kapoor et al. 2020).

Table 2: Modified SIR Model.

	Dependent Variable:	
	Log(Infected)	
social distancing index	-0.822***	-0.840***
	(0.245)	(0.247)
infectious individuals	0.571***	0.571***
	(0.014)	(0.014)
avg temperature	-0.001	-0.001
	(0.002)	(0.002)
avg precipitation	0.005**	0.005**
	(0.002)	(0.002)
public mask mandate		0.096*
		(0.052)
employee mask mandate		-0.104***
		(0.029)
County Fixed Effects	Yes	Yes
Date Fixed Effects	Yes	Yes
Observations	131,272	131,272
Adjusted R^2	0.63	0.63
Counties	2,924	2,924
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2 presents the results of the estimation. From the table, we see that social distancing lowers the transmission rate substantially. We also observe the exponent ω is 0.57, confirming the diminishing impact of infectious individuals on the contagion when more and more people become infected. Looking across the two columns of data, we observe that none of the estimates vary with the inclusion or the exclusion of a mask mandate variable, except for the coefficients on the mask mandates itself. The coefficient on employee mask mandates is negative and significant, as expected. The coefficient on an overall mask mandate is unexpectedly positive, and barely significant at the 10% significance level. One plausible explanation for this is that the imposition of the mask mandates might be somewhat endogenous, and without an instrument for the imposition of the mask mandate this reverse causality overwhelms any negative impact of a mask mandate. It is also possible that a mask mandate encourages risky behavior (such as not standing 6 feet apart) due to people feeling protected, especially if they wear masks that are not completely effective.

4. The Effect of Social Distancing and Masks on Consumer Spending

In this section, we investigate how social distancing and mask mandates affect consumer spending. For this analysis, the dependent variables are observed at the state level, and each variable is smoothed over 7 days, as described in Chetty et al. (2020). Because our index of how many businesses are open is calculated at the weekly level, with weeks defined as Monday through Sunday, we take the spending data every Sunday, such that the spending data lines up with our business-opening data. We then estimate:

$$s_{i,\tau,k} = a + \varphi\, o_{i,\tau,j} + \tau\, d_{i,\tau} + \mu\, m_{i,\tau} + \theta\, c_{i,\tau} + \lambda\, X_{i,\tau} + \epsilon_{i,\tau,k} \tag{4}$$

where $s_{i,\tau,k}$ is the consumer spending recovery index at state i on week τ for industry k. a is a constant, $o_{i,\tau,j}$ is store open rate at state i on week τ for all businesses of type j (j = essential, non-essential, or hybrid). $m_{i,\tau}$ is the average temperature in state i on week τ, $c_{i,\tau}$ is the average precipitation in state i on week τ, and $X_{i,\tau}$ consists of a string of binary indicator variables of COVID-19 related public orders in state i on week τ. We present the estimation results in Table

3.[7] In Online Appendix 2 we present figures that show the overall comparison of aggregate national spending with the spending predicted by our model for each of the industries. We observe that the fits are good except for in general merchandise and apparel, even with significant variation over time, despite a lack of time trends in the estimated models. These figures also show that the economy is still recovering from the initial plunge caused by COVID-19, but has not reached its pre-pandemic level yet.

Table 3: Consumer Spending Regression

	Dependent variable: consumer spending recovery index for the following industries:						
	the entire economy	accommodation & food service	arts, entertainment, & recreation	general merchandise stores & apparel and accessories	grocery & food store	health care & social assistance	transportation & warehousing
open rate$_E$	-0.334^{***}	-0.268^{***}	0.341^{***}	-0.250^{***}	-0.039	0.088	-0.320^{***}
	(0.055)	(0.071)	(0.086)	(0.095)	(0.061)	(0.124)	(0.049)
open rate$_H$	0.544^{***}	0.367^{***}	-0.423^{***}	0.143^{*}	-0.117^{**}	-0.227^{**}	0.507^{***}
	(0.046)	(0.060)	(0.072)	(0.079)	(0.051)	(0.103)	(0.041)
open rate$_N$	-0.061^{**}	0.102^{***}	0.196^{***}	0.146^{***}	-0.120^{***}	0.278^{***}	0.074^{***}
	(0.024)	(0.031)	(0.037)	(0.041)	(0.027)	(0.054)	(0.021)
social distancing index	-0.034^{***}	-0.046^{***}	-0.051^{***}	-0.085^{***}	-0.026^{***}	-0.045^{***}	0.001
	(0.006)	(0.008)	(0.010)	(0.010)	(0.007)	(0.014)	(0.005)
avg temperature	0.002^{***}	0.006^{***}	0.0003	0.003^{***}	0.001^{***}	0.008^{***}	0.003^{***}
	(0.0004)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)	(0.0004)
avg precipitation	0.002^{***}	0.004^{***}	0.0002	0.008^{***}	-0.002^{*}	0.003^{*}	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
public venues closure	0.016^{**}	0.013	-0.062^{***}	-0.009	0.002	-0.010	-0.002
	(0.007)	(0.009)	(0.010)	(0.011)	(0.007)	(0.015)	(0.006)
non essential closure	-0.027^{***}	-0.019^{**}	0.044^{***}	0.002	-0.030^{***}	-0.068^{***}	-0.019^{***}
	(0.006)	(0.008)	(0.010)	(0.011)	(0.007)	(0.014)	(0.006)
school closure	0.003	-0.003	0.012	0.028^{**}	0.020^{***}	0.010	-0.0004
	(0.006)	(0.008)	(0.010)	(0.011)	(0.007)	(0.014)	(0.006)
shelter in place	-0.022^{***}	-0.00004	-0.038^{***}	-0.022^{***}	0.018^{***}	0.012	-0.003
	(0.005)	(0.006)	(0.007)	(0.008)	(0.005)	(0.011)	(0.004)
gatherings limit	-0.016^{***}	-0.026^{***}	0.005	-0.012	-0.004	0.014	-0.025^{***}
	(0.005)	(0.007)	(0.008)	(0.009)	(0.006)	(0.012)	(0.005)
religious gatherings limit	0.016^{***}	0.011^{*}	0.015^{**}	0.007	0.004	-0.013	0.011^{***}
	(0.005)	(0.006)	(0.007)	(0.008)	(0.005)	(0.011)	(0.004)
public mask mandate	0.020^{***}	0.011^{*}	0.021^{***}	0.034^{***}	0.016^{***}	0.034^{***}	0.018^{***}
	(0.005)	(0.006)	(0.007)	(0.008)	(0.005)	(0.010)	(0.004)
employee mask mandate	0.034^{***}	0.037^{***}	0.038^{***}	0.054^{***}	0.014^{***}	0.006	0.026^{***}
	(0.004)	(0.006)	(0.007)	(0.008)	(0.005)	(0.010)	(0.004)
constant	-0.261^{***}	-0.630^{***}	-0.634^{***}	-0.189^{***}	0.312^{***}	-0.454^{***}	-0.783^{***}
	(0.031)	(0.040)	(0.049)	(0.054)	(0.035)	(0.070)	(0.028)
Observations	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Adjusted R^2	0.689	0.737	0.447	0.647	0.206	0.574	0.743
Note:							*p<0.1; **p<0.05; ***p<0.01

