How Non-Pharmaceutical Interventions, Politics, Race, and Economic Conditions Impacted the Rate of New Infections of COVID-19*

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PRELIMINARY DRAFT. DUE TO THE ONGOING NATURE OF COVID-19 THE ANALYSIS IS SUBJECT TO CHANGE.

Abstract

We explore daily new infections of COVID-19 in the United States from January 22, 2020 to May 17, 2020 and factors influencing the trajectory of new infections. Using daily county level infection data and state shutdown orders (SSOs), we first show that new infections fell significantly faster in areas targeted by SSOs. We then demonstrate that the magnitude of the effect on new infections depends upon the strength of the intervention, with "Shelter in Place" orders having the largest effect. We show social distancing (as measured through cellphone "ping" data), is inversely related to new infections. Last, we close by demonstrating that the county responses to SSOs, depend upon the county's characteristics.

Keywords: COVID-19; Social Distancing; Political Partisanship

*We thank Christopher Azevedo, Paul Chambers, Catherine Chambers, Henry Thompson, and David Yerger for their valuable comments and suggestions. All mistakes are our own. *****This version is different from the original. There was an error caused by updated data and this caused large changes in some of the analysis. All of the changes occurred in section 4.2 and due to contemporaneous nature of social distancing and state shutdown orders. We did not see these changes. We apologize for such carelessness.*****

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1 Introduction

We examine the effect of social distancing on new infections of the novel coronavirus (COVID-19) using daily county level infections and daily social distancing scores based off cellphone "ping" data. In addition to this data, we control for state shutdown orders (SSOs, hereafter). The three types of SSOs we focus on are: 1) Shelter in Place, 2) Stay at Home, and 3) Safe at Home. We show that before controlling for social distancing, SSOs had large and significant negative effects on new infections. However, the effects of these SSOs diminish once social distancing is controlled for. This suggests social distancing increased due to the presence of these SSOs which led to a decrease in the rate of infection. Using county level controls interacted with SSOs we then demonstrate that responses to the SSOs depends upon county level characteristics. We find that SSO response is decreasing in the percent of the county that voted Republican in the 2016 presidential election, the percent of county residents who are African American, and the percent of the county residents who are Hispanic. Responses to these SSOs are however increasing in the percent of the county with a college degree, percent of the county population that is younger than 45, and the number of "high risk" workers (e.g., employees at bars and gyms) per 100 county residents. Other characteristics are found to have no statistically significant effect on SSO response, effects under a single type of SSO, or to have very small effects.

There are a few caveats to keep in mind. We are not advocating for or against state quarantine measures. This is not a cost/benefit analysis. We are interested in the effect of SSOs on new infections controlling for social distancing and how social distancing is influenced by socio-economic county characteristics. Secondly, the pandemic is ongoing and data on COVID-related cases and deaths continue to be updated. Still, as this is the same data that health organizations (including the CDC and WHO) are utilizing to update real-time guidelines and forecast future COVID-19 deaths and cases, we believe the results from this paper may help shape policy during the current and future pandemics. The rest of the paper is organized as follows; Section 2 includes a literature review of previous studies on the efficacy of non-pharmaceutical interventions, which include social distancing, SSOs, quarantines, isolation, and other forms of non-pharmaceutical (NPI) virus transmission mitigation practices. Section 3 describes the data; the hypotheses are discussed in Section 4; results are in Section 5; and Section 6 concludes.

2 Background Literature

2.1 Effectiveness of NPIs

The first records of NPIs involve quarantining. Quarantines are the act of separating and restricting "the movement of people who are exposed to a contagious disease to see if they become sick" (CDC, 2017). This practice dates back millennia.[1] Most historians agree the first government-regulated quarantines began during the Black Plague of 1347 (Tognotti, 2013) and these practices continue to this day. For example, Hsieh et al. (2007) finds the quarantine during the 2003 Severe Acute Respiratory Syndrome (SARS) outbreak in

[1]For instance, The Old Testament refers to isolating lepers in colonies.

Taiwan reduced total infections by 461 cases and 62 deaths.[2] Simulation exercises show similar results (Li et al., 2013).[3] Quarantines were also used to reduce the spread of the 2014-2015 Ebola virus (Dénes and Gumel, 2019) in Guinea, Liberia, and Sierra Leone.

Besides quarantines, other NPIs have been used to fight disease. For example, during the Black Plague, sanitary cordon (i.e., isolation of an infected city), postponement or banning of social gatherings, isolation, disinfection, and the use of lazarettos (isolation hospital for infected individuals) were all used to slow the spread of the disease (Tognotti, 2013). If we think about some of these tools in a more modern sense, we might consider them extreme versions of what has become known colloquially as "social distancing."[4] Studies on the effectiveness of social distancing during recent pandemics also suggest their usefulness. Caley et al. (2008) estimate that social distancing interventions saved 260 per 10,000 lives in Sydney, Australia during the Spanish Flu outbreak of 1918. Kelso et al. (2009) model the effects of social distancing measures (e.g., school closures and workplace nonattendance) on a computer-simulated community and find these measures reduce cases from 7% to 73% and this spread depends on contact rate, duration, and how quickly social distancing is adopted. Finally, Fong et al. (2020) complete a meta-analysis of the effectiveness of various NPIs (including quarantine, isolation, contact tracing, workplace closures, and school closures among others). In general, Fong et al. (2020) find that NPIs reduce viral transmission. The authors conclude rapid implementation and simultaneous use of NPIs aid mitigation efforts.

3 Data Description

We use two levels of data. The first level is a set of county controls which are constant over the panel. Summary statistics for these variables are found in Table 1. Variable descriptions are follows: Med. Income is median county income in 2018, % GOP is the percent of the county that voted Republican in the 2016 election, % Black is the percent of the county residents who are Black or African American in 2018, Population is county population in 2018, Density is the number of people per square mile in the county based on 2018 county population estimates, Inc. Risk are the number employees working at businesses in which we would expect to see an increased risk of being infected with COVID-19 per 100 county residents,[5], % Poverty is the percent of households in the county below the poverty line in 2018, % Educ is the percentage of the county with a college education between the averaged over 2014-2018 and % under 45 is the percent of county that is under 45 years of age. All

[2] Hsieh et al. (2007) compares two groups of SARS virus patients; one group that was quarantined before they were symptomatic and the other group quarantined after revealing symptoms. The authors control for various factors including two sets of dummy variables accounting for dates corresponding with wide-scale quarantine (April 28) and decentralization of SARS case classification (May10) because up until that date the national committee reviewing potential cases had been overwhelmed.

[3] Li et al. (2013) study the 60-day quarantine in Beijing, China during the 2009 H1N1 pandemic by simulating the infected population with no quarantine. Li et al. (2013) find infections could have been over 5.5 times higher than what was observed.

[4] We fully acknowledge that all of these measures (including quarantines) are social distancing measures. What we are attempting to differentiate here are more centralized types of NPIs from the decentralized types but there is obviously overlap.

[5] We consider the following buisnesses to be of "High Risk": 1) bars and nightclubs (NAICS Code: 722410), full service restaurants (NAICS Code: 722511), gyms (NAICS Code: 713940), and casinos (NAICS Code: 713210).

of this data comes from public sources.[6] While these variables are time invariant over the course of the panel, as we will show, the evolution of social distancing and/or the reaction to SSOs depends on some of these variables.

Table 1: Time Invariant County Level Summary Statistics

	Mean	Std. Dev.	Min	Max
Med. Income	52.8	13.9	25.4	140.4
Population	104127.1	333486.3	88	10105518
Density	227.8	1279.1	0.034	48358.1
Mort.	4495.5	1440.9	807.2	10885.9
Infant Mort.	636.0	785.5	0	10344.8
% GOP (2016)	63.2	15.7	4.09	94.6
% Black	9.95	14.6	0.097	86.6
% Poverty	15.1	6.13	0	54
Inc. Risk	1.24	1.13	0	26.6
% College	21.5	9.46	0	78.5
% Hisp	9.65	13.8	0.61	96.4
% < 45	54.2	6.54	15.9	84.9
Observations	3142			

The second level of data is time variant county data. Summary statistics for these variables are found in Table 2. Variable descriptions are as follows: Total Infections are the number of cumulative cases of COVID-19 in county i on day t, New Infections is the difference in total infections in county i in day t from day $t-1$,[7] Day Number is the day. Day 1 corresponds to January 22 of 2020 (which is the day after the first positive COVID-19 test in the United States), SSO is a dummy variable that equals 1 if county i in day t had had any ongoing SSO, Social Distancing is county level social distancing based on cellphone data (we will discuss this variable in more detail shortly), Days of SSO is the cumulative number of days that a SSO has been in place. Last we assign each governmental order into one of three categories: 1) Shelter in Place, 2) Stay at Home, and 3) Safe at Home.[8]

There are significant differences in the characteristics of the counties that lie in states issuing SSOs (n =2,879) versus those that do not (n =263). Generally, counties lying in states that did not issue a SSO were significantly more in favor of Donald Trump in the 2016 election (t-test: .69 vs .62; $p < 0.001$), are less black (t-test: 0.1 vs 0.05; $p < 0.001$), less populated (t-test: 34,244 vs 110,517; $p < 0.001$), have a lower median income (t-test: 50,889 vs 52,982; $p = 0.019$), are less densely populated (t-test: 46.6 vs 244; $p < 0.017$), and practice more social distancing on the first day social distance was measured (t-test: 2.29 vs 1.79; $p < 0.001$). Across these two groups (counties in states with and without SSOs), there is no significant difference in the percent of the county population with a college education (t-test: 21.55 vs 21.10; $p = .455$). Last, counties in states with SSOs had more employees

[6] Small Area Income and Poverty Estimates, United States Census, and the United States Department of Agriculture (USDA). Education data comes from the USDA's Economic Research Service. Business data comes from the 2017 County Business Patterns Survey.

