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DISCUSSION PAPER SERIES

IZA DP No. 13234

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MAY 2020

ISSN: 2365-9793

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ABSTRACT

Stay-At-Home Orders, Social Distancing and Trust

Better understanding whether and how communities respond to government decisions is crucial for policy makers and health officials in response to the COVID-19 pandemic. In this study, we document the socioeconomic determinants of COVID-19 stay-at-home orders' compliance in the U.S. Using cell phone data measuring changes in average distance traveled and non-essential visitation, we find that: stay-at-home orders reduce mobility by about 8–10 percentage points; high-trust counties decrease their mobility significantly more than low-trust counties post-lockdown; and counties with relatively more self-declared democrats decrease significantly more their mobility. We also provide evidence that the estimated eeffct on compliance post-lockdown is especially large for trust in the press, and relatively smaller for trust in science, medicine or government.

JEL Classification: H12, I12, I18

Keywords: COVID-19, stay-at-home orders, social distancing, trust

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In only a few months, the outbreak of COVID-19 has claimed more than 200,000 lives and caused an unprecedented disruption in many areas of our lives. While medical researchers all over the globe are working towards developing a vaccine, the disease continues to spread with many remaining uncertainties about it.

In most countries hit by the pandemic, authorities adopted measures to impose "social distancing" to stem the uncontrolled spread of the virus, limit infections and deaths, and ease the pressure on the health system and health service providers. In the United States, counties and states' officials started implementing lockdown policies during the second half of March 2020. Endorsing these measures included cancelling group events, mandating people to work from home, closing schools and businesses, and limiting people's freedom to leave their homes. Studies so far have shown that early governmental actions along with public cooperation can indeed slow down the spread of the contagion (Anderson et al. (2020); Bai et al. (2020); Hsiang et al. (2020); Viner et al. (2020)).

While the effectiveness of the shelter-in-place protocols relies on public compliance, understanding whether and how communities respond to government decisions is crucial for policy makers and health officials in chosing the appropriate response to the COVID-19 pandemic. Interestingly, mobility data derived from cell phone location tracking (described later) suggest a large variation in behavior patterns across the U.S. states and counties. In this paper, we study the determinants of compliance to stay-at-home orders in the U.S. focusing on trust and social capital.

There exist several factors that may affect obedience, such as expectations for the duration of self-isolation (Briscese et al. (2020)), differences in risk perceptions (Allcott et al. (2020); Barrios and Hochberg (2020); Engle et al. (2020)), poverty and economic dislocation (Wright et al. (2020)), belief and trust in science (Briscese et al. (2020)), political affiliation (Allcott et al. (2020), Painter and Qiu (2020)), social responsibility and social trust, and attitudes about the virus's severity (Oosterhoff and Palmer (2020)).

The most relevant studies are possibly Engle et al. (2020) and Bargain and

Ulugbek (2020). Engle et al. (2020) also use mobility statistics from Unacast and find that stay-at-home orders are correlated with a reduction in mobility of 7.9%. This correlation gets stronger in counties with a lower share of votes for republicans[1], higher population density and relatively more people over the age of 65.[2] Bargain and Ulugbek (2020) rely on human mobility data in Europe and provide evidence that high-trust regions decrease their mobility relatively more than low-trust regions after the implementation of a lockdown.

This study contributes to the existing literature by focusing on a major set of mechanisms that might have shaped the actual compliance in the United States. More precisely, we examine the relationship between compliance and trust and altruistic tendencies, local norms, and political and religious engagement. With the way the virus spreads, social distancing is not seen as a personal choice but rather an ethical duty. Therefore, community attachment – mainly manifested by social trust – is more likely to be associated with higher preventative behavior.

We measure social capital and trust using data from the General Social Survey (GSS). To capture the effect of stay-at-home orders on compliance, we rely on cell phone data from Unacast's COVID-19 Toolkit, which measures changes in average distance traveled, non-essential visitation and human encounters. We also rely on Google Community Mobility reports as an additional measure of mobility. The Google cell phone data indicates percent change in visits to the following six categories of places: grocery and pharmacy, parks, transit stations, retail and recreation, residential, and workplaces. In our empirical model, we include state and day of the week fixed effects and compare counties' social capital and trust-levels before and after statewide stay-at-home orders in a double difference framework.

[1] van Holm et al. (2020) also find that liberals are more concerned about COVID-19 and more likely to change their behavior.

