Political Beliefs affect Compliance with COVID-19 Social Distancing Orders

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Abstract

Social distancing is vital to mitigate the spread of the novel coronavirus. We use geolocation data to document that political beliefs present a significant limitation to the effectiveness of state-level social distancing orders. Residents in Republican counties are less likely to completely stay at home after a state order has been implemented relative to those in Democratic counties. Debit card transaction data shows that Democrats are more likely to switch to e-commerce spending after state orders are implemented. We also find that Democrats are less likely to respond to a state-level order when it is issued by a Republican governor relative to one issued by a Democratic governor. These results are robust to controlling for other factors including time, geography, local COVID-19 cases and deaths, county characteristics, and other social distancing orders. We conclude that bipartisan support is essential to maximize the effectiveness of social distancing orders.

Keywords: COVID-19, Coronavirus, Political polarization, Geolocation data, Credit card transaction data
JEL: P16, C55, H7

☆We thank SafeGraph Inc. and Facteus for data access. Academics and others working for the public good can access the geolocation and debit card data used in this paper here: https://www.safegraph.com/covid-19-data-consortium

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I. Introduction

Both the World Health Organization and Center for Disease Control have recognized social distancing as the most effective way to slow down the spread of the novel coronavirus. Early evidence from China and the 1918 US flu pandemic also highlight the importance of mandatory social distancing policies in fighting the spread of the disease (Kraemer et al. (2020); Correia et al. (2020); Chudik et al. (2020)). Observing the effectiveness of social distancing from Asia and Europe, many regions in the US have also issued stay-at-home and shelter-in-place orders. As of April 20, 2020, 42 states have issued explicit orders that urge their residents to stay home. As of this writing roughly 316 million Americans are now disciplined by some level of social distancing requirements.

It is important for the government to understand how effective these orders are for at least two reasons. First, there are states that have not issued statewide social distancing orders, and this analysis would help them make better-informed decisions going forward. Second, understanding the effectiveness of current policies may allow states that have a policy in place to make adjustments as necessary. In this paper, we leverage geolocation tracking data sourced from smartphones as well as debit card transaction data to analyze the effectiveness of state-level social distancing policies and show that political beliefs are an important limitation for whether people adhere to these orders.

Potentially due to the recent increase in political polarization in the US (Boxell, Gentzkow, and Shapiro, 2020), there are concerns regarding how political beliefs would heterogeneously affect compliance with social distancing orders. For instance, a pastor from Arkansas told the Washington Post "in your more politically conservative regions, closing is not interpreted as caring for you. It's interpreted as liberalism, or buying into the hype." The same report also documents that people from more liberal areas show more distrust in President Trump's initial message and are more proactive about social distancing.[1] The press has also highlighted that

[1] "Without guidance from the top, Americans have been left to figure out their own coronavirus solutions." Washington Post. March 15, 2020.

President Trump initially downplayed the severity of the coronavirus pandemic, suggesting that Republicans may not take social distancing orders seriously.[2] Supporting this conjecture, survey evidence from Pew Research shows that 83% of Republicans agree that Trump is "doing an excellent/good job responding to the coronavirus outbreak" whereas only 18% of Democrats agree.[3]

Does this media coverage solely pick up extreme observations that are not representative of how residents with differing political beliefs behave? Or is there some generalizability of these anecdotes? These are important questions as the answers could help policymakers understand the difference in the treatment effect of stay-home orders among different subpopulations and better allocate time and resources.

To analyze these questions, we create a measure of social distance based on the location of a sample of smartphones throughout the day. From this data we measure social distancing as the percentage of people who stay home for an entire day relative to all people identified in a census block group.[4] This daily data covers January through April 23^{rd} of 2020. We also collect data on debit card transactions, government-sanctioned social distancing orders, county-level demographics, and county-level voting results from the 2016 presidential election. The union of these datasets allows us to study whether partisanship affects adherence to social distancing orders through a difference-in-differences framework.

We find that state-level social distancing orders are associated with a significant increase in social distancing. Specifically, the change in the proportion of people who completely stay at home is 1.4 percentage points (pps) higher in areas with a state-level policy relative to areas without a policy. Analyzing differential responses to state policies, we find that Republican counties respond less to social distancing orders relative to Democratic counties. A one standard deviation increase in the county-level share of votes for Donald Trump in the

[2] "Analyzing the Patterns in Trump's Falsehoods About Coronavirus." New York Times. March 27, 2020.
[3] "Polling Shows Signs of Public Trust in Institutions amid the Pandemic." Pew Research Center. April 17, 2020. Note: Poll conducted March 19-24.
[4] Our results are also robust to using a measure of daily at-home dwell time.

2016 election is associated with a 0.6pps lower percentage of people who stay at home after a state social distancing order relative to the average county. These findings are robust to the inclusion of county and date fixed effects, state×date fixed effects, and controls for county demographics (e.g., population and income), other local policies (e.g., closing schools), and reports of county-level coronavirus cases and deaths.

We next analyze debit card transaction data to examine whether partisanship influences e-commerce consumption in relation to social distancing orders. We find that Democratic counties are more likely to shift to online spending relative to Republican counties after a state-policy is implemented. A one standard deviation decrease in the Trump vote share is associated with a 0.2pps increase in a county's fraction of online spending relative to the average county after a state-policy is implemented. This result provides one channel as to how Democratic counties adjust their behavior more than Republican counties in response to social distancing orders. Further, our consistent results across both geo-location and debit card data suggest that biases in any single dataset are not driving our results.

Our final tests focus on whether the political affiliation of the governor announcing a state-level social distancing order affects compliance. If Republican's lower response to social distancing orders is due to President Trump's early dismissal of the pandemic, we may likewise find that Democrats' response to orders may vary based on the political affiliation of who gives the order. We identify "aligned" counties as those with the same political affiliation as the governor and "misaligned" counties as those with conflicting political identities. We find that misaligned counties have a 0.4pps lower response to state policy social distancing orders relative to aligned counties. This difference is driven by misaligned Democratic counties, which have a 2pps lower response relative to aligned Democratic counties. These results suggest that the difference in compliance to social distancing orders based on partisanship is likely due to how credible residents find government officials and not an information transmission channel.