[7] Due to the fluid nature of the pandemic, we truncate new infections at zero. There are cases of "negative" new infections but these instance are rare and likely due to reporting discrepancies.

[8] The assignments of each order are based off of the titles of the mandated shutdowns. In order of strength, we expect the following ordering: Shelter in Place> Stay at Home>Safe at Home.

Table 2: Time Variant County Level Summary Statistics

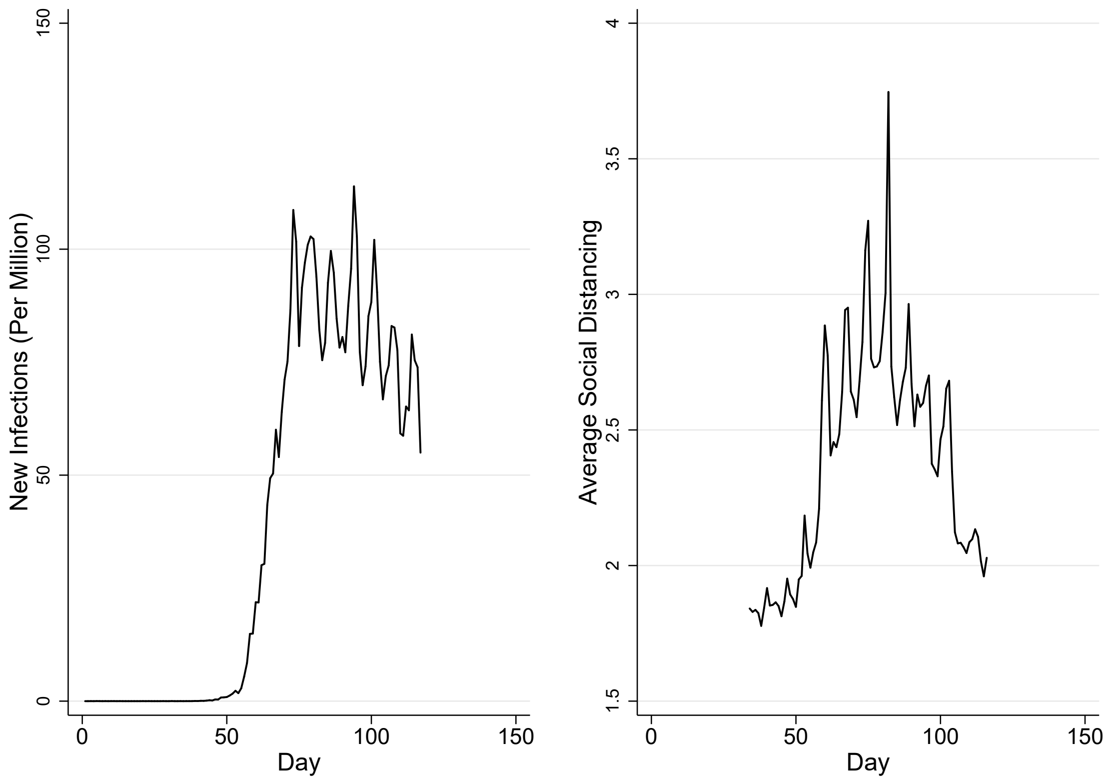
	Mean	Std. Dev.	Min	Max
Total Infections	114.6	1245.6	0	62218
New Infections	4.03	39.0	0	2663
Day Number	59	33.8	1	117
Social Distancing	2.37	0.91	1	5
Social Distancing (V)	1.51	1.12	1	5
Social Distancing (D)	1.61	0.84	1	5
Social Distancing (E)	3.45	1.61	1	5
SSO	0.29	0.45	0	1
Days of Local Res.	3.29	11.2	0	59
Shelter in Place	0.036	0.19	0	1
Stay at Home	0.22	0.41	0	1
Safe at Home	0.035	0.18	0	1
Observations	367736			

per 100 county residents working at a business that we classified as having increased risk (t-test: 1.26 vs 0.94; $p < 0.001$). None of the counties in states that did not issue a SSO reported a positive COVID-19 case on or before February 22, 2020.

3.1 Cellphone Ping Data

Social distancing is measured using social distance scores based on cellphone ping data. Typically, this data is used to ensure internet connectivity and device authentication (Sprenger, 2019). We believe cellphone data to be a reliable proxy for social distancing due to it providing an approximate location of cellphones and the fact that a majority of American adults that own a cellphone regularly carry it with them.[9] We are not alone in this belief. Cellphone data has been used in recent studies as a proxy for social distancing (Peak et al., 2018; Gollwitzer et al., 2020; Gao et al., 2020). Cellphone data comes from Unacast (2020) and starts on February 22, 2020 (or day 34 of our panel).[10] We did not calculate social distancing scores. Social distancing scores were assigned and calculated by Unacast using the ping data. The score we focus on (Social Distancing in Table 2) is based on a combination of three metrics that range from 1-5 with 5 indicating a high level of social distancing.[11]

Figure 1: Trends in New Infections and Social Distancing



Notes: New infections by day (left) and daily average social distancing scores (right). Day 1 corresponds to January 22, 2020, which is when the CDC started tracking data. The first reported case in the US was the day before; January 21. Social distancing data does not start until February 22, 2020 which corresponds to day 34.

3.2 Infections and Social Distancing

Figure 1 presents the number of new infections in the United States (per million) and the national average social distance score by day. Day 1 in Figure 1 corresponds to January 22, 2020. Corresponding figures for each US state can be found in Figures A1, A2, A3, and A4 - with the first two presenting new infections and the latter two relating to social distancing. New infections have risen quickly since mid March and continued to do so until late March and early April, when they began to level off. Social distancing saw a similar pattern with a rapid rise after President Donald Trump's March 16th announcement, in which he recommended strict new guidelines, but declined after April 10th. These figures also point to "seasonality" - with new infections peaking on Friday and social distancing generally peaking on Sunday.

Social distancing and new infections vary across time and geography. To illustrate why this is important, and to motivate the research question, in Figure 2 we present social distance scores, by US county, on March 21 and the total number of infections on that day and 10, 20, and 30 days after. Initially, infections appear most concentrated in densely populated areas of the East Coast (particularly around New York City and Newark), southern California, and southern Florida. Over the course of the next 30 days, the number of cases increased dramatically in the United States, particularly in the Southeastern and Southwestern parts of the United States. The areas with some of the larger increases in the number of COVID-19 cases also happen to broadly correspond with areas that practiced less social distancing 30 days prior. For instance, the Southeastern portion of the United States had relatively few cases of COVID-19 in mid March of 2020 but during this period practiced relatively less social distancing. As we will show, this led to an increase in the total number of infections weeks later.