[2] Canning et al. (2020) conducted an online survey in the U.S. and found that older people were as likely to leave their homes as younger people, but people over the age of 50 had less than half the predicted number of close contacts than those who were younger than 30. Moore et al. (2020) find that younger respondents are less likely to report being compliant. Their survey also provides evidence that the primary reasons reported for non-compliance were non-essential work requirements, concerns about health, and beliefs that the respondent is taking sufficient precautions.

We first confirm the result that stay-at-home orders reduce mobility. Our estimates suggest that statewide orders reduce mobility by about 8–10 percentage points, and thus increase time spent at home. We also find that residents of counties with relatively higher COVID death rates, within a state, are less likely to visit places such as parks, groceries and their workplaces.

Our main finding is that counties with relatively more trust in others decrease their mobility significantly more once a lockdown policy is implemented. This result is robust to accounting for several confounding factors at the county-level such as the number of confirmed COVID-19 cases and deaths, and demographic, geographic, epidemiological and socio-economic characteristics. Exploiting the different trust measures in the GSS, we show that the estimated effect on compliance post-lockdown is especially large for trust in the press, and relatively small for trust in science, medicine or government.

We also test the importance of three additional (plausible) determinants of compliance: religion, crime and political affiliation. We do not find any evidence that religiosity is related to non-essential visits and travel distance neither pre- nor post-lockdown. For crime, we rely on data from the GSS on whether the respondent is afraid to walk alone at night. We find that counties with relatively more residents being afraid to walk alone at night travel less prior to the stay-at-home order, but that this effect decreases in size post-lockdown. Last, we find that counties with relatively more self-declared democrats decrease significantly more their mobility post-lockdown.

Last, we conduct subsample analyses to test whether the determinants of compliance with stay-at-home orders vary for counties with specific characteristics, i.e., the level of poverty, urbanization, educational attainment of the residents and political identity of the governor. In general, we do not find strong evidence that it is the case, suggesting that, within a state, the differential effect of the lockdown is quite homogeneous across counties for trust and the other determinants. One exception is that residents of democrat-majority counties were significantly more

likely to follow guidelines to stay at home only in urban counties.

We structure the remainder of the paper as follows. In section 1, we present the data sources and descriptive statistics. Section 2 presents the methodology. In section 3, we provide the regression results. The last section concludes.

1 Data

1.1 COVID-19 Known Cases and Deaths

Data on COVID-related deaths and cases are collected by the John Hopkins Coronavirus Research Center on a daily basis at the county level.[3] The number of confirmed cases is updated on a daily basis at night. Note that confirmed cases include presumptive positive cases.[4] In the main analysis, we rely on deaths rather than cases to avoid measurement error issues, but show that our main findings are unchanged when controlling for known cases rather than COVID-19-related deaths. Appendix Table A1 provides summary statistics.

1.2 Social Distancing

We extract data on social distancing from the Unacast's COVID-19 Toolkit and from "Google LLC" Community Mobility reports.

Unacast, originally specialized in the analysis of human mobility data, has launched the Social Distancing Scoreboard to raise awareness and reinforce the importance of social distancing in relation to slowing the spread of COVID-19. The interactive Scoreboard is updated daily using location data from cell phones and aims to empower organizations to evaluate the effectiveness of social distancing initiatives at the local level by comparing the community's social distancing behavior to its 'normal' levels of activity prior to the pandemic.

[3]Data sources: Coronavirus COVID-19 Global Cases by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University; the Red Cross; the Census American Community Survey; the Bureau of Labor and Statistics.

[4]We do not rely on recovered cases since the estimates are based on local media reports, and may be substantially lower than the true number. Also note that New York City borough deaths data does not include probable COVID-19 deaths, as this data is not reported.

Using the location data from cell phones, Unacast calculates the average visitation for each day of the week prior to the COVID-19 outbreak (defined as March 8th and earlier) as a baseline. Unacast then compares those baselines to visits on the corresponding days of the week post-pandemic, i.e., compare Saturdays to Saturdays. Importantly, the scores express the rate of change in how visit counts responded to the virus spreading, rather than absolute numbers of visits. While the accuracy and frequency of cellular tracking data will vary from county to county, our identification relies on within-county over time. In other words, a given county is compared to itself over time, rather than compared to other counties.