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

We find that social distancing is negatively correlated with spending in all industries. Looking closer, we find that accommodation and food services are affected the most by changes in social distancing, while grocery and food store sales are the least sensitive to social distancing. Not surprisingly, higher open rates are generally associated with higher consumer spending. Open rates for essential and hybrid businesses are usually quite high, so the large coefficients reflect that when even essential businesses are closed, the economy really closes. Note that because of the relative sizes of the variation in the underlying variables, social distancing has a larger effect on spending than the nonessential open rate.

We further observe that mask mandates for the public and for employees are associated with increases in spending by a total of 5.4 percentage points. This finding demonstrates that while much of the opposition to mask orders has been driven by a desire to support businesses, consumers want the other people in the business to be masked in order to feel safe patronizing them. Thus, mask policies are strongly pro-business. We also find that non-essential businesses (e.g., general merchandise stores & apparel and accessories, arts, entertainment, & recreation, etc.) that were hit harder tend to benefit the most from mask mandates. We observe that other public health orders have a smaller effect on sales, reducing spending by a total of 3.3 percentage points.[8]

5. The Impact of Government Orders and Politics on Social Distancing?

Our goal in this section is to understand how government orders and political views affect the level of social distancing. To do this, we estimate the following model:

[8] Note that the different government orders have high correlations, so taking the sum of the effects is the most reliable measure of their total impact.

$$d_{i,t} = \alpha_i + \beta_{dow(t)} + \delta\, q_{i,t} + \varphi\, p_t + \mu\, m_{i,t} + \theta\, c_{i,t} + \lambda\, X_{i,t} + \zeta_{i,t} \quad (5)$$

where the response variable $d_{i,t}$ is the social distancing index of county i on date t. α_i and $\beta_{dow(t)}$ are county fixed effects and day-of-the-week fixed effects, respectively. $q_{i,t}$ and p_t represent the county and national week-over-week percentage changes in the number of confirmed cases, respectively.[9] $m_{i,t}$ is the average temperature (in centigrade), $c_{i,t}$ is the average precipitation (in millimeters), $X_{i,t}$ consists of a string of binary indicator variables of COVID related public orders (the closure of public venues, the closure of non-essential businesses, the closure of schools, shelter-in-place orders, limits on social gatherings, limits on religious gatherings, county public mask mandates and employee mask mandates.

The results are in Table 4. We observe that social distancing increases when cases of COVID are increasing, but is driven more by nation-wide increased than by local case increases. We also find that social distancing increases with rainfall, which helps ensure the reasonableness of using rain as an instrument for our COVID-19 spread regressions in Section 3. Similarly, warmer temperatures are associated with less social distancing, as going outside becomes more enticing. We observe that most of the government policies encouraging distancing do lead to increased social distancing. Finally, mask mandates reduce the amount of social distancing, as mask mandates may make many people feel safer in public. This is consistent with mask mandates increasing spending (as noted in Section 4), but may be at odds with public health policy. In Online Appendix 2 we present our predicted values of social distancing index against the observed values, which shows that the model fits well.

[9] We used April – June for estimation and reserved July and August to test how our model performs out-of-sample. We found that having only WOW percentage change in cases (not the actual number of cases) generates the lowest out-of-sample MSE.