We have four primary hypotheses:

Hypothesis 1 *Counties lying in states with SSOs will have fewer new infections relative to counties lying in states without similar policies.*

Hypothesis 2 *Counties with higher social distancing scores will have fewer new infections relative to counties with lower social distancing scores.*

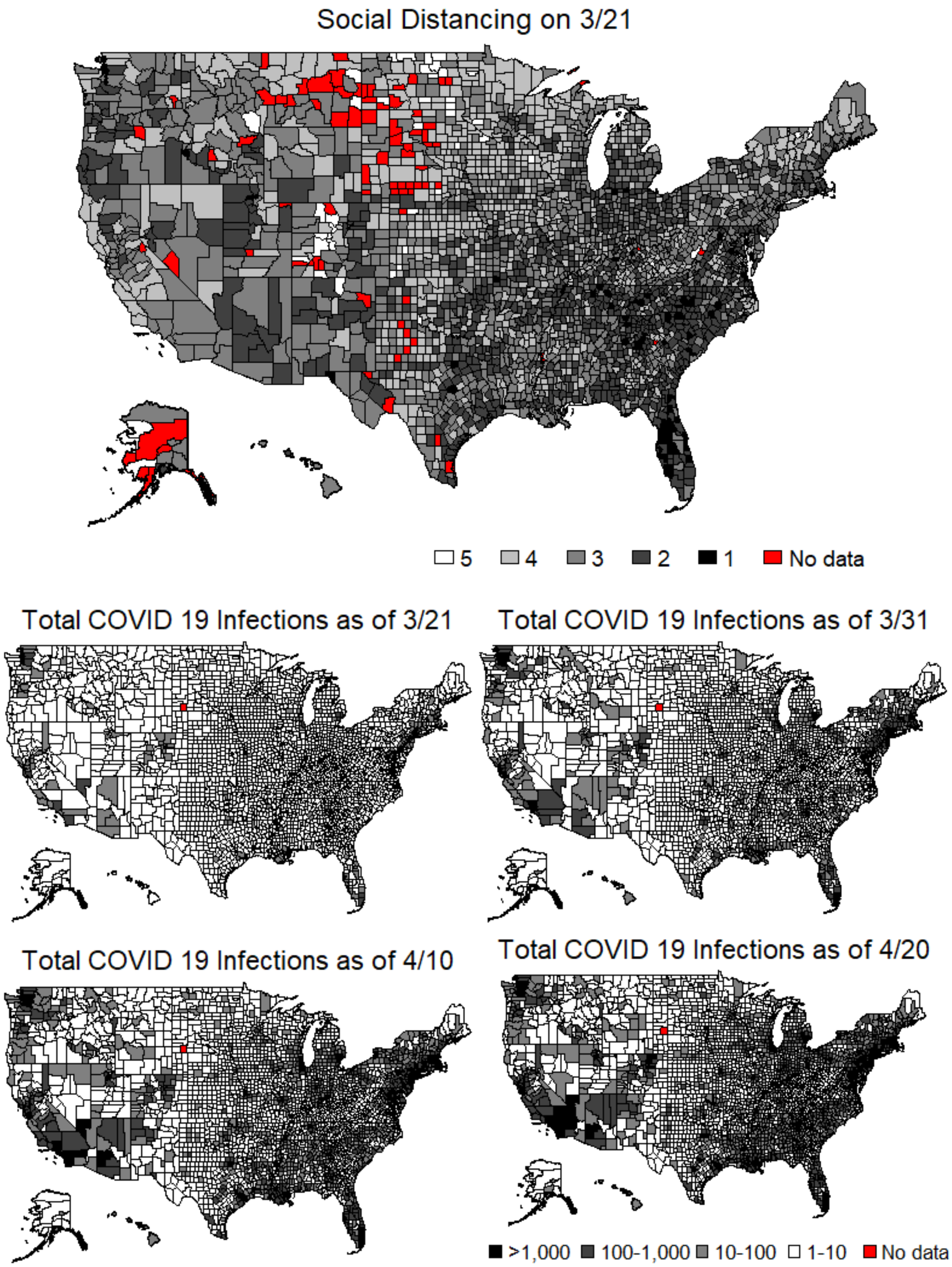
Hypotheses 1 and 2 are based on the literature discussed above as well as current experiences fighting the spread of COVID-19. What we are learning is rapidly evolving but in the first couple of months of the pandemic (January and February 2020) a number of mitigation strategy studies involving China (Fan et al., 2020; Pan et al., 2020), India (Mandal

[9]Further, a study by the Center (2019) finds 92% of American adults own a cellphone and 67% own a smart phone. The same study finds 90% of cellphone owners say they "frequently" carry their phone.

[10]The origin of Unacast comes from TIDAL, a Norwegian music streaming service. The TIDAL creators were interested in tracking the concerts its users were attending in order to design better music playlists for them. The company was bought by the rap artist Jay-Z in 2014.

[11]Metric 1 includes the average of the percent reduction in distance traveled per device relative to the baseline (Distance or Social Distancing (D)). Metric 2 includes the difference in the percentage change to time spent at non-essential point of interests (restaurants, pubs, etc.) relative to the baseline (Visitation or Social Distancing (V)). Metric 3 includes the number of daily close encounters per cellphone per square kilometer relative to the national pre-COVID-19 time period average (Encounters or Social Distancing (E).

Figure 2: Total Infections and Social Distancing by US County



Notes: Social distancing scores on March 21, 2020 (top panel) and total infections on March 31, April 10, and April 20. Darker colors correspond to less social distancing (i.e., lower social distancing scores) and more infections.

and Mandal, 2020), and Italy (Guzzetta et al., 2020) have shown quarantine, isolation, and other NPIs are effective in reducing the number of cases.[12]

We also expect that the strength of the SSO to have some effect on the rate of new transmissions. This is because strict SSOs have proved fairly effective in preventing new infections (c.f., Tian et al., 2020). This should not be surprising. Pandemic responses are an almost perfect example of a public goods problem and numerous experimental studies, often using the voluntary contribution mechanism (c.f., Isaac and Walker, 1988), have shown that one of the most effective ways maintaining cooperation is some form of punishment. Generally, this literature shows that monetary punishments are more effective in maintaining cooperation than their non-monetary counterparts (c.f., Masclet et al., 2003). This brings us to Hypothesis 3:

Hypothesis 3 *Social distancing will be increasing in the existence of SSOs.*

Hypothesis 3 is based off the above analogy and, if it holds, we should expect the more serious "Shelter in Place" orders to have larger effects on new infections and social distancing relative to their less serious counterparts. Peoples are recognizing the need for some form punishment to maintain cooperation (Marsh, 2020; Cheung, 2020) so even these relatively SSOs reduce transmissions and increase social distancing. Marsh (2020); Cheung (2020) also suggest Hypothesis 4:

Hypothesis 4 *County level responses to SSOs will be dependent upon county level characteristics.*

We expect some groups to take social distancing/SSOs less seriously than others; some of the reasons are driven by politics while others have a more economic flavor. We are not alone in the belief that politics influence social distancing behavior. For instance, Allcott et al. (2020) study the differences in partisan response to COVID-19.[13] The authors find counties with a high prevalence of 2016 Trump supporters are less inclined to engage in social distancing. We extend the idea of partisan social distancing to variable response to SSOs with the variable response being shaped by county characteristics (i.e., the variables in Table 1).

4 Results

We divide the results into three parts. First, we show that new infections are not immediately impacted by contemporaneous social distancing and SSOs. Rather, as we will show, it takes about three weeks for these effects to "burn in." Second, we explore the effects of social distancing and SSOs on new infections. As we will demonstrate, SSOs significantly reduced the rate of new infections but primarily through changes in social distancing. Next

[12] Banholzer et al. (2020) conduct an analysis of the effectiveness of various NPIs using cross-country data for 20 countries. They find all NPIs lead to reductions in new cases, with venue closures being the most effective.

[13] Incidentally, they theoretically motivate their study then regress the number of point of interest (POI) visits on county partisanship and other U.S. county control variables using data from January 26 to April 4. POI visits come from cellphone ping data collated by (SafeGraph INC, 2020).

we explore the effect of the SSOs and their interactions with various county level characteristics on social distancing. Here we find evidence of heterogeneous effects that vary primary due to differences in racial demographics, political party affiliation, age, and education.