The Scorecard assigns a letter grade of A through F to all states and counties based on their social distancing behavior. The allocated score is based on three different metrics: the percent change in average distance travelled, the percent change in "non-essential visitation", and the change in "human encounters". We rely on the first two metrics for our analysis.[5] Non-essential visits include (but are not limited to) travels to venues like spas, cinemas, jewellers, and clothing stores. The categorization of essential and non-essential locations is based on guidelines issued by various policymakers in the U.S.

For our analysis, we rely on daily data from March 3rd to April 24th at the county-level. As of April 24th, for instance, data showed that average mobility in the nation as a whole had fallen by approximately 45% since February (see Appendix Table A1). Of note, these figures conceal the uneven geography of social distancing and tremendous variation in behavior change across the U.S. states, and across counties within the same state.

Figure 1 and Appendix Figure A1 highlight the geographic variation in the two Unacast mobility measures for two dates: one before any stay-home order was announced (March 15th, 2020) and one after all lockdowns were imposed (April 15th, 2020). While the pre-policy maps show the voluntary community actions

[5]The "change in human encounters" measure is based on the encounter density which tracks how close two devices come to one another. This index is widely dispersed, especially for the top 5% values (around 85 counties). Note that this index is not correlated with the implementation of safer-at-home policies, nor county COVID-19 death rate. Results available upon request.

against the pandemic's spread[6], the post-policy figures show the level of obedience to authorities. Despite the obvious decrease in mobility after governmental actions, these maps reveal clearly that U.S. counties are highly variable in their level of compliance.

We also rely on Google Community Mobility reports to measure compliance to stay-at-home orders. Google has temporarily published a set of COVID-19 reports intended to help remediate the impact of the pandemic. Each published dataset is for a specific geographic location and includes the percent change in visits to places like grocery stores and parks. There are six categories: grocery and pharmacy, parks, transit stations, retail and recreation, residential, and workplaces. (See Appendix for the detailed list of places per category.) The mobility data show how visits and duration of stay change compared to a baseline for the same areas and same day of the week prior the virus spread.

1.3 Stay-Home Orders

We collected data on counties and states COVID-related declaration and policies, as well as the declarations' date, from the National Association of Counties – County Explorer (NACo). While all 50 states and the District of Columbia have declared a state of emergency, the NACo continuously updates its data as new declarations and policies in response to the COVID-19 pandemic are issued across the country.

The dataset contains details on the type of measures adopted by different states and counties. Policies include emergency declaration, business closures and/or safer-staying-at-home declarations.

1.4 General Social Survey

For data on attitudes and behaviors, we rely on the General Social Survey (GSS). The GSS gathers data on contemporary American society and covers a wide range of topics including civil liberties, intergroup tolerance, morality and confidence over

[6]See Brzezinski et al. (2020) for more on social distancing in the absence of lockdown policies

the years 1993-2016. We rely on repeated question from 2000 to 2014 to form our pooled sample on 436 counties.[7]

We focus on behavioral and attitudinal questions related to politics and religion, as well as trust in governmental institutions, press, medicine, science, and trust in others. For instance, questions related to trust are stated as follows: "*I am going to name some institutions in this country. As far as the people running these institutions are concerned, would you say you have a great deal of confidence, only some confidence, or hardly any confidence at all in them?*". See the Appendix for the wording on all selected questions.

To build our county-level measures, we rely on respondents' answer to the selected question and compute weighted shares. While the questions on religiousness and fear are straightforward as they are binary outcomes, we code a respondent as a democrat if they think of themselves either as a "strong democrat" or "not very strong democrat". For questions on trust in institution, we consider that a person has trust if their answer to the above mentioned question is either "a great deal" or "only some".

2 Identification Strategy

2.1 Identification Strategy

For the purpose of this study, we employ a double difference framework to compare counties' social capital and trust-levels before and after statewide lockdown orders. Using fixed effects, we control for state time-invariant and day-specific characteristics, which allows us to examine the within-state variation across counties.

As the pandemic spreads, individual preventative behavior might depend on two primary factors. First, people would limit their mobility and human interaction based on community actions in order to protect themselves even in the absence of government interventions. This preventative behavior tends to vary between dif-

[7]There are eight General Social Surveys since 2000 (2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014) covering a total of 436 counties. Appendix Table A2 shows that our sample of counties is quite representative of the United States.

ferent levels of trust, local norms, and political or religious affiliations. Once the stay-at-home policies are implemented, citizens may also comply to orders differently.[8]

Our identification strategy will not only allow us to assess the independent actions and compliance levels separately, but also evaluate how individuals with different trust levels and different community attachments comply with authorities' policies.