Our findings are related to the literature examining how political beliefs can influence behavior. Examining politically-charged fake news, Long, Chen, and Rohla (2019) find that conservative-media dismissals of the dangers of hurricane Harvey and Irma led to lower evacuation rates for conservatives relative to liberals. Painter (2020) shows that consumers respond along partisan lines when firms issue political statements. There is also evidence that politics can influence economic expectations (Gerber and Huber (2010); McConnell et al. (2018)). We extend this literature to the recent pandemic setting, showing that partisan beliefs can influence responses to government orders.

Several concurrent papers also examine partisan differences in social distancing in response to the coronavirus. Allcott et al. (2020) use survey and geolocation data to study partisan differences in social distancing and also find the Democratic counties are more likely to socially distance. Barrios and Hochberg (2020) use Google search data and an alternative source of geolocation data to measure the perception of risk that Republicans and Democrats feel regarding COVID-19. Engle et al. (2020) and Andersen (2020) also use GPS data to show an association with the county level share of Trump vote and social distancing.[5] We differ from these studies by focusing on how partisanship affects response to state-level social distancing orders, which we argue is more relevant to policy-makers. Additionally, our paper is the only one to show consistent evidence across both geolocation and debit card data.

II. Data

The primary datasets we use in this study are (1) geolocation data from SafeGraph, (2) debit card transaction data from Facteus, (3) the timing and location of government-sanctioned social distancing orders from the New York Times, and (4) county-level election results from the 2016 Presidential election.

[5] Outside of partisanship, Briscese et al. (2020) provide survey evidence that expectations regarding the duration of social distancing measures affect compliance in Italy and Wright et al. (2020) show that income is also associated with compliance to social distancing orders. Regarding consumption data, Baker et al. (2020) document differences in spending between Republicans and Democrats during the pandemic but do not study shifts in online spending nor do they focus on social distancing orders.

A. Geolocation Data

To create a measure of social distance compliance, we rely on anonymized location data from SafeGraph Inc. covering daily movements for January 2020 until April 23^{rd}, 2020. SafeGraph partners with mobile application services that have opt-in consent from users to collect location data. The partnerships allow SafeGraph to see location data from approximately 35 million unique devices in a given month. To preserve anonymity, the data is aggregated to the census block group (CBG) level and all CBG's with fewer than five observations are omitted. This geolocation data is advantageous as it allows us to see the movement behavior of a large sample of Americans. Further, prior studies using SafeGraph data find the data are generally representative of the US population (Chen, Haggag, Pope, and Rohla, 2019) and in particular representative of voting patterns in the US (Chen and Rohla, 2018).

From the SafeGraph data we create the following variable to track social distancing:

$$Social\ Distance_{c,t} = \frac{Completely\ Home_{c,t}}{Total\ Device\ Count_{c,t} - Working_{c,t}} \tag{1}$$

where $Completely\ Home_{c,t}$ is the number of devices in county c on day t that never left home. Home is measured as the common nighttime location of each mobile device over a 6 week period to a Geohash-7 granularity (about 153 square meters). $Total\ Device\ Count_{c,t}$ is the total number of devices identified in county c on day t, and $Working_{c,t}$ is the number of devices that leave home and go to another location for more than three hours during the period of 8 am to 6 pm local time.[6] A higher percentage of $Social\ Distance_{c,t}$ indicates more residents in the area are complying with the social distancing order. The average for $Social\ Distance_{c,t}$ is 35.2% across the entire sample, 33.1% for the before state-policy sample,

[6]We use three hours in order to adjust for both part-time and full-time workers. We also confirm our results are robust to the inclusion of workers in the social distancing measure in Table A.4 in the internet appendix. Full documentation for the SafeGraph social distancing data can be found here: https://docs.safegraph.com/docs/social-distancing-metrics

and 44.2% for the after state-policy sample.

Though the SafeGraph data is extensive and useful for our setting, it does have some limitations. The data is nationally representative but relies on smartphones to track location and as of 2018 23% of American adults did not own a smartphone.[7] Thus inferences from the geolocation data can only be drawn about those who own smartphones. Further, some smartphones may exit the sample if the phone is permanently turned off or the apps used to track location are deleted from the phone. Date fixed effects help address this limitation. Finally, the data is generated through intermittent and somewhat random "pings" to smartphones and is not monitored continuously throughout the day. This means short trips outside the home may be missed if the phone is not pinged during that time. This could introduce bias as more densely populated areas - which tend to be Democratic - are able to make short trips out of the house whereas rural areas - which tend to be Republican - must make longer trips for daily necessities (e.g., groceries). We address this potential bias using multiple approaches to control for population and population density.

B. Debit Card Transaction Data

Our debit card data comes from Facteus, a data aggregation firm. The dataset is sourced from over 12 million debit cards and covers daily transactions at the zip-code level from January 2020 to April 17^{th} 2020. The data is primarily sourced from payroll cards, government cards, and challenger banks and therefore is primarily made up of younger consumers in the middle- to lower-income brackets.[8] This differs from the SafeGraph data, which skews slightly towards higher income individuals. While neither dataset identically represents the entire US, consistent results in both datasets suggest that no one bias in either dataset is driving the results.

One effective way for Americans to comply with social distancing orders is to switch their consumption towards e-commerce. Because the debit card data allows us to see the amount

[7]Mobile Fact Sheet. Pew Research Center. June, 2019.

[8]We provide a breakdown of representativeness by generation in Table A.2 in the internet appendix.

spent on each brand at the zip-code level, we are able to create a proxy for the amount spent online by identifying brands that operate primarily online. These brands include online retailers (e.g., Amazon), grocery delivery services (e.g., Instacart), and shipment services (e.g, FedEx).[9] We then create the following measure for the proportion of consumption spent on e-commerce:

$$\%\ Online\ Spending_{c,t} = \frac{Online\ Transactions_{c,t}}{Total\ Transactions_{c,t}} \tag{2}$$

where $Online\ Transactions_{c,t}$ is the dollar amount spent at e-commerce firms in county c on date t and $Total\ Transactions_{c,t}$ is the total amount spent in county c on date t. We note that this is a lower bound measure of online spending, as the Facteus data does not differentiate spending between the website and brick and mortar locations of a single brand.[10] Therefore some transactions that happen online may not be recognized as online in our data.[11] For a given county-day the average number of transactions we observe is 1,639, with an average total spent of $55,820 and an average proportion of amount spent online of 8.2%.