Table 4: Social Distancing Regression

	Dependent variable
	social distancing index
local WOW % change in cases	0.002***
	(0.0003)
national WOW % change in cases	0.298***
	(0.003)
open rate$_E$	−0.334***
	(0.015)
open rate$_N$	−0.533***
	(0.006)
open rate$_H$	−0.984***
	(0.016)
avg temperature	−0.042***
	(0.0002)
avg precipitation	0.005***
	(0.0001)
public venues closure	0.044***
	(0.004)
non essential closure	0.083***
	(0.004)
school closure	0.087***
	(0.003)
shelter in place	0.213***
	(0.003)
gatherings limit	−0.009***
	(0.003)
religious gatherings limit	0.004
	(0.003)
public mask mandate	−0.002
	(0.002)
employee mask mandate	−0.212***
	(0.003)
County Fixed Effects	Yes
Day-of-week Fixed Effects	Yes
Observations	375,636
Adjusted R^2	0.805
Note:	*p<0.1; **p<0.05; ***p<0.01

To further understand what drives social distancing, we regress the county-level fixed effects (α_i) from equation (5) on several fixed county-level variables. These include the fraction of the population that is Asian, Black and Hispanic, the fraction the population that are of seniors older than 70 or children younger than 18, the fraction of the population that commutes using public transportation, the log of population density and the log of median income. Finally, we include the fraction of Trump voters in the 2016 presidential election.

The results of this second-stage estimation appear in Table 5. We observe that social distancing increases with the proportion of the population that is Asian and Hispanic. Communities that are more affluent engage in more social distancing, as do those where more of the population uses public transportation (which Liu et al. 2020 show leads to greater COVID-19 spread). Not surprisingly, seniors are more likely to social distance, while areas with more children engage in less social distancing.

Table 5: County Fix Effect Regression

	Dependent variable:
	county fixed effect
log median income	0.259***
	(0.038)
frac white	0.163
	(0.118)
frac black	0.024
	(0.121)
frac asian	1.648***
	(0.398)
frac hispanic	1.063***
	(0.064)
frac public transit commuter	−0.277
	(0.285)
frac senior	1.841***
	(0.325)
frac youth	−0.949***
	(0.310)
log population density	0.215***
	(0.006)
Trump vote share	−0.669***
	(0.070)
Constant	0.250
	(0.421)
Observations	2,722
Adjusted R^2	0.577
Note:	*p<0.1; **p<0.05; ***p<0.01

Finally, we observe that the fraction of the population to vote for Trump in 2016 is strongly related to the level of social distancing observed in the county. This is not surprising, but drives the differences in the levels of social distancing we can expect to observe due to political considerations. Further, the size of the impact of a swing in Trump voting fractions (which range from 4% to 95%) is approximately 50% larger than size of the effect of all of the government orders together. We examine these impacts in the next section.

6. The Effect of Politics on Disease Spread and Spending

In the previous sections we observe that social distancing affects the rate of disease spread and levels of consumer spending. However, we also observe that social distancing is tied to the political views of the electorate in each county. That is not surprising because the party leaders have taken different approaches towards COVID-19. For example, Trump has stated that while some people will be "affected badly," "we have to get our country open, and we have to get it open soon."[10] Biden on the other hand has stated "Americans deserve a President who will ensure that re-opening is as effective and safe as possible."[11] Note that Trump does not see the different levels of social distancing to be due to differences in the safety of opening up in different locations. For example, Trump has stated "On November 4th, it will all open up. … They want to make our numbers look as bad as possible for the election."[12] We also control for demographics

[10] https://www.npr.org/2020/05/06/851631806/president-trump-wants-to-reopen-economy-despite-cdc-warnings. Accessed on Oct. 29, 2020.
[11] https://joebiden.com/reopening/#. Accessed on Oct. 29, 2020.
[12] https://www.washingtontimes.com/news/2020/aug/24/donald-trump-blue-states-will-open-up-nov-4-democr/. Accessed Oct. 29, 2020.

and population density in order to ensure that the political effects we observe are truly driven by politics instead of other coincidental factors.

The public has largely followed the philosophies of these leaders and taken different approaches to social distancing. However, a key question is how much the spread of COVID-19 and the loss of consumer spending is affected by social distancing. To do this, we compare what the paths of social distancing and consumer spending would look like if everyone followed a largely Republican level of social distancing with what these would be if everyone followed a largely Democratic level of social distancing.

To do this, we compare the level of social distancing that would have occurred, holding all else equal, if all counties had 10% of the electorate vote for Trump and compare that to the level of social distancing that would have occurred if 90% of the electorate in each county had voted for Trump. We plug in the two numbers along with the actual values of other variables and the estimated coefficients into equations 1 and 5. We then iteratively simulate the social distancing index and the number of cases during the same sample period (4/1-8/16). This iterative approached is used because the level of social distancing is affected by the changes in the number of COVID-19 cases. For comparability, we keep the residuals to the estimated levels for each observation. The level of simulated Social Distancing under these scenarios is presented in Figure 1. The 10% Trump level social distancing index is shown to be on average 0.5 unit higher than it would have been under the 90% Trump level distancing.