4.1 The" Burn In" of NPIs and Social Distancing

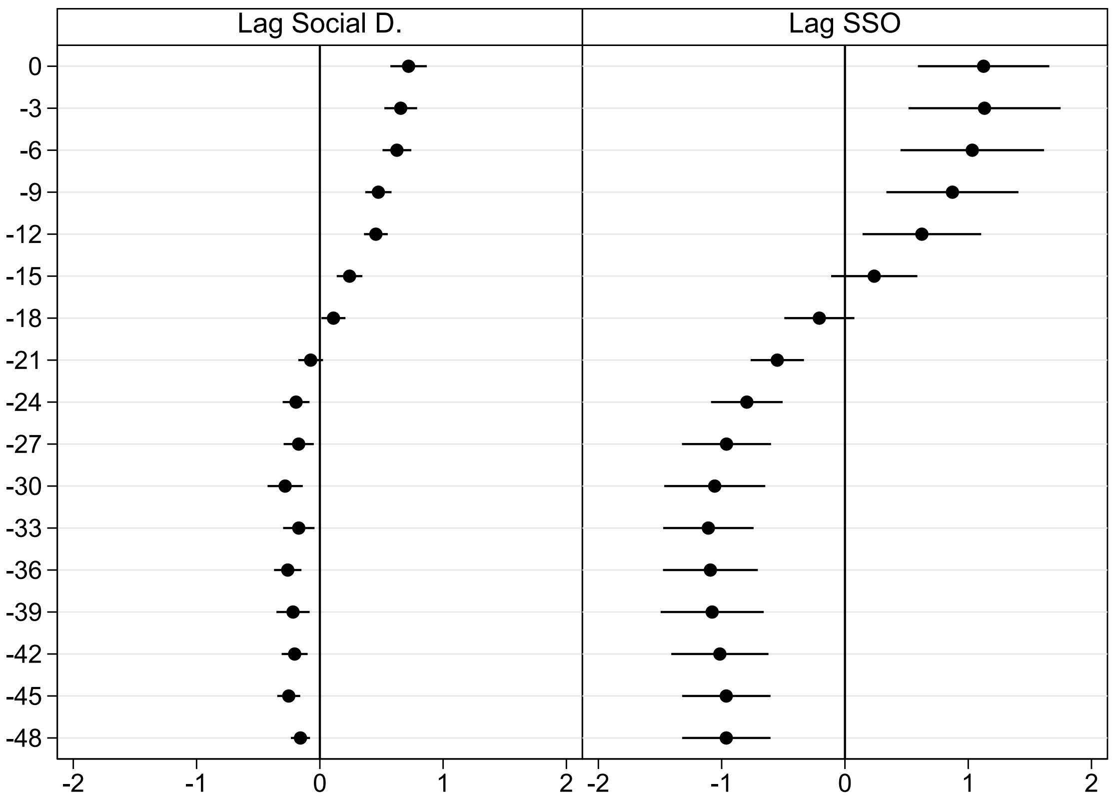
We now discuss the lag between changes in behavior and the rate of infection: namely, we expect immediate lags and contemporaneous social distancing/governmental SSOs to be positively associated with new infections. This does not mean that social distancing is causing new infections but rather that early social distancing is caused by locals observing a large number of infections. However, if this behavior is maintained we would expect to see new infections to fall in future weeks. So it is not the social distancing on day t that reduces new infections but the social distancing on day $t - x$ where x is a few weeks, measured in days, in the past.

In Figure 2, we try to determine the best "x" by estimating new infections using a fixed effects poisson (county is the fixed effect) with state clustered standard errors. This specification is chosen due to the relatively high variance of new infections. Many US counties experience zero or very few new infections daily (count data). As such, typical linear models that assume variables are normally distributed are not suitable. Consequently, we rely on nonlinear estimation methods that are commonly applied to problems involving count data (Lovett and Flowerdew, 1989; Coxe et al., 2009; Hutchinson and Holtman, 2005). As our data is panel in nature, we use the fixed effects poisson model (Hausman et al., 1984). This is convenient as these models are common in studies involving the transmission rate of infectious diseases and pandemic studies (Ma, 2020; Persico et al., 2020; Homaira et al., 2018, 2012; Nasreen et al., 2014). Last, because of the large number of fixed effects, we use the poisson pseudo-likelihood regression with multiple levels of fixed effects stata package to estimate each of these models (Correia et al., 2019). The reported coefficients are semi-elasticities - meaning they give the percentage increase in the dependent variable cause by a one unit increase in the explanatory variable. Therefore, the estimated effect size is not constant and will be larger when in counties and days when the rate of new infections is high.

Each dot in Figure 3 represents a coefficient that is estimated from a model with only a single lagged social distancing score/presence of SSO that is x days in the past (where $x \in \{0, 48\}$ and a linear day trend. Here we find that it takes approximately 3 weeks for social distancing and SSOs to have an effect. Ex-post this pattern is not surprising and is independently being leveraged to prevent the spread of COVID-19 in other parts of the world. For example, Prime Minister Modi of India initially implemented a 3 week lockdown in India March 24 to thwart the spread of COVID-19 (Gettleman and Schultz, 2020).[14]

[14] When asked about the motivation behind a 3 week quarantine, Dr. Kolandasamy, Director of Public Health in Tamil Nadu (an Indian state), told reporters that after the two-week COVID-19 incubation period it is necessary to add "another week for the residual infection to die out, for the tail end, to be entirely safe, and you arrive at 21 days." (Kannan, 2020).

Figure 3: Trends in New Infections and Social Distancing



Notes: The effect of lagged Social Distancing (left) and SSOs (right) on new infections of COVID-19. Each dot corresponds to a fixed effects poisson model with state clustered standard errors. The dot is the coefficient estimate on new infections and error bars are the 95% confidence interval.

4.2 The Effect of SSOs and Social Distancing on New Infections of COVID-19

In Table 3 we present the estimated new infections for a county i on day t using a series of fixed effects poisson models. The fixed effect is the county and standard errors are clustered at the state.[15] The primary independent variables are the 21 day lag of social distancing, SD (-21), and a dummy variable that is equal to one if a SSO has been in effect 21 days in the past, Local R. (-21).[16] Each of these models also include an indicator variable for each day of the week (minus Sunday). Model 1 simply demonstrates that before controlling for social distancing and/or SSOs new infections are increasing by about 3 percent each day.

Result 1 *Counties lying in states with SSOs have fewer new infections relative to counties lying in states without similar policies.*

Result 2 *Counties with higher social distancing have fewer new infections relative to counties with lower social distancing scores.*

We find evidence in support of Hypotheses 1 and 2 when we control for social distancing or the existence of a SSO. This is shown in model 2 and 3 in Table 3. Here we find that a one unit increase in the 3 week lagged social distance score is associated with a 9 % decline in new infections. Model 3 estimates the effect of SSOs on new infections, *before* controlling for lagged social distancing. Here we find the existence of a SSO reduces new infections by nearly 60% however after controlling for lagged social distancing (Model 4) we find the effect falls substantially and is no longer statistically significant. The effect of social distancing remains remarkably consistent but is no longer significant.

We turn our attention to Models 5 and 6. As before, each of these models estimate the effect of social distancing on new infections of COVID-19 but, unlike the previous models, we restrict the sample to states (Model 5) in which a SSO was *not* issued by a state or local government (Arkansas, Nebraska, North Dakota, South Dakota, Utah, and Wyoming) and states that had at least one SSO issued by a state or local government. These models are important as they demonstrate the inconsistency of the effect of social distancing on new infections of COVID-19 while also suggesting that the rate of new infections is increasing faster in states without SSOs. Additionally, they suggest that the effect of social distancing on new infections is augmented by the existence of a SSO (e.g., those in states with SSOs might also be more likely to wear a mask).

We now move on to Table 4 in which we analyze the effects SSOs (of different strength) and levels of social distancing on new infections of COVID-19. As before, each of the regressions presented in Table 4 is a fixed effects poisson with state clustered standard errors and include a daily time trend and day-of-the-week controls as additional control variables. Variable descriptions are as follows: SD_X (-21) is an indicator variable that is equal to one if county i in time $t-21$ had a social distance score of X (where X is 2, 3, 4, or 5). Shelter in Place/Stay at Home/Safe at Home is a dummy variable that is equal to 1 if 21 days prior there was a Shelter in Place/Stay at Home/Safe at Home order in effect.

[15] Changing the clustering does not change significance in any meaningful way.

[16] The lags are motivated from the results presented in Figure 3.

Table 3: The Effect of Policy Interventions and Social Distancing on New COVID-19 Infections

	1	2	3	4	5	6
Day Number	0.026^{***}	0.014^{***}	0.036^{***}	0.015^{***}	0.032^{***}	0.014^{***}
	(7.09)	(3.30)	(10.52)	(2.62)	(3.52)	(3.13)
SD (-21)		-0.093^{*}		-0.083	0.056	-0.088^{*}
		(-1.74)		(-1.24)	(0.45)	(-1.65)
SSO (-21)			-0.59^{***}	-0.044		
			(-5.32)	(-0.33)		
LL	-817260.1	-626108.9	-798456.9	-626025.7	-20442.9	-603948.4
Counties	2880	2879	2880	2879	209	2670
Observations	239040	178498	239040	178498	12958	165540

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: The Effect of Policy Interventions II

	1	2	3	4	5
Day Number	0.011^{**}	0.036^{***}	0.012^{*}	0.032^{***}	0.011^{**}
	(2.36)	(11.17)	(1.82)	(3.30)	(2.22)
SD_2 (-21)	0.19^{**}		0.25^{**}	0.084	0.20^{**}
	(2.17)		(2.24)	(0.72)	(2.21)
SD_3 (-21)	-0.065		0.072	0.15	-0.054
	(-0.63)		(0.73)	(1.34)	(-0.53)
SD_4 (-21)	-0.27^{**}		-0.11	0.14	-0.27^{**}
	(-2.14)		(-0.99)	(0.41)	(-2.09)
SD_5 (-21)	-0.42^{***}		-0.29	-0.45	-0.41^{***}
	(-2.82)		(-1.55)	(-0.75)	(-2.60)
Shelter in Place (-21)		-0.97^{***}	-0.52^{***}		
		(-8.45)	(-3.96)		
Stay at Home (-21)		-0.41^{**}	0.046		
		(-2.47)	(0.25)		
Safe at Home (-21)		-0.36^{**}	0.13		
		(-2.48)	(0.67)		
LL	-621946.7	-783609.5	-610665.6	-20405.9	-599742.6
Counties	2879	2880	2879	209	2670
Observations	178498	236160	178498	12958	165540

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

P-values for all of the results we will discuss are found in Table A3 in the Appendix. Model 1 in Table 4 shows a similar relationship to what was observed in Table 3; social distancing decreases the rate of new infections of COVID-19. Model 1 in Table 4 illustrates that modest increases in social distancing (from low social distancing) does not have desirable effects. For instance, moving from a social distancing score of one to two *increases* the rate of new infections by 19% . However, social distancing reduces new infections dramatically if the level of distancing is sufficiently large (e.g., SD_5 in Model 1 of Table 4). Model 2 in Table 4 illustrates that not all SSOs have the same effect. While Stay at Home and Safe at Home Orders are found to reduce the rate of new COVID-19 infections (and by a similar amount), the effect size is much smaller than the stricter Shelter in Place. Model 3 generally replicate these results - though now only Shelter in Place significantly reduce infections. This is expected however because social distancing is highly correlated with SSOs. Finally, Models 4 and 5 illustrate that counties in states without SSOs are seeing a larger increase in new infections and that social distancing, when government SSOs are not in effect, do not significantly reduce infections.