2.2 Model Specification

Our objective is to investigate the relationship between the socio-political norms, such as trust and affiliations and social distancing patterns amid the pandemic spread.

We estimate the following specification:

$$y_{cst} = \lambda_s + \gamma_t + \alpha CommunityAttachment_c + \kappa PostLockdown_{cst} + \beta CommunityAttachment_c \times PostLockdown_{cst} + X_c'\omega + \varepsilon_{cst}, \quad (1)$$

where y_{cst} respectively includes our three metrics measuring social distancing: percent change in average distance travelled, percent change in non-essential visitation, and change in human encounters' density in county c of state s on day t (day refers to the day of the week, and takes on 7 distinct values). We include a full set of state dummies λ_s to control for time-invariant state characteristics, and day dummies γ_t to capture the influence of aggregate trends. The dummy variable $PostLockdown_{cst}$ equals one if the day is after the date of policy implementation in county c of state s.[9] $CommunityAttachment_c$ includes a wide set of county-level variables: share of individuals with high trust in others, share of religious individuals, share of those afraid to go out in their neighborhood at night, and share of

[8] See more on community actions and government obedience in Brzezinski et al. (2020).

[9] The policy implementation could be either at the state- or at the county-level depending on whether it was first implemented by state or local authorities.

democrats. Our main coefficient of interest is thus β, corresponding to the interaction term between community attachments and the post-lockdown policy dummy.

X_c is a vector of covariates and allows us to control for confounding factors including demographic controls (population, population density, percent of urban population, percent of men, and percent of elders over 65 years old), geographic controls (presence of an airport, and whether the county is coastal and/or a state capital city), epidemiological controls (natural log of the number of COVID-19 relates cases and deaths), and socioeconomic controls (share of independents, share of individuals below official poverty, average per capita income, and share of individuals with a college degree or more). Note that data on socioeconomic variables is from the American Community Survey (ACS-5 years estimates) for the latest available years (2014 to 2018).[10] Standard errors are clustered at the state level.

As an additional exercise, we look at the effect of different trust-related measures on compliance to social distancing orders. These measure include confidence in the congress, the federal government, the press, medicine and science. We rely on the model above, except that these variables are not pooled together as they are highly correlated and their inclusion in one specification might conceal their effect. Our hypothesis is that people who put more trust in their institutions are more likely to comply with government orders aiming to assure their safety. Moreover, those who have more confidence in the press and medicine would tend to adopt a more preventative behavior and obey the authorities more.

To examine the heterogeneous effect of community attachments on social distancing, we split the counties' sample based on several socio-economic characteristics, such as poverty, urban population, education, and the state governor's political affiliation. In other words, we look at how social capital and trust shape citizens' compliance with social distancing in different settings.

[10]Data on the share of urban population is based on the last census before the pandemic outbreak, i.e., 2010.

3 Main Results

3.1 Double Difference

Table 1 presents estimates of equation (1). The dependent variable is our indices of non-essential visits in columns 1–2 and total travel distance in columns 3–4, respectively. Only county-day observations up to 10 days after the implementation of the safer-at-home order and 10 days prior to the implementation are included. In columns 1 and 3, we only include state fixed effects, day of the week fixed effects and our epidemiological county-level controls. We are thus comparing counties within a state, before and after a safer-at-home policy in all specifications. In columns 2 and 4, we extend the list of controls to include demographic, geographic, and socio-economic controls. Our controls include the following county-level characteristics: population density, the percentage of urban residents, the percentage of individuals aged more than 65, the percentage of men, the percentage of independents (not republicans nor democrats), per capita income, the percentage of population below the official level of poverty, the percentage of residents with a college degree or more, and dummies for whether the county is coastal, capital of the state, and has an airport.[11]

The estimates for our safer-at-home order are statistically significant at conventional levels for non-essential visits and travel distance, and suggest that the introduction of an order reduces visits and total travel distance by about 8–10 percentage points. The inclusion of additional control variables has no effect on the magnitude and significance of our "After Lockdown" variable. We also find that county COVID-19 death rates are significantly negatively related to our two indices – conditional on an order being in place. This finding means that residents of counties with relatively higher COVID-19 death rates within a state, are more likely to stay home.