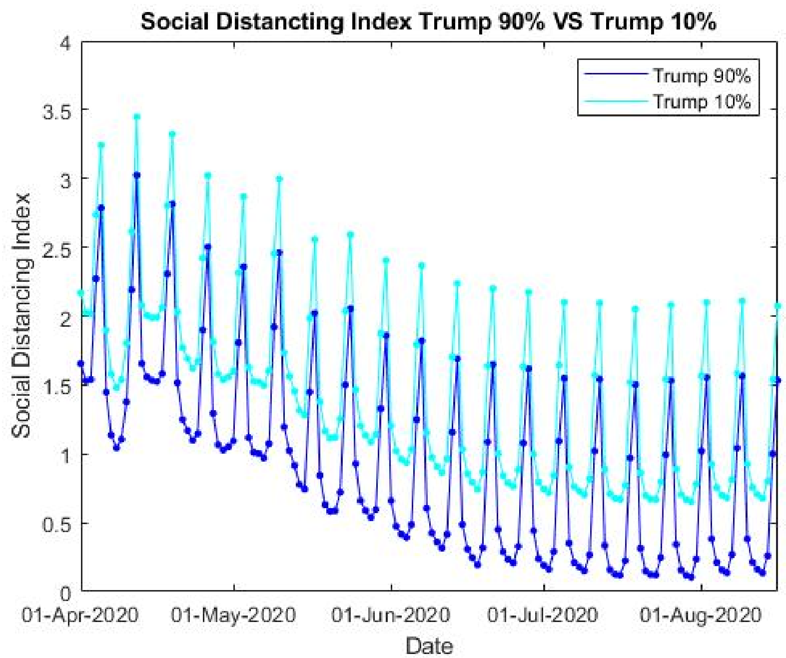


Figure 1 Social distancing index 90% Trump vs. 10% Trump

In Figure 2, we plot the number of COVID-19 cases that we forecast would have occurred under each of these levels of social distancing. We can readily observe that there would be a significantly larger number of cases under the 90% Trump level of social distancing than under the 10% Trump level of social distancing.[13] Our forecasts show that the 90% Trump level of social distancing would have led to 7,289,811 confirmed cases, whereas the 10% Trump level of distancing would have led to 3,773,379 confirmed cases (compared to the actual cases of 4,093,162 over the focal 4-full-month period[14]). The numbers suggest that the two very different

[13] We plot out the forecasted number of confirmed cases. When estimating the model, we assume that only 10% of cases are confirmed. However, the dynamics do not change much if another ratio is used. Please see Liu et al. 2020 for more details.

[14] We notice that the difference between actual cases and cases generated by the 10% Trump level distancing is relatively small. This is potentially due to that Trump-supporting areas are usually less densely populated and have fewer initial cases during our focal period.

social distancing levels would have translated to a difference of 3,516,432 confirmed cases. Using the 2.6% death ratio from confirmed cases[15], this would imply that the 90% Trump level of distancing would lead to 91,428 more deaths than would be obtained under the 10% Trump level of social distancing. For comparison, just under 6 million cases and 182,000 deaths occurred in the U.S. by Sept. 1, 2020, so the different in these policies reflect a large difference in the number of cases.

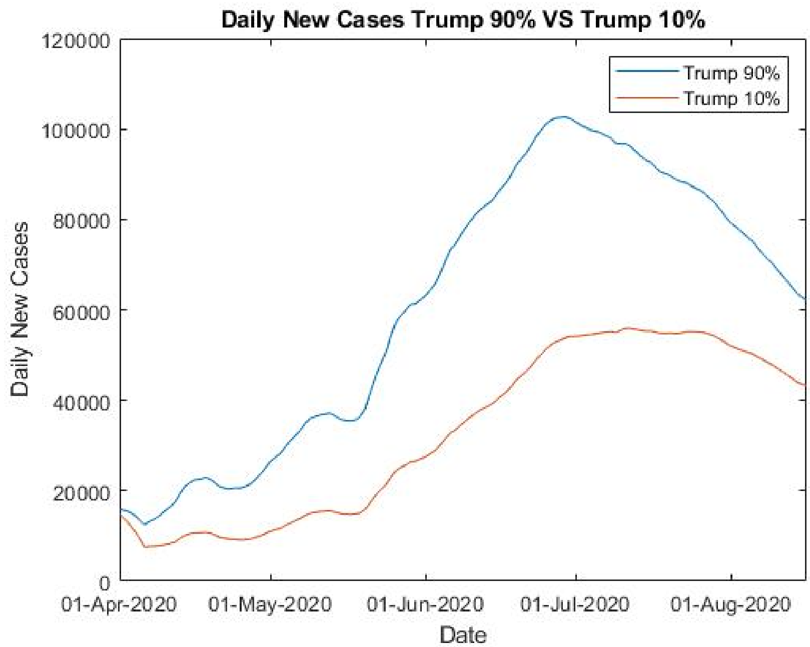


Figure 2 Daily new cases with 90% Trump vs. 10% Trump level social distancing

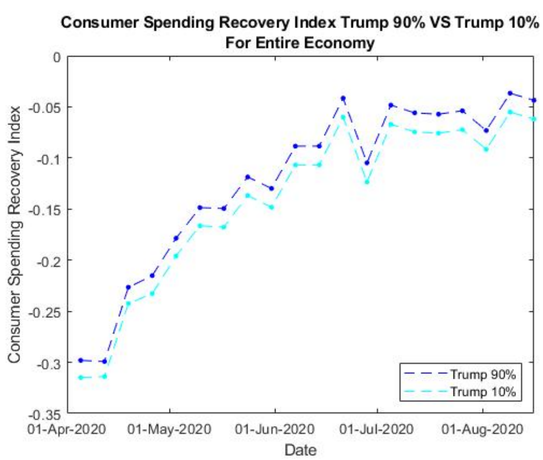
We next calculate the changes in the level of consumer spending under the two scenarios. We plot the counterfactuals in consumer spending in Figure 3.[16] We find that consumer spending is only marginally affected by the politically-driven differences in social distancing. In particular,

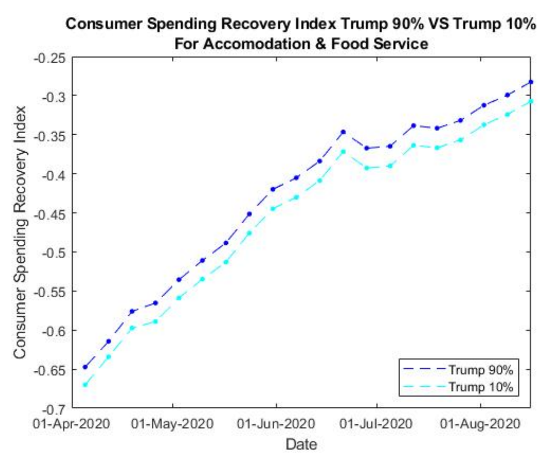
[15] Johns Hopkins University COVID-19 Mortality Analyses, https://coronavirus.jhu.edu/data/mortality. Accessed on October 29, 2020.
[16] We apply dotted lines in between weekly points.