4.3 The Effect of Politics, Race, Income, and Poverty on Social Distancing

Given that we have demonstrated that social distancing, and to some extent SSOs, significantly reduce new infections, we now turn our attention to social distancing. In particular, we are most interested in how social distancing is influenced by SSOs and how responsiveness to SSOs varies depending on county level observables. We do so using a set of fixed effects linear regressions estimating social distance scores. In each of these models, we interact the county level observables (which are time invariant) with the various types of stay at home orders to get an idea of how responses to SSOs vary depending on county characteristics. As before, the fixed effect is the county and standard errors are clustered at the state.

Result 3 *Social distancing is increasing in the existence of SSOs but, even after controlling for county level characteristics, all of the SSOs have a similar effect on social distancing.*

In Table 5 we present the estimated coefficients for each of the three SSOs under 6 different specifications, Model 1 can be considered a baseline model in which we estimate the average effect of each of the SSOs relative to the no-order baseline. Model 2 interacts each of the SSOs with nine county characteristics (Med. Income, Density, % GOP, % Black, % Poverty, Inc. Risk, % College, % Hisp, and %<45). Model 3 is the same as Model 2 but controls for the day of the week and includes a linear time trend. This is our preferred specification. Model 4 is the same as 3 but includes a quadratic time trend.[17] Model 5 is the same as 4 but also includes the total number of infections in the previous day. Model 6 is similar to 5 but includes the total number of deaths instead of infections. Coefficients not shown in Table 5 are found in Tables A4, A5, and A6 of the Appendix. All of the hypothesis tests that we base our analysis on can be found in Table A3 of the Appendix.

Somewhat surprisingly the SSOs' effects are for the most part not statistically different from each other. This is true under all models presented in Table 5. The only SSO that

[17]For the motivation behind the quadratic see Figures A3 and A4 that are found in the appendix.

Table 5: The Effect of Policy Interventions, Race, and Politics on Social Distancing

	1	2	3	4	5	6
Safe at Home	0.47***	-0.21	-0.21	-0.26	-0.25	-0.26
	(9.92)	(-1.13)	(-1.07)	(-1.24)	(-1.21)	(-1.22)
Stay at Home	0.61***	0.58***	0.58***	0.21	0.21	0.21
	(15.17)	(3.15)	(3.03)	(1.14)	(1.13)	(1.14)
Shelter in Place	0.63***	0.27	0.27	0.031	0.027	0.0038
	(5.87)	(0.57)	(0.56)	(0.09)	(0.07)	(0.01)
LL	-172585.4	-165015.8	-154983.5	-115971.6	-115811.4	-115913.6
Counties	3054	3039	3039	3039	3039	3039
Adj. R^2	0.23	0.27	0.33	0.51	0.51	0.51
Observations	250428	249198	249198	249198	249198	249198

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

is "consistently" different from at least one other is Stay at Home which is shown to be significantly different from the omitted group (i.e., No Order) and Safe at home. The others (Safe at Home and Shelter in Place) are found to increase social distancing relative to the omitted group in model 1 but the remaining models, in which we interact the SSOs with county characteristics, suggest otherwise. These other models in Table 5 also shed light on why these differences across SSOs in model 1 are so modest: they are average effects and there is quite a bit of county level heterogeneity. This heterogeneity affects how responsive counties are to the various orders and brings us to our final result.

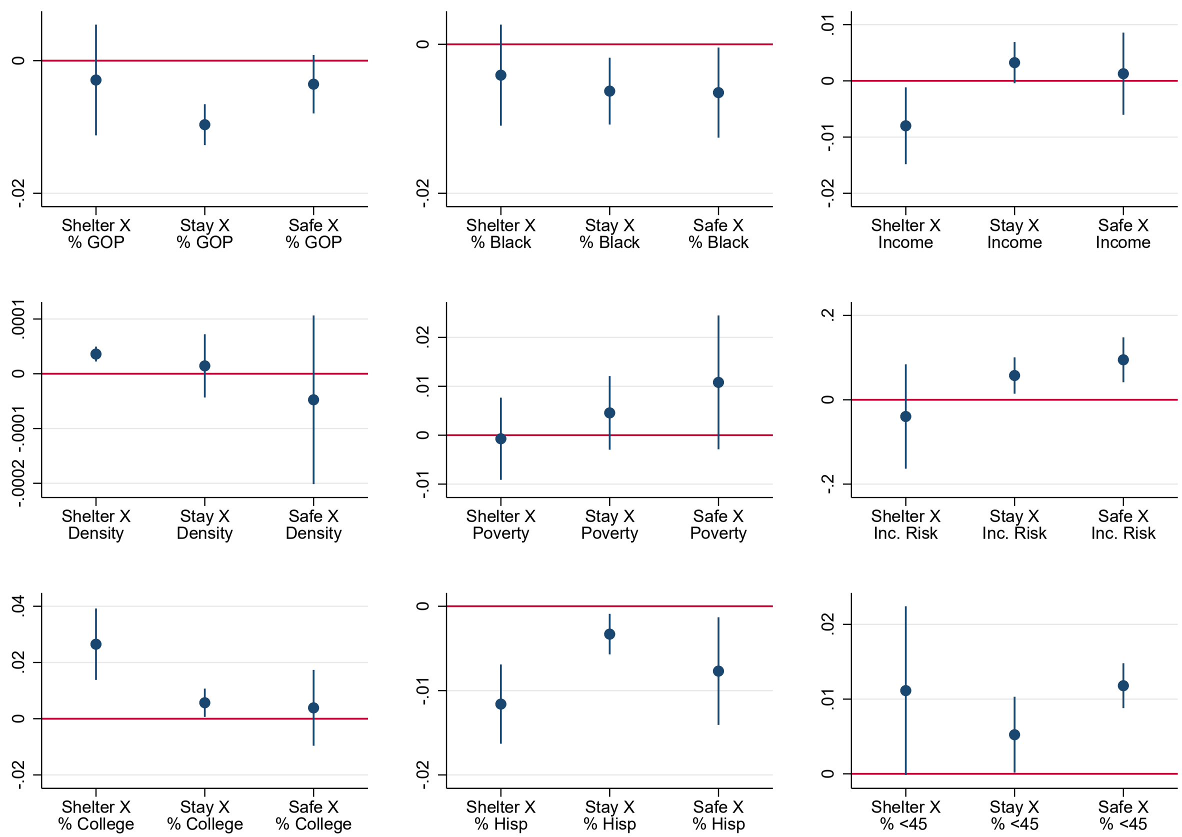
Result 4 *County level response to SSOs is dependent upon county level characteristics. However, some characteristics have no effect.*

We find evidence in support of Hypotheses 4. Though our preferred specification is Model 3, results across Models 3, 4, and 5 are consistent. This can be seen in Tables A4, A5, and A6 of the Appendix. To assist with interpretation, in Figure 4 we present each of the estimated coefficients using our preferred specification, along with the 95% confidence intervals. Regardless of SSO type, increases in % Education and % > 45 are associated with increases in social distancing. Both effects are strongest under Shelter in Place orders. Similar effects are also seen under Inc Risk - though in this case the effect is actually negative under Shelter in Place and is not statistically different from zero. Oddly, income decreases social distancing under shelter in place orders. Last counties with higher percentages of black residents, Hispanics, and Republicans social distance less under Stay at Home and Safe at Home SSOs - though this relationship is not present under Shelter in Place orders.