We now turn to our main results. We do not find evidence that residents of

[11] Arguably, counties with an airport might be more affected by the pandemic and may have lower/higher levels of trust.

high- and low-trust counties were behaving differently prior to the implementation of safer-at-home policy. However, we find that counties where individuals trust other people more do comply significantly more with social distancing orders. In other words, our estimates suggest that trust in others significantly decreases mobility once lockdown policies are implemented. We confirm the robustness of this result by including to the model our set of socio-economic and geography controls in columns 2 and 4. The inclusion of these additional control variables has no effect on the magnitude and significance of our "After Lockdown" variable and the interaction term with our trust measure

We also investigate the role of other determinants such as religiosity and crime. As a proxy for perceptions of crime, we rely on the percentage of respondents who answer that they are afraid to walk alone at night. For religion, we rely on the percentage of respondents self-declaring being religious. We do not find any evidence that religion is related to mobility pre- or post-lockdown. While there is no effect of the county's share of religious people on the level of compliance, neighborhood fear is related to compliance. With a higher share of people afraid to go out in their neighborhood at night (i.e., less-safe neighborhoods), mobility is reduced pre-lockdown (negative coefficients for non-essential visits and distance traveled). However, estimates on the interaction term are positive for all social distancing measures and statistically significant for the average distance traveled measure, suggesting that counties with more dangerous neighborhoods tend to comply less with governmental orders. Adding socio-economic controls decreases the size of the estimates for the variable "neighborhood fear" and the interaction term. A plausible explanation is that neighborhood safety is highly correlated with other socio-economic characteristics such as poverty and rural areas.

Our last key determinant is political affiliation. We rely on self-reported political affiliation to build our county-level measure of the percentage of democrats, independents and republicans. Our findings on the effect on the political affiliation are in line with Engle et al. (2020), who provide evidence that counties with

a lower share of votes for republicans comply more with stay-at-home orders. Our estimates suggest that a 1 percentage point increase in the share of democrats in a specific county is associated with a 15% decrease in non-essential visits and 9% decrease in distance traveled, conditional on counties' pre-COVID-19 socioeconomic charateristics.

In Table 2 and Appendix Table A3, we show the estimates of equation (1) using different trust measures as explanatory variables. Each column in these tables represents a separate regression respectively on "non-essential visits" and "distance traveled". As in the first table, the analysis is limited to 10 days before and 10 days after the stay-at-home orders. Estimates show a negative effect of almost all trust related measures on mobility, suggesting that counties with a higher share of trust in different institutions tend to adopt a more preventative behavior and comply more with authorities' orders during the pandemic. The effect of trust in press on the "non-essential visits" metric post-lockdown is significantly larger in magnitude than the interaction term for the other trust measures, such as medicine, science, government (congress and federal). With the press constantly reporting updates on the nature of the virus, as well as details on the lockdown adoption measures, it is expected that people who trust in the press would adjust their behavior more than those who don't.

3.2 Subgroup Analyses

Table 3 and Appendix Table A4 provide subgroup analyses. We investigate the effect of trust and other determinants after the lockdown for the following samples (columns in parentheses): (1) below and (2) above median poverty; (3) rural (4) urban counties; (5) below and (6) above median education. We find that the differential effect of the lockdown by county is quite homogeneous across the different subgroups for trust, religion and fear of walking outside at night. In contrast, we find that counties with relatively more self-declared democrats were significantly

more likely to follow guidelines to stay home only in urban counties.[12]

Last, we explore whether our conclusions vary depending on the political affiliation of the state governor.[13] Appendix Table A5 shows the estimates. Odd columns (1 and 3) are for counties in the states with a democratic governor, while even columns (2 and 4) correspond to sampling counties with a republican governor. The dependent variable is our index for non-essential visits in columns 1–2 and total travel distance in columns 3–4, respectively. Overall, the estimates suggest that our variables of interest have a homogeneous impact on compliance in states with a democratic versus a republican governor.

3.3 Robustness Check

As a robustness check, we replicate our main results in Table 1 by relying on the Google COVID-19 Community Mobility reports for our mobility measures. Table 4 shows estimates on changes in people's activities for the six different categories.[14] Estimates in this table confirm the robustness of our previous findings; we find that counties where individuals have more trust in others are more likely to comply to lockdown orders by remaining at their place of residence and significantly lowering their visit or stay at workplace, grocery markets, and other retail places. The estimates for the interaction term are statistically significant for all the categories mentioned above.