going from a 10% Trump to a 90% Trump level of social distancing only increases the consumer spending by 1.8 percentage points. To better demonstrate the difference in actual dollar amounts instead of an index, we obtain the 2020 monthly national personal consumer expenditure (PCE) from https://fred.stlouisfed.org/series/PCE. We then multiply the respective ratios of the average[17] monthly consumer spending recovery index under the two hypothetical scenarios to the actual recovery index by the actual monthly PCE amounts. We then sum up the monthly numbers and arrive at a $93.6 billion difference in total consumer spending over the 4-month period,[18] which corresponds to a 91,428 difference in deaths for the same period. These two counterfactual numbers suggest a tradeoff of approximately $1 million per life. This figure does not count the inconvenience of being sick even if one does not die, or the costs of hospitalizations for sick individuals.[19] Using the government's value of a life at $7.4-9.6 million,[20] that means that the social distancing choices by pro-Trump voters are under-valuing these lives. Another approach to valuing a life is to assume that lives are valued at $100,000-$400,000 per year of lost life (Hall et al. 2020). Using the ratio of years to deaths in the U.S. according to Mitra et al. 2020 (Table 3, assuming a lifespan of 80 years), we get a ratio of approximately 7 years per COVID death. That implies a valuation of $700,000 - $2,800,000 per death.

[17] We use the 2018 state level PCE as the weighting factor for each state in computing the national level consumer spending recovery index under two scenarios (e.g., a 1% recovery in NY is not equivalent to a 1% recovery in MO).
[18] August is not a full month in our sample
[19] According to https://www.cdc.gov/coronavirus/2019-ncov/covid-data/covidview/index.html#:~:text=The%20overall%20cumulative%20COVID%2D19,193.7%20hospitalizations%20per%20100%2C000%20population, there have been over 500,000 hospitalizations for COVID-19 by Oct. 17, 2020. https://www.healthcarefinancenews.com/news/hospitalized-care-covid-19-averages-34662-45683-varying-age#:~:text=Nationally%2C%20the%20median%20charge%20amount,according%20to%20a%20new%20study estimates the cost of the hospitalization is approximately $20,000, so hospitalization costs alone come to $10 billion.
[20] https://www.nytimes.com/2020/05/11/upshot/virus-price-human-life.html.

One thing going from 10% Trump to 90% Trump social distancing misses is that the baseline COVID danger and economic activity is different in the Trump-supporting and the Trump-opposing counties. As noted in the beginning of this section, Trump did not merely ask for counties that wanted to open to open, but to get areas that opposed opening to open as well. Thus, we also compare what would have happened under the 90% Trump levels of social distancing to the actual levels of distancing that occurred (rather than the counterfactual that everyone engaged in 10% Trump levels of distancing). With this tradeoff, we observe that if everywhere opened up to these levels, we would have had 83,000 additional deaths. However, we would only have increased consumer spending by $55.4billion. Such a move then only reflects a value of $667,000 per life saved. Thus, it appears that areas that engaged in more social distancing did have a greater risk of death compared to the economy than those areas that engaged in less social distancing, and forcing these areas to open up would only make sense if one had a very low value on the lives that would be lost.