C. Government Social Distancing Orders

There are a few sources that track the social distancing policies at varying geographical levels. We choose to use the data assembled by the New York Times because it is comprehensive and provides precise information on both the timing and geography of the social distancing order.[12] Importantly for our study, it also provides official documentation for the order, allowing us to identify the policy announcer in each case. California, the most populous state, was the first to order a state-wide stay at home order effective March 19. Since then, a total of 42 states have issued social distancing orders. We merge the political affiliation of all governors with the NYT data as it is not included in their report. We also gather daily data

[9] The complete list of identified e-commerce firms is shown in Table A.3 in the internet appendix.

[10] A notable exeption is Walmart, which is separated into brick and mortar spending and Walmart.com spending.

[11] To ensure the unclassified online transaction are not biasing our measure, we confirm our results are robust to using the natural log of $Online\ Transactions_{c,t}$ as the dependent variable in Table A.5 in the internet appendix.

[12] "See Which States and Cities Have Told Residents to Stay at Home." New York Times. April 20, 2020.

on the number of reported cases and deaths in each county from the NYT.[13]

There are also instances of governors who refrain from issuing state-wide social distancing orders. These refusals often cite concern on the economy as the main reason. In these cases, NYT also collects information at the city/county level. This data is not useful in our analysis however, as most city/county level orders are not made by political officers. For example, county level social distancing orders in Missouri have largely been made by public health officials. For this reason, we exclude all counties that have implemented a county-level social distancing order from our analysis. Excluding these counties is also beneficial as these counties were likely to have unofficial local policies (e.g., closing parks to the public) that would be difficult to systematically identify.

D. Political Affiliation and Demographic Data

Our setting also requires a proxy for the political preference of US residents. We use the results of the 2016 US Presidential election to measure a county's political preference. Specifically, we collect county-level voting data from the MIT Election Data and Science Lab (MIT, 2018) and use the vote share won by Donald Trump to measure the degree to which a county leans Republican or Democrat. Lastly, we collect county-level demographic data from the 2018 American Community Survey database.

III. Results

A. Partisan Differences in Adherence to Social Distancing Orders

We examine whether political beliefs affect the response to state-level social distancing orders using the following generalized difference-in-differences estimation:

$$Social\ Distancing_{c,t} = \beta * (State\ Policy \times Trump\ Vote) + \delta' * controls + \gamma_c + \gamma_t + \epsilon_{c,t} \tag{3}$$

[13] "We're Sharing Coronavirus Case Data for Every U.S. County." New York Times. March 28, 2020. Note: Updated through April 27, 2020.

Where $Social\ Distancing_{c,t}$ is the percentage of smart devices that were completely at home in county c on day t, $State\ Policy = 1$ if a state level social distancing order has gone into effect,[14] and $Trump\ Vote$ is the county level vote share that went to Donald Trump in the 2016 election. We z-score $Trump\ Vote$ to have a mean of zero and standard deviation of one. The β coefficient on the interaction term will capture the marginal response to social distancing orders based on how much a county leans Republican or Democrat. We include controls for the one-day lag of the natural log of the cumulative number of cases and deaths due to the coronavirus in a county. We also include as controls dummy variables that identify when a state closed k-12 schools, day cares, gyms, and movie theatres and banned nursing home visits, non-essential business, and sit-in restaurants.[15] We include county fixed effects to control for time-invariant local factors like county size or exposure to certain industries. We also include date fixed effects to control for common factors across time like the release of coronavirus-related news on a certain day. Additionally, in certain tests we include state×date fixed effects to capture state-specific trends as well as any other state-policies not controlled for. We double-cluster standard errors at the county and date level.

While we have taken careful steps to mitigate confounding factors, there still exists some potential for endogeneity. In particular, the timing and strength of policy implementation may be endogenous to the expectations of politicians regarding the effectiveness of other social distancing strategies (e.g., loosely defined recommendations to practice social distancing). Though our day fixed effects adjust for timing issues and controls for the number of cases and deaths account for how seriously a county may take the pandemic, we cannot completely rule out this possibility. We argue, however, that the potential for endogeneity (above and beyond what is accounted for in our empirical design) is minimal and that the policy-relevance of our findings are still helpful as guidance for policy-makers throughout this and future pandemics.

We report the results of estimating equation (3) in Table 1. In column (1) we estimate a

[14]We exclude from our analysis days where a state policy went into effect at 12pm or later.

[15]We thank Julia Raifman, Kristen Nocka, and their contributors for sharing this data. Note: we are using the April 27, 2020 version of this data.

baseline specification to examine how much social distancing increases after a state-policy order at the aggregate level. We find that counties with state social distancing orders have a completely-at-home rate that is 1.4 pps higher (4% increase from the unconditional mean) than counties with no state policies in place. This finding highlights the importance of implementing state-level policies, especially when considering this effect is after controlling for county-level coronavirus cases and deaths as well as a host of other state-level business closures. We next estimate equation (3) to analyze how political partisanship affects adherence to social distancing orders (column 2). Consistent with the argument that Republicans were influenced by Trump's early dismissal of the pandemic, we find that a higher vote share to Trump is associated with a lower proportion of people staying completely at home. Specifically, a one standard deviation increase in the vote share to Trump is associated with a 0.6pps decrease in proportion of people staying completely at home after a state policy relative to a county with an average vote share to Trump.

We also analyze these effects in event-time in Fig. 1. We interact our state policy variable with indicator variables for how far away a date is from the state policy enactment and report the resulting coefficients. By construction, these coefficients capture the time-series of differences in social distancing compliance between treated and control counties. The baseline result (Panel A) shows little difference between the social distancing in our treatment and control counties before state policies are enacted and a significant jump in the difference once a state policy goes into effect. On day zero, counties with state-policies practice social distancing by 2.5pps more than counties with no policy. This difference attenuates as counties move further away from the date of the state-policy order. In Panel B, we conduct the event study on subsamples of Republican and Democratic counties.[16] The partisan split event study shows a significant difference in the response to state-policies when comparing Republican counties (>50% Trump) and Democratic counties, with Democratic counties responding more.