Similarly to our previous results, coefficients on the interaction between the post-lockdown dummy and religiosity suggest that being religious has no effect on compliance to social distancing orders. When it comes the effect of crime perception, results follow the same pattern as with Unacast data. Pre-lockdown mobility is reduced with a higher share of people afraid to go out in their neighborhood at night and estimates on the interaction term are positive for all mobility measures

[12] We also find that self-declared democrats were significantly more likely to follow guidelines to stay home in more educated counties (poor counties) for non-essential visits (total travel distance).

[13] Baccini and Brodeur (2020) show that democratic governors were faster at implementing stay-at-home orders.

[14] See Section 1 for more details on the outcome variables.

and statistically significant for visits to workplace, grocery and retail stores. These findings confirm that counties with less-safe neighborhoods tend to comply less with social distancing policies. Moreover, results show that an increase with the share of democrats is associated with a decrease in mobility specifically for the workplace, transit stations, grocery and retail categories.

4 Conclusion

The uneven geography of social distancing observed from cell phone location tracking data in the United States suggests that not all Americans altered in the same way their behavior in response to the spread of COVID-19. Among many factors that may have affected this distribution, trust is seen as a major contributor. Amid the pandemic, the Chief Executive Director of the World Health Organization (WHO) Emergency Programme, Michael J. Ryan, highlighted the importance of trust by saying: "Governments looking for long-term solutions for managing COVID-19 could start with their relationship with the general public."

Our findings support this statement by providing suggestive evidence of the effect of trust on preventative behavior and public compliance with government orders in the midst of the pandemic. By relying on county-level variation in the U.S. and employing a double difference framework, we find that areas where individuals trust other people more are significantly more likely to comply with stay-at-home orders. Further investigation on social capital factors showed that abiding by the social distancing rules is lower in less-safe neighborhoods and higher in counties with relatively more self-declared democrats. These findings are robust to the inclusion of a wide set of controls related to epidemiological, demographic, geographic, and economic characteristics of the counties in question.

Furthermore, we examine the effect of different trust measures such as trust in public institutions, medicine, and press. We find that counties with a higher share of citizens trusting the press are more likely to adjust their behavior to lockdown declarations following their announcement. This result could be driven by the fact

that the novel virus and the lockdowns are dominating the news.

To sum up, this study suggests that building trust, combined with strategic controls and clear communication, could provide a successful tool for authorities to safely adapt to a new normal and promote pro-social public behavior of social distancing.