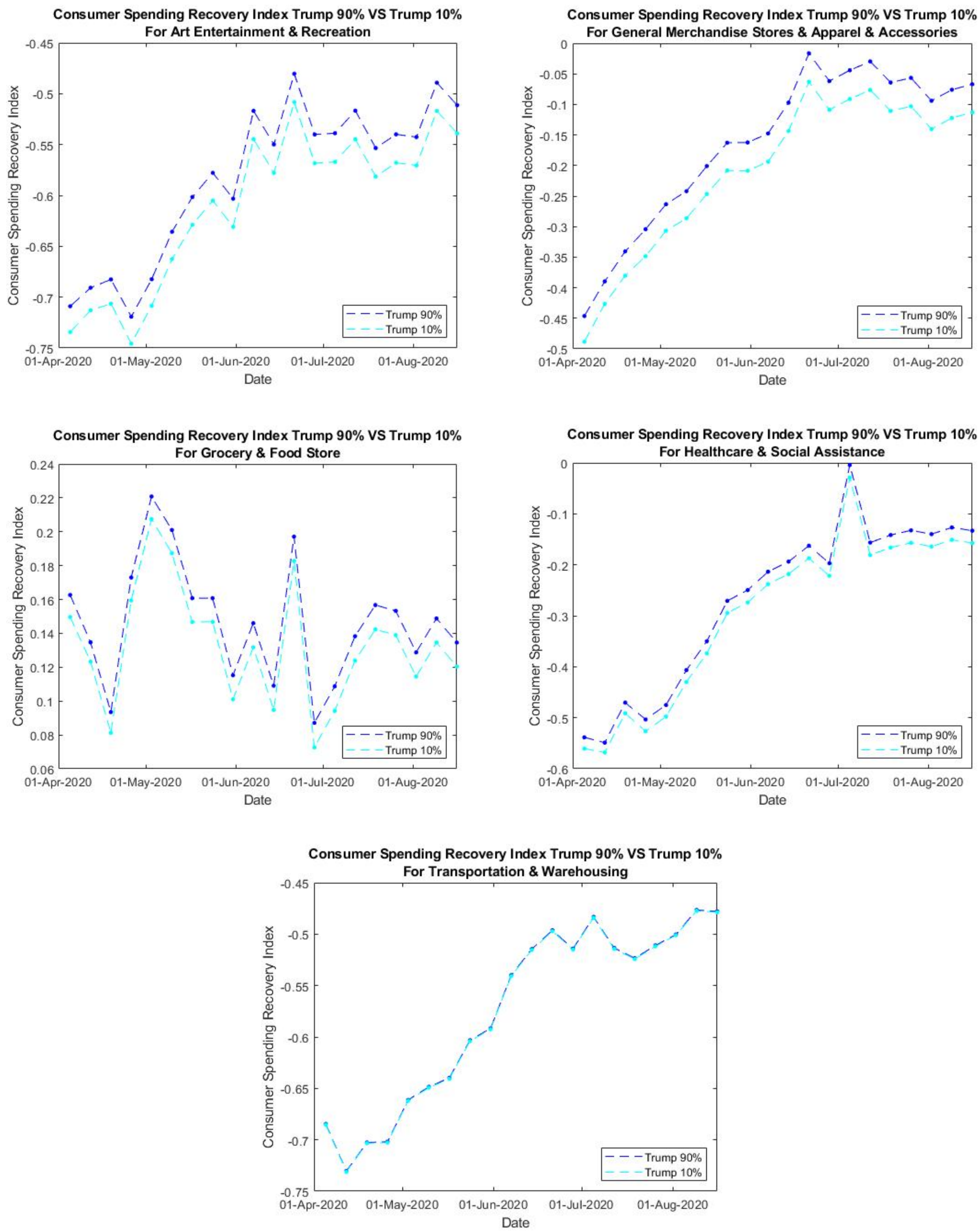


Figure 3 consumer spending recovery index for all industries with 90% Trump vs. 10% Trump level distancing

7. Conclusion

This paper examines the impact of social distancing and masking policies on the spread of COVID-19 and consumer spending. We observe that social distancing and requiring masks for employees reduces the spread of COVID-19, while mask mandates on the public do not. Further, we observe that social distancing reduces consumer spending, while both public and employee mask mandates increase spending. This suggests that the desire to prevent mask mandates has held back the economic recovery.

We also find that the political parties are aligned with different levels of social distancing. We observe that politically driven differences in social distancing would change the levels of COVID-19 cases and deaths by a significant amount, but that the effect on consumer spending is relatively smaller. This is especially the case when we examine how deaths and spending would change as we move from actual outcomes to 90% Trump levels of social distancing. We show that such a move would cause 83,000 more deaths, but only increase consumer spending by $55.4billion, reflecting a value of $667,000 per life saved. Thus, the social distancing that occurred late in the pandemic appears to reflect that the boost on the economy from opening up would be small relative to the costs of deaths and increased COVID-19 cases.