[16]Goodman-Bacon (2018) recommends subsample tests as the simplest way to incorporate a third-difference when there is variation in treatment-timing.

Table 1
Partisan Response to Social Distancing Orders

	Social Distancing					
	(1)	(2)	(3)	(4)	(5)	(6)
State Policy	0.014***	0.017***	0.007		0.016***	0.017***
	(3.76)	(4.46)	(0.96)		(4.31)	(4.58)
State Policy×Trump Vote Share		-0.006***	-0.007***	-0.004***	-0.005***	-0.005***
		(-4.89)	(-4.68)	(-3.35)	(-4.09)	(-4.17)
State Policy×Population					0.006**	
					(2.49)	
State Policy×Pop/Sq.Mi.						0.005**
						(2.39)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	No	Yes	Yes
State × Date FE	No	No	No	Yes	No	No
R^2	0.708	0.708	0.695	0.774	0.709	0.742
Observations	332,368	332,368	94,153	332,256	332,368	321,741

Note: This table reports regression results from estimating equation (3). The unit of observation is a county-day. *State Policy* equals one if the underlying county is in a state that has a social distancing order in place on the day of observation and equals zero otherwise. Column (1) reports the baseline difference-in-differences estimation of the effect of state-level government-sanctioned social distancing orders. Column (2) includes an interaction term between *State Policy* and *Trump Vote Share* in the 2016 election from the underlying county. Column (3) repeats the same analysis as Column (2) while excluding observations that occur greater than five days before a state policy is implemented. We also exclude all observations before March 15th in our control sample in Column (3). We include State × Date fixed effects in Column (4). In Columns (5) and (6) we include interactions of *State Policy* with *Population* and *Population per Square Mile* from the underlying county, respectively. All continuous interaction variables are z-scored to a mean of zero and standard deviation of one. County and date fixed effects are included unless otherwise noted. t-statistics, based on standard errors double-clustered at the county and date level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

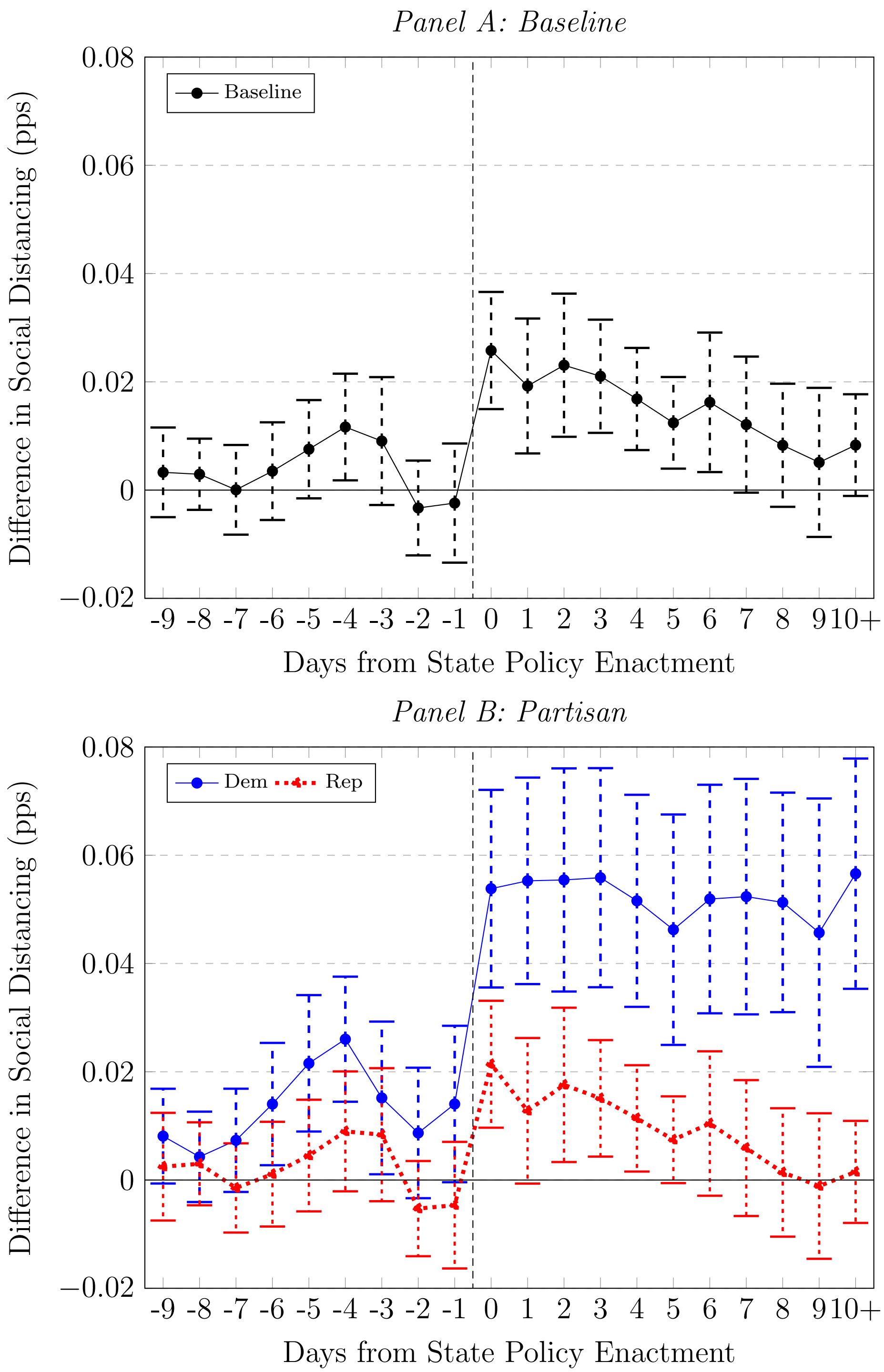

Fig. 1
Changes in Social Distancing around State Policies
This figure plots coefficients of β_j from the following regression of social distancing on the interaction of state policies for shelter in place in event time, where day 0 is the first date the state order went into effect. Panel A plots the entire sample. Panel B plots subsamples for Rep. and Dem. counties, where Rep. counties are those where Trump received over 50% of the vote in the 2016 Presidential election. Controls are the same as used in Table 1 column (1). County and date fixed effects are included. Standard errors are double-clustered at the county and date level.

$$Social\ Distancing_{c,t} = \sum_j \beta_j (State\ Policy \times days\ to\ treatment) + \delta' * controls + \gamma_c + \gamma_t + \epsilon_{c,t}$$

Further, the Democratic counties response persists through the entire sample, whereas the Republican county response trends toward zero.