5 Discussion and Conclusion

The first reported case of COVID-19 in the United States was January 21, 2020 at a nursing home in the US state of Washington. In the four and a half months since then the virus has infected well over 1.5 million Americans, caused over 80,000 deaths, and has disrupted the lives of every American. In this paper, we measure the effect of SSOs on the infection rate

Figure 4: The Effect of Policy Interventions, Race, and Politics on Social Distancing



Notes: Estimated coefficients and 95% confidence intervals of the interactions between SSOs and county characteristics (from top left to bottom right: SSO, % GOP, % Black, median income (1000s), Population density (per square mile), % living under the poverty line, number of workers per 100 county residents working in a "increased risk" industry, % of county population with a college degree, % Hispanic, and % of county residents under the age of 45. Model is model 3 in Table 5 which is a fixed effects regression with state clustered standard errors. Dependent variable is social distancing. Other explanatory variables not shown include a daily time trend and weekday dummy variables. These coefficients are available upon request.

as well as the effect of social distancing on the infection rate. Though we find both impacted new infections, the effects are entangled. Models 5 and 6 in Table 3 (4 and 5 in Table 4 too) show that increases in social distancing in states with SSOs have more significant effects on new infections compared to states that had no such SSOs. This suggests that other NPIs (such as face masks) were being more commonly used in states with SSOs (e.g., Stay at Home) than in states without SSOs. Overall, our results are comparable to independent contemporaneous works (Friedson et al., 2020; Courtemanche et al., 2020; Dave et al., 2020).

Many of our results relating to the county characteristics that influence social distancing make intuitive economic sense: younger and more educated counties respond more to SSOs than older and less educated counties. Even ignoring the political "elephant in the room" this is not surprising. These groups (i.e., younger and more educated) might believe that they are giving up more if they contract the virus (e.g., lifetime utility) and therefore engage in more social distancing once a SSO has been imposed. The larger response to SSOs in counties with more employees working at a "high risk" business also has an easy explanation; these business had to close down (or faced increased restrictions). If a county had a disproportionately large number of these types of businesses then, mechanically, we would expect the area to have a stronger response to the SSO. Last, under several SSOs (particularly the Shelter in Place variety) there were fines associated with breaking the SSO. Therefore, it is not surprising to see that richer counties social distanced less in response to these SSOs as they are more likely to be able to afford the fine.

Some of our results are a bit more puzzling. We find despite its effectiveness in reducing viral transmission, Republicans, African Americans, and Hispanics all respond less to SSOs than other groups - even after controlling for population density and multiple other county characteristics. While we offer no certain explanation as why these groups respond less to SSOs we can offer a few educated guesses. As it pertains to Republicans, there are a few obvious possibilities. "Essential" jobs include blue-collar jobs like construction, law enforcement, and agriculture work which may attract individuals who are more likely to vote Republican. So the observed lack of social distancing in these groups may be caused by labor decisions. Second, the lack of response in Republican voting counties is possibly related to President Trump downplaying the threat of COVID-19 (c.f., Allcott et al., 2020). Alternatively, given that GDP growth has been shown to increase the probability an incumbent wins reelection (c.f., Fair, 1996), it might also be the case that Republicans are behaving strategically in a way to increase the probability of a 2020 Republican Presidential election victory. Finally, it may be the case that relatively lighter responses to SSOs could be driven by distrust in the media. (Jurkowitz et al., 2020) find that Republicans, relative to Democrats, consider fewer news media sources to be reliable sources of information.

As it pertains to African Americans and, to a lesser extent Hispanics, there are two obvious explanations. First, on average African Americans are less able to work from home. A study by the Economics Policy Institute (Gould and Shierholz, 2020) report that only about 20% of African Americans can work from home, compared to nearly 30% for whites. Additionally, several recent news articles show that African Americans represent a disproportionate share of "essential workers" (Maxwell and Solomon, 2020; Scott, 2020). Another possibility is that because African Americans trust government and health officials less (Mangum, 2011, Mangum; Wilkes, 2015), they are less willing to acquiesce to SSOs. Some studies suggest this mistrust stems from the "Tuskegee experiment" conducted from

1932-1972 (Baker et al., 2005; Bates and Harris, 2004).[18] While it is tempting to posit that African Americans might, like Republicans, consider the news media to be inaccurate, this does not seem plausible. Atske et al. (2019) find that they are actually more likely to expect news stories to be accurate (80%) than whites and Hispanics (70% and 71%, respectably).

[18]The "Tuskegee Experiment" was a study conducted by the Public Health Service at Tuskegee University on African American males during which time patients were unaware they were infected with syphilis and also not given penicillin treatment (Park, 2017). Alsan and Wanamaker (2018) show that the "Tuskegee Effect" resulted in a decrease of life expectancy by nearly 1.5 years for African Americans when the study was disclosed to the public.

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A Appendix

Table A1: States with No Governmental NPI

States With No Lockdown Order	Date of First Case
Arkansas	11-Mar
Iowa	9-Mar
Nebraska	6-Mar
North Dakota	12-Mar
South Dakota	9-Mar
Utah	7-Mar
Wyoming	12-Mar

Table A2: Hypothesis Tests from Table 4

Null Hyp	1	2	3	4	5
HO: SD_2=SD_3	0.01		0.01	0.59	0.01
HO: SD_2=SD_4	0.00		0.00	0.86	0.00
HO: SD_2=SD_5	0.00		0.00	0.33	0.00
HO: SD_3=SD_4	0.00		0.01	0.98	0.00
HO: SD_3=SD_5	0.01		0.01	0.25	0.02
HO: SD_4=SD_5	0.35		0.20	0.04	0.39
HO: Shelter=Stay		0.00	0.00		
HO: Shelter=Safe		0.00	0.00		
HO: Stay=Safe		0.73	0.58		

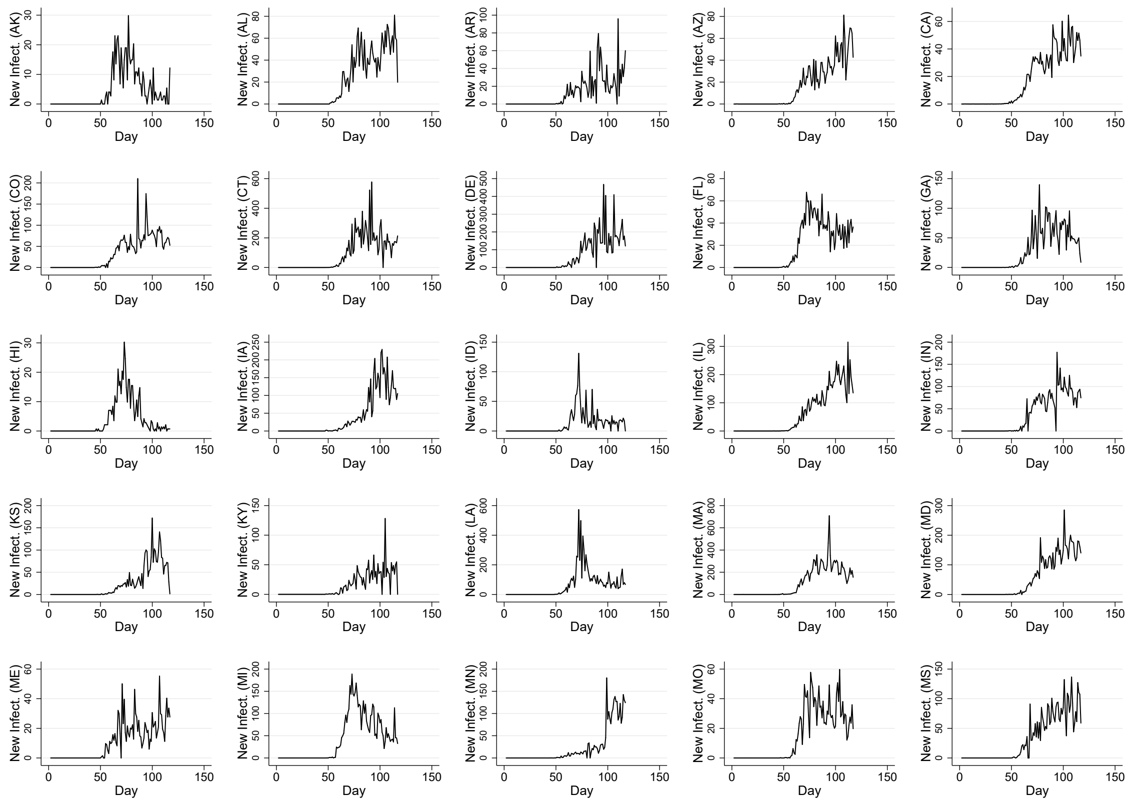
Notes: P-values from F-tests that test for the equality of coefficients. Column labels correspond to the model number in Table 4.