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Online Appendix

Online Appendix 1: Categorization of Categories

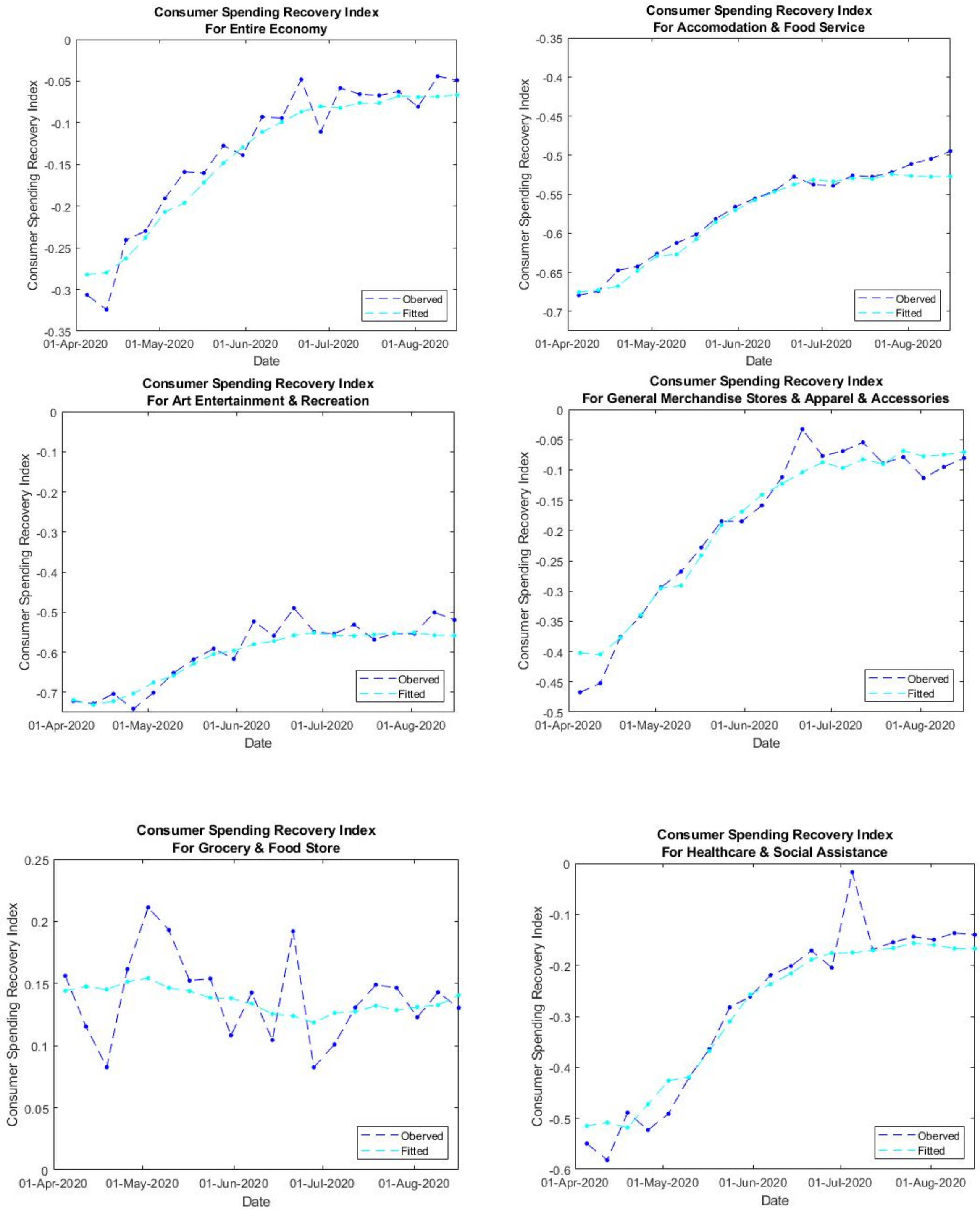
Top Category	(E)ssential, (N)onessential, (H)ybrid
Depository Credit Intermediation	E
Activities Related to Credit Intermediation	E
Nondepository Credit Intermediation	E
Other Investment Pools and Funds	E
Other Financial Investment Activities	E
Securities and Commodity Contracts Intermediation and Brokerage	E
Investigation and Security Services	E
Child Day Care Services	N
Elementary and Secondary Schools	N
Colleges, Universities, and Professional Schools	N
Other Schools and Instruction	N
Technical and Trade Schools	N
Educational Support Services	N
Amusement Parks and Arcades	N
Motion Picture and Video Industries	N
Radio and Television Broadcasting	E
Gambling Industries	N
Spectator Sports	N
Automotive Parts, Accessories, and Tire Stores	E
Gasoline Stations	E
Automotive Repair and Maintenance	E
Automotive Equipment Rental and Leasing	N
Motor Vehicle Body and Trailer Manufacturing	E
Grocery Stores	E
Specialty Food Stores	E
Grocery and Related Product Merchant Wholesalers	E
Drugs and Druggists' Sundries Merchant Wholesalers	E
Electronics and Appliance Stores	H
Building Material and Supplies Dealers	H
Home Furnishings Stores	H
Building Equipment Contractors	H
Lumber and Other Construction Materials Merchant Wholesalers	H
Hardware, and Plumbing and Heating Equipment and Supplies Merchant Wholesalers	H
Lawn and Garden Equipment and Supplies Stores	H
Household Appliances and Electrical and Electronic Goods Merchant Wholesalers	H
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	H
Services to Buildings and Dwellings	H
Residential Building Construction	H
Building Finishing Contractors	H
Household Appliance Manufacturing	H
Hardware Manufacturing	H
Health and Personal Care Stores	E
Medical and Diagnostic Laboratories	E

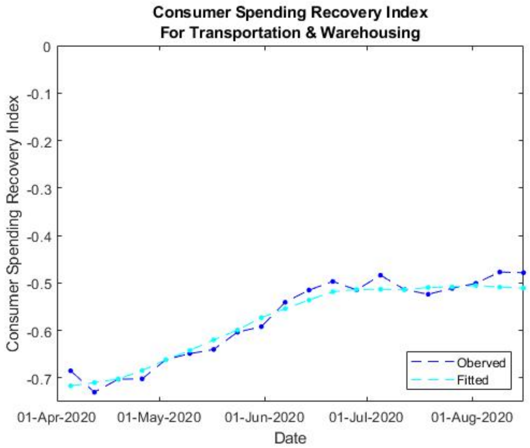
Offices of Physicians	E
Offices of Dentists	N
Outpatient Care Centers	E
Personal Care Services	E
Offices of Other Health Practitioners	E
General Medical and Surgical Hospitals	E
Other Ambulatory Health Care Services	E
Home Health Care Services	E
Nursing Care Facilities (Skilled Nursing Facilities)	E
Specialty (except Psychiatric and Substance Abuse) Hospitals	E
Florists	N
Clothing Stores	N
Sporting Goods, Hobby, and Musical Instrument Stores	N
Continuing Care Retirement Communities and Assisted Living Facilities for the Elderly	E
Consumer Goods Rental	N
Soap, Cleaning Compound, and Toilet Preparation Manufacturing	E
Machinery, Equipment, and Supplies Merchant Wholesalers	H
Commercial and Industrial Machinery and Equipment Rental and Leasing	H
Lessors of Real Estate	H
Other Personal Services	H
Agencies, Brokerages, and Other Insurance Related Activities	H
Beer, Wine, and Liquor Stores	H
Freight Transportation Arrangement	H
Motor Vehicle Parts Manufacturing	H
Automobile Dealers	H
Employment Services	E
Grantmaking and Giving Services	E
Business, Professional, Labor, Political, and Similar Organizations	E
Business Support Services	E
Chemical and Allied Products Merchant Wholesalers	H
Agriculture, Construction, and Mining Machinery Manufacturing	H
Alumina and Aluminum Production and Processing	H
Printing and Related Support Activities	H
Other Motor Vehicle Dealers	H
Electronic Shopping and Mail-Order Houses	E
Other Miscellaneous Manufacturing	H
Clay Product and Refractory Manufacturing	H
Motor Vehicle Manufacturing	H
Bakeries and Tortilla Manufacturing	E
Other Professional, Scientific, and Technical Services	H
Specialized Freight Trucking	E
Motor Vehicle and Motor Vehicle Parts and Supplies Merchant Wholesalers	E
Other Leather and Allied Product Manufacturing	H
Spring and Wire Product Manufacturing	H
Petroleum and Petroleum Products Merchant Wholesalers	E
Miscellaneous Nondurable Goods Merchant Wholesalers	H
Support Activities for Mining	H
Professional and Commercial Equipment and Supplies Merchant Wholesalers	H
Miscellaneous Durable Goods Merchant Wholesalers	H