Though not significantly different the pre-period in Panel B suggests that Democrats may have begun adopting social distancing behavior prior to the announcement of state policies. To ensure that any difference in pre-trends is not driving our results in Table 1 column (2), we re-estimate equation (3) while excluding observations that occur greater than five days before a state policy is implemented. We also exclude all observations before March 15th in our control sample. We continue to find a significant difference in social distancing behavior based on the vote share to Trump (column 3), suggesting that pre-trends are not driving our results. We also find consistent results when including state$\times$date fixed effects in column (4), suggesting that state-trends are not influencing our results.

Because more populous areas are more at risk, there could be an increasing intensive margin effect based on the population of the area.[17] To control for this possibility, we include the interaction of our state policy indicator with the population of a county (z-scored to mean 0 and standard deviation one) in column (5) of Table 1. We continue to find a significantly negative coefficient on $State\ Policy \times Trump\ Vote$, suggesting population differences are not driving the effect. We repeat this test using population density in column (6) and again find consistent results.[18]

B. Changes in E-commerce Spending around Social Distancing Orders

We next test whether there is a difference in online consumption for Republican and Democratic counties around state policies using the following difference-in-differences estima-

[17] We provide suggestive evidence of this in Fig. A.1 in the internet appendix.

[18] We run a series of additional robustness checks for our main result in Table A.4 in the internet appendix. These tests include (1) the inclusion of workers in the social distancing measure, (2) using the natural log of the median dwell time at home as the dependent variable, (3) including interaction of state policy with county level population, density, income, age, and education, and (4) including county level controls instead of county fixed effects.

tion:

$$\% \; Online \; Spending_{c,t} = \beta * (State \; Policy \times Trump \; Vote) + \delta' * controls + \gamma_c + \gamma_t + \epsilon_{c,t} \tag{4}$$

As mentioned previously, moving consumption towards e-commerce is one way to help adhere to social distancing orders. Therefore a significant difference in online spending along partisan lines would suggest a difference in effort to comply with social distancing orders.

We show results from estimating equation (4) in Table 2. Consistent with our conjecture, we find a significant difference in the change in online spending around state-policy implementation based on the share of vote share to Trump. Specifically, a one standard deviation increase in Trump vote share is associated with a 0.2pps lower proportion of online spending after a state policy relative to a county with an average vote share to Trump. The effect represents a 3.5% deviation from the median amount spent online of 5.7%. This result is robust to the inclusion of the interaction of both population and population density with the state policy variable.[19]

To examine whether the partisan difference in online spending is driven by an increase in Democratic e-commerce spending or a decrease in Republican e-commerce spending, we re-examine our event-time model within this new setting. Specifically, we again interact our state policy variable with indicator variables for how far away a date is from the state policy enactment and report the resulting coefficients for subsample tests on Democratic and Republican counties. The results, shown in Fig. 2, show that the difference in the proportion of online spending is driven by an increase by Democratic counties that are under social distancing orders. Prior to the enactment of state-policies, there is no significant difference in the percent of online spending for the treated Republican and Democratic counties. After

[19]Additional robustness checks include the following: (1) including the interaction of state policy with population, population density, income, age, and education, (2) using state×date fixed effects, and (3) using the natural log of total online spending as the dependent variable (see Table A.5 in the internet appendix.)

Table 2

Partisan Differences in Online Spending around Social Distancing Orders

	% Online Spending		
	(1)	(2)	(3)
State Policy	-0.0007	-0.0008	-0.0008
	(-0.41)	(-0.45)	(-0.44)
State Policy×Trump Vote Share	-0.0021***	-0.0020***	-0.0021***
	(-3.00)	(-2.72)	(-2.81)
State Policy×Population		0.0007**	
		(2.37)	
State Policy×Pop/Sq.Mi.			0.0008***
			(4.29)
County FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
R^2	0.365	0.365	0.364
Observations	300,392	300,392	294,168

Note: This table reports results from estimating equation (4). The unit of observation is a county-day. *State Policy* equals one if the underlying county is in a state that has a social distancing order in place on the day of observation and equals zero otherwise. Column (1) includes an interaction term between *State Policy* and *Trump Vote Share* in the 2016 election from the underlying county. In Columns (2) and (3) we include interactions of *State Policy* with *Population* and *Population per Square Mile* from the underlying county, respectively. All continuous interaction variables are z-scored to a mean of zero and standard deviation of one. County and date fixed effects are included. t-statistics, based on standard errors double-clustered at the county and date level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

state-policies are implemented, there is a steady and significant increase in the percent of online spending for Democratic counties, persisting through the entire post-period. In contrast, there is no significant change in online spending for the treated Republican counties. These results suggest that online spending is one channel through which Democrats adjust their behavior to comply with social distancing orders relative to Republicans.

C. The Effects of Political Misalignment on Compliance with Social Distancing Orders

There are two possible channels that may explain our results thus far. First, an "information" channel would suggest that Democrats are more informed about the potential spread