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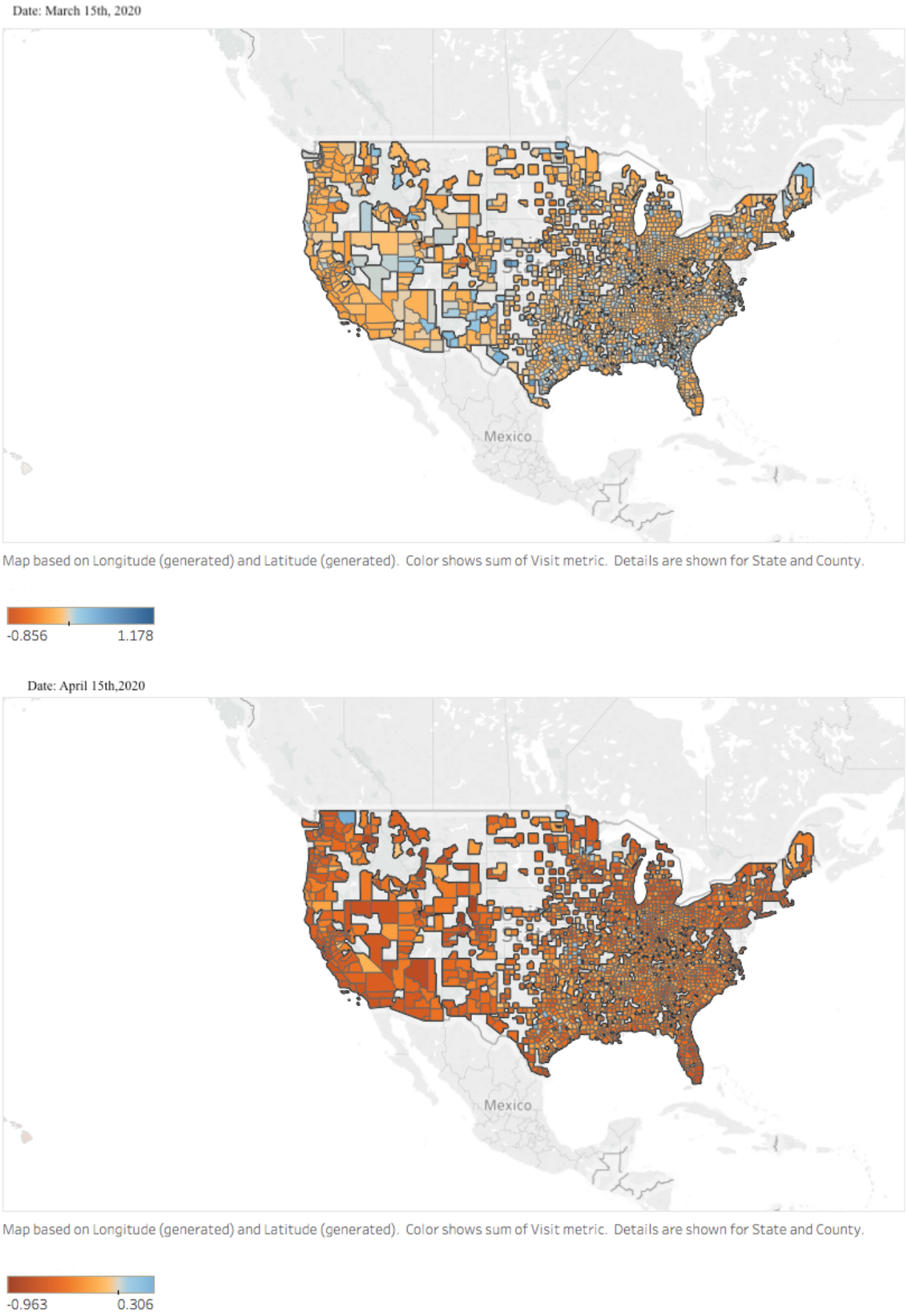

Figure 1: Percentage Change in Non-essential Visitation on March 15th and April 15th respectively *Source*: Unacast's COVID-19 Toolkit.

Table 1: Safer-at-Home Policies, Social Distancing and Trust - Within 10 Days of Lockdown

	Non-Essential Visits (1)	Non-Essential Visits (2)	Travel Distance (3)	Travel Distance (4)
Trust People	-0.094	0.012	-0.028	0.032
	(0.056)	(0.055)	(0.048)	(0.032)
After Lockdown	-0.079*	-0.077*	-0.102***	-0.099***
	(0.040)	(0.039)	(0.025)	(0.025)
After Lockdown	-0.158**	-0.160**	-0.079*	-0.085**
× Trust	(0.070)	(0.069)	(0.040)	(0.040)
Religious	-0.034	-0.012	-0.027	-0.019
	(0.026)	(0.024)	(0.024)	(0.023)
After Lockdown	0.023	0.021	0.002	0.003
× Religious	(0.029)	(0.029)	(0.014)	(0.014)
Neighborhood Fear	-0.155**	-0.051	-0.087*	-0.023
	(0.063)	(0.043)	(0.043)	(0.027)
After Lockdown	0.063	0.045	0.077**	0.061
× Fear	(0.062)	(0.062)	(0.037)	(0.038)
Democrats	-0.003	0.068*	0.024	0.074***
	(0.047)	(0.036)	(0.034)	(0.025)
After Lockdown	-0.146***	-0.148***	-0.080*	-0.088*
× Democrats	(0.046)	(0.048)	(0.045)	(0.048)
COVID-19 Deaths	-0.129***	-0.068**	-0.116***	-0.062*
per 10,000	(0.026)	(0.027)	(0.029)	(0.033)
State FE	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes
Epidemio controls	Yes	Yes	Yes	Yes
Geographic controls	No	Yes	No	Yes
Socio-Econ controls	No	Yes	No	Yes
Observations	7,665	7,623	5,355	5,355
R-Squared	0.36	0.48	0.57	0.65