Animal Food Manufacturing	E
Fruit and Vegetable Preserving and Specialty Food Manufacturing	E
Individual and Family Services	H
Engine, Turbine, and Power Transmission Equipment Manufacturing	H
Ship and Boat Building	H
Direct Selling Establishments	H
Architectural and Structural Metals Manufacturing	H
Basic Chemical Manufacturing	H
Personal and Household Goods Repair and Maintenance	E
Office Supplies, Stationery, and Gift Stores	H
Newspaper, Periodical, Book, and Directory Publishers	E
Drycleaning and Laundry Services	H
Offices of Real Estate Agents and Brokers	H
Accounting, Tax Preparation, Bookkeeping, and Payroll Services	H
Other General Purpose Machinery Manufacturing	H
Cut and Sew Apparel Manufacturing	H
Warehousing and Storage	E
Insurance Carriers	E
Electrical Equipment Manufacturing	E
Travel Arrangement and Reservation Services	E
Scientific Research and Development Services	H
Converted Paper Product Manufacturing	E
Water, Sewage and Other Systems	E
Administration of Human Resource Programs	E
Management of Companies and Enterprises	H
Other Food Manufacturing	E
Foundation, Structure, and Building Exterior Contractors	E
Couriers and Express Delivery Services	E
Other Textile Product Mills	H
Rubber Product Manufacturing	H
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	H
Other Transportation Equipment Manufacturing	H
Advertising, Public Relations, and Related Services	H
Farm Product Raw Material Merchant Wholesalers	E
Support Activities for Crop Production	E
Remediation and Other Waste Management Services	E
Paint, Coating, and Adhesive Manufacturing	H
Data Processing, Hosting, and Related Services	E
Religious Organizations	H
Coating, Engraving, Heat Treating, and Allied Activities	H
Other Electrical Equipment and Component Manufacturing	H
Performing Arts Companies	N
Greenhouse, Nursery, and Floriculture Production	N
Other Wood Product Manufacturing	N
Death Care Services	E
Audio and Video Equipment Manufacturing	H
Apparel Knitting Mills	H
Other Support Services	H
Commercial and Service Industry Machinery Manufacturing	H

Textile Furnishings Mills	H
Waste Treatment and Disposal	H
General Rental Centers	H
Metalworking Machinery Manufacturing	H
Metal and Mineral (except Petroleum) Merchant Wholesalers	H
Steel Product Manufacturing from Purchased Steel	H
Other Furniture Related Product Manufacturing	H
Sound Recording Industries	H
Petroleum and Coal Products Manufacturing	E
Special Food Services	E
Household and Institutional Furniture and Kitchen Cabinet Manufacturing	H
Postal Service	E
Oil and Gas Extraction	E
Other Crop Farming	E
Other Fabricated Metal Product Manufacturing	H
Restaurants and Other Eating Places	H
Drinking Places (Alcoholic Beverages)	H
General Merchandise Stores, including Warehouse Clubs and Supercenters	H
Other Miscellaneous Store Retailers	N
Shoe Stores	N
Electronic and Precision Equipment Repair and Maintenance	H
Jewelry, Luggage, and Leather Goods Stores	N
Book Stores and News Dealers	N
Furniture Stores	N
Used Merchandise Stores	N
Beverage Manufacturing	E
Footwear Manufacturing	N
Apparel, Piece Goods, and Notions Merchant Wholesalers	N
Furniture and Home Furnishing Merchant Wholesalers	N
Department Stores	N
Traveler Accommodation	E
Other Amusement and Recreation Industries	N
Rail Transportation	E
School and Employee Bus Transportation	E
Interurban and Rural Bus Transportation	E
Other Support Activities for Transportation	E
RV (Recreational Vehicle) Parks and Recreational Camps	H
Wired and Wireless Telecommunications Carriers	E
Other Telecommunications	E
Cable and Other Subscription Programming	E
Natural Gas Distribution	E

Online Appendix 2. In-sample fit for consumer spending and social distancing index




Consumer Spending Recovery Index
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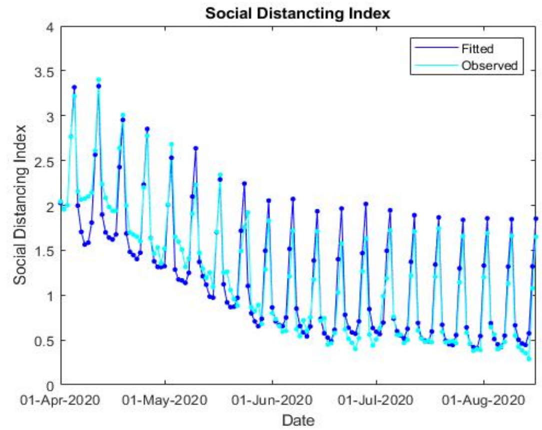
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