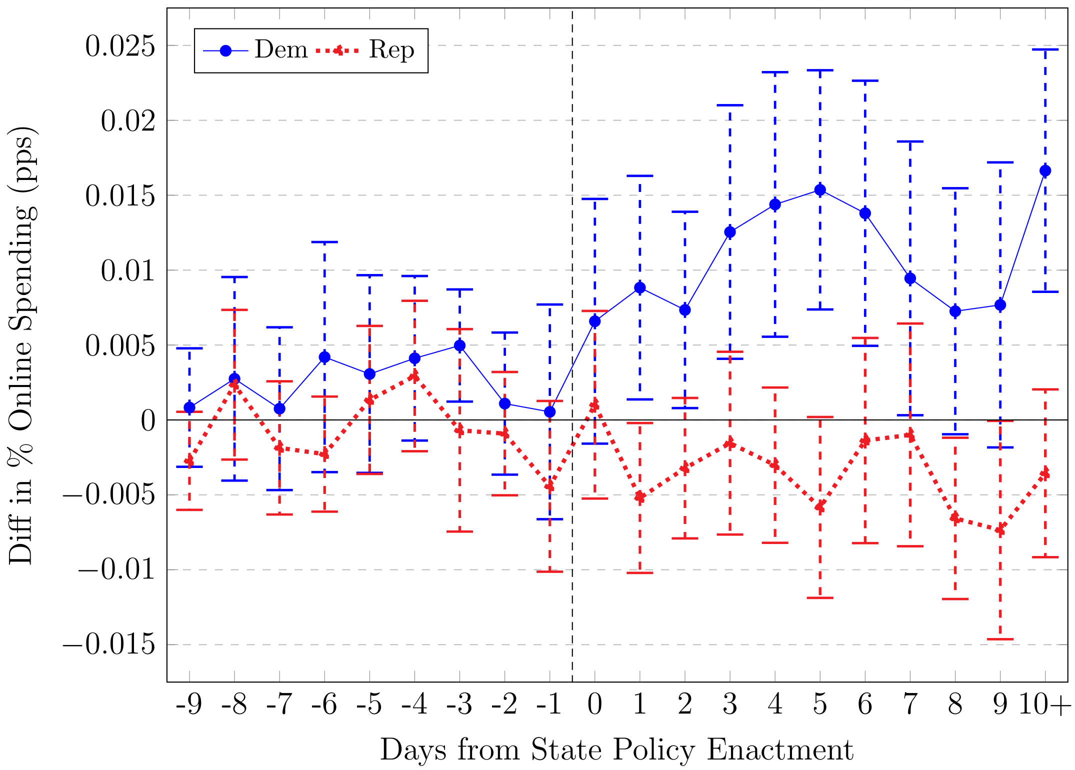

Fig. 2

Partisan Differences in Online Spending in Event Time

This figure plots coefficients of β_j from the following regression of the fraction of online spending on the interaction of state policies for shelter in place and the event time, where day 0 is the first date the state order went into effect. Rep. counties are those where Trump received over 50% of the vote in the 2016 Presidential election. The unit of observation is a county-day. Controls include the lag of the natural log of the number of cases and deaths from COVID-19 at the county level as well as state level indicators if a state had closed k-12 schools, day cares, gyms, and movie theatres and banned nursing home visits, non-essential business, and sit-in restaurants. County and date fixed effects are included. Standard errors are double-clustered at the county and date level.

$$\%\ Online\ Spending_{c,t} = \sum_j \beta_j (State\ Policy \times days\ to\ treatment) + \delta' * controls + \gamma_c + \gamma_t + \epsilon_{c,t}$$

of coronavirus and thus react more intensely when government measures are put in place. Second a "credibility" channel would suggest that Republicans, who may rely on President Trump's word more than local government official's, do not find the state policy warnings credible and therefore react less to social distancing orders.

To distinguish between these two potential channels, we re-visit the geolocation data and create the variable *misalignment* which indicates whether the political affiliation of a county is misaligned with the political affiliation of the person who issues a state policy order. For example, $misalignment = 1$ for a Republican county in Colorado, where the Democratic Governor Jared Polis issued a stay at home order. On the other hand, $misalignment = 0$ for a Democratic county in Colorado.[20] Our final tests examine equation (3) but instead interact the state policy indicator with the misalignment variable. If the results are driven by the information channel, we would expect to find no difference based on misalignment. If the results are driven by the credibility channel, we would expect a lower response in misaligned counties relative to aligned counties as the misaligned counties would find the social distancing order less credible.

Table 3 reports the misalignment results. Consistent with the credibility channel, we find that misaligned counties respond less to social distancing orders relative to aligned counties. After a state policy is enacted, the proportion of people who completely stay home is 0.4pps lower in misaligned counties relative to aligned counties.

To further examine the credibility channel, we repeat the misalignment test on subsamples of Republican and Democratic counties. We find no difference in behavior between aligned and misaligned Republican counties (column 2) but a significant difference in behavior in Democratic counties (column 3). Specifically, misaligned Democratic counties respond 2pps less than aligned Democratic counties. Additional tests that include the interaction of county demographics with the state policy variable (see Table A.6) suggest the results are not driven by differences in county characteristics. Further we find no significant difference in the average

[20]This measure is analogous to the ideological mismatch measure used in Kempf and Tsoutsoura (2018).

Table 3
The Effect of Misaligned Political Beliefs on Adherence to Social Distancing Orders

	Social Distancing		
	(1)	(2)	(3)
	Full Sample	Rep	Dem
State Policy	0.017***	0.013***	0.054***
	(4.15)	(3.02)	(6.17)
State Policy×Misalign	-0.004**	0.002	-0.020***
	(-2.05)	(0.59)	(-4.39)
State Policy×Pop/Sq.Mi.	0.005**	0.083***	0.005***
	(2.49)	(5.11)	(2.71)
County FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
R^2	0.741	0.724	0.806
Observations	321,741	262,713	59,028

Note: This table reports the impact of misaligned political beliefs between residents and the policy announcer (the governor) on social distancing behavior. The unit of observation is a county-day. *Misalign* equals one if the county is Democratic (Republican) and the governor is Republican (Democratic) and equals zero otherwise. *State Policy* equals one if the underlying county is in a state that has a social distancing order in place on the day of observation and equals zero otherwise. Column (1) reports result for the full sample. Column (2) and (3) report results for Republican and Democratic subsamples, respectively. Controls are the same as those used in Table 1 column (6). County and date fixed effects are included. t-statistics, based on standard errors double-clustered at the county and date level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

share of Trump vote in aligned vs. misaligned Democratic counties (34.28% vs. 34.05%), suggesting the effect is not driven by differences in how Democratic a county is. These results suggest that the perceived credibility of the public official issuing a social distancing order is an important influence in that order's effectiveness.