Table A3: Hypothesis Tests from Table 5

Null Hyp	1	2	3	4	5	6
HO: Shelter=Safe	0.18	0.35	0.34	0.47	0.49	0.52
HO: Shelter=Stay	0.87	0.55	0.55	0.64	0.64	0.59
HO: Stay=Safe	0.03	0.00	0.00	0.09	0.10	0.09

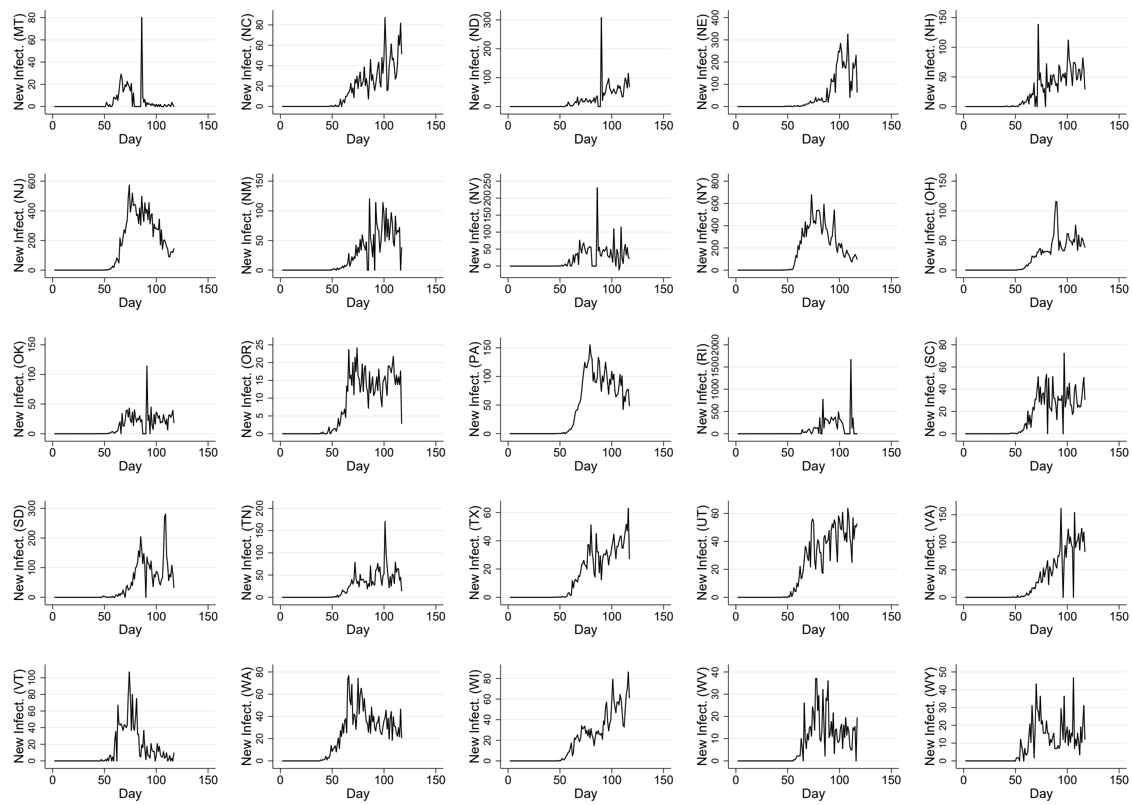
Notes: P-values from F-tests that test for the equality of coefficients. Column labels correspond to the model number in Table 5.

Figure A1: New Infections by Day and State (AK - MI)



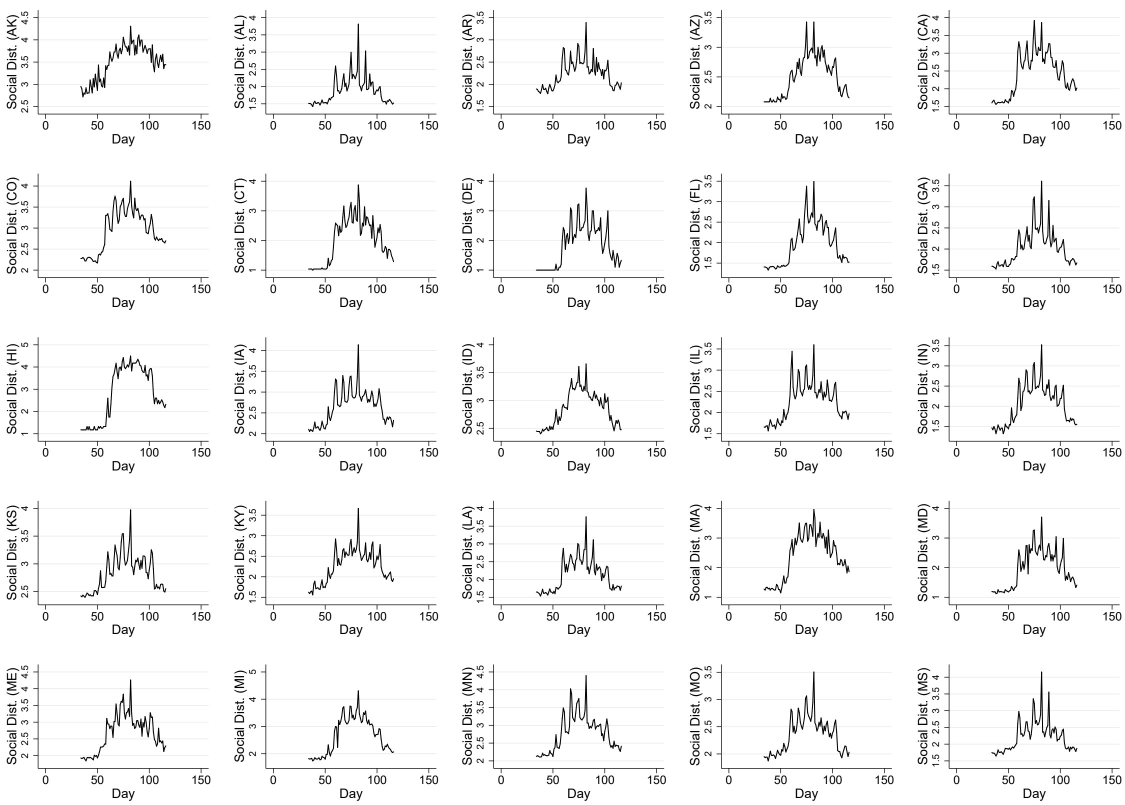
Notes: New COVID 19 infections by state and day. From top left to bottom right: Alabama, Alaska, Arkansas, Arizona, California, Colorado, Connecticut, Delaware, Florida, Georgia, Hawaii, Iowa, Idaho, Illinois, Indiana, Kansas, Kentucky, Louisiana, Massachusetts, Maryland, Maine, Michigan, Minnesota, Missouri, and Mississippi.

Figure A2: New Infections by Day and State (MT - WY)



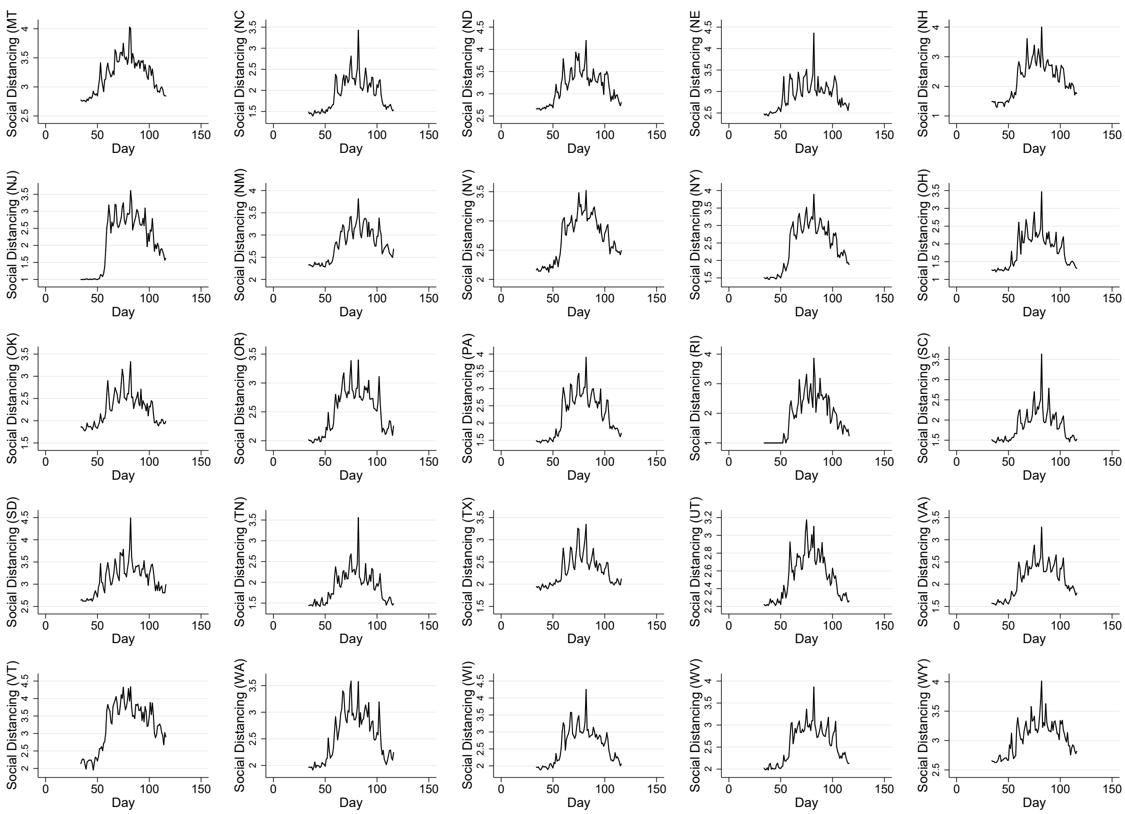
Notes: New COVID 19 infections by state and day. From top left to bottom right: Montana, North Carolina, North Dakota, Nebraska, New Hampshire, New Jersey, New Mexico, Nevada, New York, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, Vermont, Washington, Wisconsin, West Virginia, and Wyoming.