IV. Conclusion

Social distancing is one of the most effective ways to mitigate the spread of the novel coronavirus. In this paper, we study political limitations to government-mandated orders intended to get people to practice social distancing. Our results suggest that faith in the credibility of officials issuing government orders affects adherence to those policies. In particular, Republican and politically-misaligned Democratic counties respond significantly less to social distancing policies. We also provide evidence that Democrats are more likely to switch to e-commerce consumption after social distancing orders are implemented. Our results highlight the need for bipartisan support of the effectiveness of social distancing in order to mitigate the spread of the coronavirus.

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Internet Appendix Table A.1
Summary Statistics - SafeGraph and Population

Panel A: Social Distancing Behavior

	All		Before State Policy		After State Policy	
	Mean	SD	Mean	SD	Mean	SD
Social Distance	0.352	0.086	0.331	0.075	0.442	0.075
Observations	335344		271131		64213	

Panel B: County Population

	All		Dem Counties		Rep Counties	
	Mean	SD	Mean	SD	Mean	SD
Population (000s)	87.20	304.55	276.88	662.30	45.20	80.12
Population/Sq.Mi.	76.06	892.02	282.37	2065.08	29.70	67.79
Observations	335344		60798		274546	

Note: This table reports summary statistics of our social distancing and population data. The unit of observation is a county-day and covers January 1st to April 23rd, 2020. Panel A reports summary statistics on social distancing behavior for all observations as well as split on before and after government sanction. Panel B reports summary statistics on population and population density for all observations as well as split on political affiliation. Data source: smartphone geolocation data from SafeGraph Inc and county demographics from the 2018 American Community Survey.

Internet Appendix Table A.2
Summary Statistics for Consumption Data

Panel A: County-Day Level Spending Data

Variable	Mean	S.D.	10%	Median	90%
Online Transactions	103	334	4	32	205
Online Value ($)	3,352	11,074	88	912	6,792
Total Transactions	1,639	6,125	51	491	3,404
Total Value ($)	55,820	197,905	1,525	15,996	116,019
Fraction of Value from Online	8.2%	9.3%	2.2%	5.7%	15.6%

Panel B: Age Breakdown by Card Type

	Payroll	Debit	General Purpose	Government
SILENT	0.2%	0.2%	0.8%	0.1%
BOOMERS	7.8%	6.2%	15.9%	4.1%
GEN X	22.8%	30.3%	34.6%	28.5%
MILLENNIALS	50.9%	56.7%	44.4%	64.9%
GEN Z	18.4%	6.6%	4.2%	2.4%

Note: This table reports summary statistics of spending data. Panel A reports county-day level online and in-store spending statistics. Both number of transactions and transaction values are rounded to the nearest integer for ease of interpretation. Panel B reports age breakdown by card type. Data source is Facteus, covering transactions from January 1, 2020 to April 17, 2020.

Internet Appendix Table A.3
List of Online Shopping Brands

Brand	Average Daily Value ($)
ALIEXPRESS	101,008
AMAZON	5,960,829
BLUE APRON	1,876
DELIVERY.COM	2,314
EBAY	300,980
ETSY.COM	110,033
FEDEX	112,198
FREESHIPPING.COM	3,675
GRUBHUB	9,002
INSTACART	81,378
JUSTFAB.COM	20,451
OVERSTOCK.COM	17,331
PEAPOD GROCERY DELIVERY	4,157
SHIPT	51,069
UBER EATS	370,482
USPS	1,620,802
WAYFAIR	241
WISH.COM	276,450
WALMART.COM	1,021,049

Note: This table reports all the online purchase brands we recognize in our data and the average daily total transaction values for each brand. Transaction values are rounded to the nearest dollar for ease of interpretation. Data source is Facteus, covering transactions from January 1, 2020 to April 17, 2020.

Internet Appendix Table A.4

Partisan Response to Social Distancing Orders - Robustness

	(1) Include Workers	(2) Ln(Dwell)	(3) Interactions	(4) County Controls
State Policy	0.013***			
	(3.95)			
State Policy×Trump Vote Share	-0.005***	-0.017***	-0.003***	-0.005***
	(-3.94)	(-4.29)	(-3.12)	(-3.95)
State Policy×Population			0.005	
			(1.37)	
State Policy×Pop/Sq.Mi.			0.003*	
			(1.84)	
State Policy×Income			0.020***	
			(15.51)	
State Policy×Age			-0.002*	
			(-1.80)	
State Policy×Education			-0.002	
			(-0.76)	
County FE	Yes	Yes	Yes	No
Date FE	Yes	No	No	No
State × Date FE	No	Yes	Yes	Yes
R^2	0.819	0.711	0.814	0.737
Observations	332,368	332,256	321,629	321,629

Note: This table reports robustness checks for change in social distancing behavior. Column (1) includes workers in the social distancing measure. Column (2) uses the natural log of the median dwell time at home as the dependent variable and includes State × Date fixed effects. Column (3) includes the interaction of state policy with county level population, density, income, age, and education and State × Date fixed effects. Column (4) includes county level controls instead of county fixed effects. All continuous interaction variables are z-scored to a mean of zero and standard deviation of one. County and date fixed effects are included unless otherwise noted. t-statistics, based on standard errors double-clustered at the county and date level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Internet Appendix Table A.5

Partisan Differences in Online Spending around Social Distancing Orders - Robustness

	(1) % Online	(2) % Online	(3) Total Online
State Policy	0.0011		
	(0.63)		
State Policy×Trump Vote Share	-0.0025***	-0.0057***	-0.0520**
	(-3.31)	(-5.51)	(-2.13)
State Policy×Pop/Sq.Mi.	0.0008***		
	(4.31)		
State Policy×Population	0.0015*		
	(1.78)		
State Policy×Income	0.0025***		
	(3.61)		
State Policy×Age	0.0042***		
	(4.33)		
State Policy×Education	-0.0010		
	(-1.20)		
County FE	Yes	No	No
Date FE	Yes	No	No
State × Date FE	No	Yes	Yes
R^2	0.365	0.144	0.531
Observations	294,168	294,061	294,061

Note: This table reports robustness checks for change in online spending behavior. Column (1) includes the interaction of state policy with population, population density, income, age, and education. Column (2) uses State × Date fixed effects. Column (3) uses the natural log of total online spending as the dependent variable. All continuous interaction variables are z-scored to a mean of zero and standard deviation of one. County and date fixed effects are included unless otherwise noted. t-statistics, based on standard errors double-clustered at the county and date level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Internet Appendix Table A.6

The Effect of Misaligned Political Beliefs on Adherence to Social Distancing Orders - Robustness

	Social Distancing		
	(1)	(2)	(3)
	Full Sample	Rep	Dem
State Policy	0.019***	0.020***	0.036***
	(4.96)	(5.13)	(4.12)
State Policy×Misalign	-0.003*	-0.002	-0.006*
	(-1.67)	(-0.97)	(-1.83)
State Policy×Pop/Sq.Mi.	0.003**	0.058***	0.004**
	(2.11)	(5.25)	(2.54)
State Policy×Population	0.009***	-0.004	0.010***
	(2.68)	(-0.44)	(2.91)
State Policy×Income	0.022***	0.020***	0.022***
	(15.51)	(13.11)	(12.06)
State Policy×Age	-0.001	0.000	-0.006***
	(-1.43)	(0.19)	(-4.04)
State Policy×Education	-0.006*	0.020*	-0.009**
	(-1.89)	(1.97)	(-2.56)
County FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
R^2	0.751	0.731	0.819
Observations	321,741	262,713	59,028

Note: This table reports robustness checks for the misaligned political belief tests. We repeat the same setting as Table 3 but includes interaction of state policy with county level population, density, income, age, and education. Column (1) reports results for the full sample. Column (2) and (3) report results for Republican and Democratic subsamples, respectively. County and date fixed effects are included. t-statistics, based on standard errors double-clustered at the county and date level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

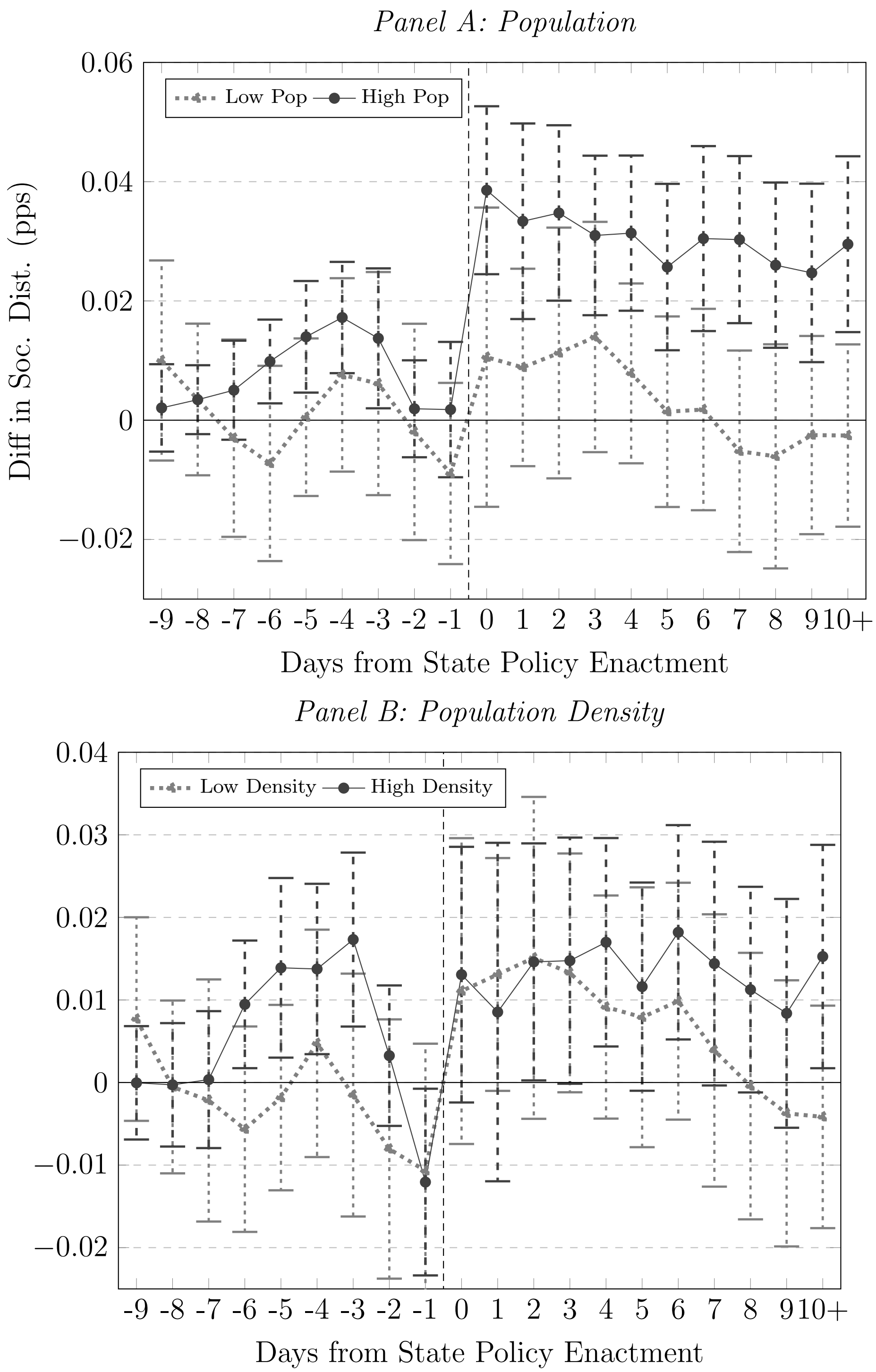

Fig. A.1

Changes in Social Distancing around State Policies by Population and Population Density

This figure plots coefficients of β_j from the following regression of social distancing on the interaction of state policies for shelter in place in event time, where day 0 is the first date the state order went into effect. Panel A plots the highest and lowest quintiles of counties based on population. Panel B plots the highest and lowest quintiles based on population density. Controls are the same as used in Table 1 column (1). County and date fixed effects are included. Standard errors are double-clustered at the county and date level.

$$Social\ Distancing_{c,t} = \sum_j \beta_j (State\ Policy \times days\ to\ treatment) + \delta' * controls + \gamma_c + \gamma_t + \epsilon_{c,t}$$