Figure A3: Social Distancing by Day and and State (AK - MI)



Notes: Social distancing by state and day. From top left to bottom right: Alabama, Alaska, Arkansas, Arizona, California, Colorado, Connecticut, Delaware, Florida, Georgia, Hawaii, Iowa, Idaho, Illinois, Indiana, Kansas, Kentucky, Louisiana, Massachusetts, Maryland, Maine, Michigan, Minnesota, Missouri, and Mississippi.

Figure A4: Social Distancing by Day and State (MT - WY)



Notes: Social distancing by state and day. From top left to bottom right: Montana, North Carolina, North Dakota, Nebraska, New Hampshire, New Jersey, New Mexico, Nevada, New York, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, Vermont, Washington, Wisconsin, West Virginia, and Wyoming.

Table A4: Shelter in Place (or Table 5 Continued)

	1	2	3	4	5	6
Shelter in Place	0.63^{***}	0.27	0.27	0.031	0.027	0.0038
	(5.87)	(0.57)	(0.56)	(0.09)	(0.07)	(0.01)
Shelter in Place X % GOP		-0.0029	-0.0029	-0.0051^{*}	-0.0050^{*}	-0.0049^{*}
		(-0.71)	(-0.70)	(-1.84)	(-1.90)	(-1.83)
Shelter in Place X % Black		-0.0040	-0.0041	-0.0057^{***}	-0.0059^{***}	-0.0057^{***}
		(-1.24)	(-1.23)	(-3.21)	(-3.32)	(-3.23)
Shelter in Place X Income		-0.0082^{**}	-0.0080^{**}	-0.0049^{**}	-0.0054^{***}	-0.0048^{**}
		(-2.42)	(-2.35)	(-2.10)	(-2.95)	(-2.11)
Shelter in Place X Density		0.000036^{***}	0.000036^{***}	0.000027^{***}	0.000017^{***}	0.000020^{***}
		(5.33)	(5.31)	(5.72)	(4.00)	(4.60)
Shelter in Place X % Pov.		-0.00085	-0.00073	0.0040^{*}	0.0041^{**}	0.0045^{**}
		(-0.21)	(-0.17)	(1.88)	(2.60)	(2.28)
Shelter in Place X % College		0.027^{***}	0.027^{***}	0.023^{***}	0.022^{***}	0.022^{***}
		(4.26)	(4.19)	(4.18)	(4.57)	(4.36)
Shelter in Place X Inc. Risk		-0.041	-0.040	-0.014	0.0030	-0.0031
		(-0.67)	(-0.64)	(-0.28)	(0.07)	(-0.07)
Shelter in Place X % <45		0.011^{*}	0.011^{*}	0.0084^{**}	0.0090^{**}	0.0086^{**}
		(2.00)	(1.98)	(2.26)	(2.47)	(2.32)
Shelter in Place X % Hisp		-0.012^{***}	-0.012^{***}	-0.0071^{***}	-0.0077^{***}	-0.0073^{***}
		(-5.06)	(-4.96)	(-6.43)	(-6.18)	(-6.30)
LL	-172585.4	-165015.8	-154983.5	-115971.6	-115811.4	-115913.6
Counties	3054	3039	3039	3039	3039	3039
Adj. R^2	0.23	0.27	0.33	0.51	0.51	0.51
Observations	250428	249198	249198	249198	249198	249198

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Safe at Home (or Table 5 Continued)

	1	2	3	4	5	6
Safe at Home	0.47***	-0.21	-0.21	-0.26	-0.25	-0.26
	(9.92)	(-1.13)	(-1.07)	(-1.24)	(-1.21)	(-1.22)
Safe at Home X % College		0.0040	0.0039	0.0036	0.0036	0.0036
		(0.59)	(0.58)	(0.62)	(0.61)	(0.62)
Safe at Home X % GOP		-0.0036	-0.0035	-0.0049**	-0.0049**	-0.0049**
		(-1.62)	(-1.62)	(-2.53)	(-2.55)	(-2.54)
Safe at Home X % Black		-0.0064**	-0.0065**	-0.0037***	-0.0037***	-0.0037***
		(-2.03)	(-2.15)	(-3.54)	(-3.58)	(-3.56)
Safe at Home X Income		0.0012	0.0013	0.0011	0.0012	0.0012
		(0.34)	(0.35)	(0.40)	(0.41)	(0.40)
Safe at Home X Density		-0.000058	-0.000048	-0.000098***	-0.00010***	-0.00010***
		(-0.79)	(-0.62)	(-3.25)	(-3.19)	(-3.22)
Safe at Home X % Pov.		0.011	0.011	0.0063	0.0063	0.0063
		(1.56)	(1.59)	(1.10)	(1.10)	(1.10)
Safe at Home X Inc. Risk		0.095***	0.095***	0.11***	0.11***	0.11***
		(3.57)	(3.58)	(4.46)	(4.47)	(4.47)
Safe at Home X % <45		0.012***	0.012***	0.0089***	0.0089***	0.0089***
		(7.92)	(7.88)	(4.32)	(4.29)	(4.30)
Safe at Home X % Hisp		-0.0077**	-0.0077**	-0.0064***	-0.0064***	-0.0064***
		(-2.40)	(-2.42)	(-2.76)	(-2.74)	(-2.76)
LL	-172585.4	-165015.8	-154983.5	-115971.6	-115811.4	-115913.6
Counties	3054	3039	3039	3039	3039	3039
Adj. R^2	0.23	0.27	0.33	0.51	0.51	0.51
Observations	250428	249198	249198	249198	249198	249198

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Stay at Home (or Table 5 Continued)

	1	2	3	4	5	6
Stay at Home	0.61***	0.58***	0.58***	0.21	0.21	0.21
	(15.17)	(3.15)	(3.03)	(1.14)	(1.13)	(1.14)
Stay at Home X % College		0.0057**	0.0057**	0.0061***	0.0061***	0.0061***
		(2.28)	(2.27)	(2.83)	(2.83)	(2.83)
Stay at Home X % GOP		-0.0096***	-0.0097***	-0.0097***	-0.0096***	-0.0096***
		(-6.38)	(-6.28)	(-6.58)	(-6.56)	(-6.58)
Stay at Home X % Black		-0.0066***	-0.0063***	-0.0053***	-0.0053***	-0.0053***
		(-2.92)	(-2.82)	(-2.77)	(-2.82)	(-2.79)
Stay at Home X Income		0.0032*	0.0032*	0.0043**	0.0042**	0.0042**
		(1.71)	(1.78)	(2.49)	(2.48)	(2.49)
Stay at Home X Density		0.000014	0.000014	0.000023	0.000016	0.000020
		(0.48)	(0.50)	(0.90)	(0.71)	(0.85)
Stay at Home X % Pov.		0.0044	0.0046	0.0084**	0.0084**	0.0084**
		(1.16)	(1.22)	(2.11)	(2.12)	(2.11)
Stay at Home X Inc. Risk		0.058***	0.058***	0.055**	0.056**	0.056**
		(2.70)	(2.68)	(2.57)	(2.59)	(2.57)
Stay at Home X % <45		0.0054**	0.0052**	0.0032	0.0033	0.0032
		(2.13)	(2.07)	(1.36)	(1.43)	(1.39)
Stay at Home X % Hisp		-0.0033***	-0.0033***	-0.0035***	-0.0036***	-0.0035***
		(-2.82)	(-2.76)	(-3.16)	(-3.25)	(-3.19)
LL	-172585.4	-165015.8	-154983.5	-115971.6	-115811.4	-115913.6
Counties	3054	3039	3039	3039	3039	3039
Adj. R^2	0.23	0.27	0.33	0.51	0.51	0.51
Observations	250428	249198	249198	249198	249198	249198

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$