Notes: The dependent variable is our indexes for non-essential visits in columns 1–2 and total travel distance in columns 3–4, respectively. The sample is restricted to within 10 days (before and after) of the implementation of a safer-at-home order. Standard errors are clustered at the state-level. Socio-Economic controls at the county-level include income per capita, % below poverty, % with higher education, total population and % independent. Epidemiological controls at the county-level include death rate from COVID-19 per 10,000 people, population density, % urban, % old and % male. Geographic controls at the county-level include dummies for an airport in the county, being on the coast and having the state capital city. *** p<0.01, ** p<0.05, * p<0.1

Table 2: Safer-at-Home Policies, Social Distancing and Alternative Measures of Trust

	Non-Essential Visits				
	(1)	(2)	(3)	(4)	(5)
After Lockdown	-0.160***	-0.162***	-0.169***	-0.143***	-0.174***
	(0.022)	(0.024)	(0.029)	(0.021)	(0.035)
Trust Congress	-0.054				
	(0.046)				
After Lockdown	-0.058				
× Trust Congress	(0.047)				
Trust Fed		-0.024			
		(0.046)			
After Lockdown		-0.051			
× Trust Fed		(0.053)			
Trust Medicine			-0.027		
			(0.040)		
After Lockdown			-0.019		
× Trust Medicine			(0.043)		
Trust Press				0.013	
				(0.043)	
After Lockdown				-0.116**	
× Trust Press				(0.050)	
Trust Science					-0.053
					(0.046)
After Lockdown					-0.008
× Trust Science					(0.057)
State FE	Yes	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Epidemio controls	Yes	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes
Socio-Econ controls	Yes	Yes	Yes	Yes	Yes
Observations	7,623	7,623	7,623	7,623	7,623
R-Squared	0.48	0.48	0.48	0.48	0.48

Notes: The dependent variable is our index for non-essential visits. The sample is restricted to within 10 days (before and after) of the implementation of a safer-at-home order. Standard errors are clustered at the state-level. Socio-Economic controls at the county-level include income per capita, % below poverty, % with higher education, total population and % independent. Epidemiological controls at the county-level include death rate from COVID-19 per 10,000 people, population density, % urban, % old and % male. Geographic controls at the county-level include dummies for an airport in the county, being on the coast and having the state capital city. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Social Distance & Trust – Interaction Terms – Within 10 Days of Lockdown

	Non-Essential Visits					
	(1)	(2)	(3)	(4)	(5)	(6)
Trust People	-0.029	0.147*	0.078	0.019	0.036	-0.015
	(0.069)	(0.081)	(0.072)	(0.056)	(0.060)	(0.058)
After Lockdown	-0.095*	-0.039	-0.253**	-0.049	-0.090	-0.085*
	(0.050)	(0.058)	(0.090)	(0.046)	(0.064)	(0.050)
After Lockdown	-0.105	-0.260***	-0.154*	-0.152**	-0.146	-0.107
× Trust	(0.100)	(0.075)	(0.076)	(0.069)	(0.105)	(0.069)
Religious	-0.019	-0.013	0.017	-0.001	-0.012	-0.009
	(0.038)	(0.028)	(0.038)	(0.028)	(0.039)	(0.033)
After Lockdown	0.024	0.014	0.087*	0.005	-0.014	0.035
× Religious	(0.037)	(0.029)	(0.042)	(0.034)	(0.021)	(0.037)
Fear	-0.087*	-0.001	-0.318***	-0.031	-0.104	-0.030
	(0.047)	(0.067)	(0.104)	(0.042)	(0.076)	(0.042)
After Lockdown	0.081	-0.024	0.009	0.087	-0.121	0.099
× Fear	(0.067)	(0.089)	(0.057)	(0.063)	(0.088)	(0.076)
Democrats	0.051	0.088	-0.093	0.095**	0.007	0.070
	(0.055)	(0.086)	(0.242)	(0.045)	(0.149)	(0.044)
After Lockdown	-0.159*	-0.142***	0.218	-0.191***	-0.028	-0.182***
× Democrats	(0.079)	(0.050)	(0.160)	(0.063)	(0.076)	(0.064)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,620	3,003	1,260	6,363	1,596	6,027
R-Squared	0.46	0.52	0.37	0.48	0.39	0.48

Notes: The dependent variable is our index for non-essential visits. The sample is restricted to within 10 days (before and after) of the implementation of a safer-at-home order. Standard errors are clustered at the state-level. Columns have restricted subsamples: (1) below and (2) above median poverty; (3) rural (4) urban counties; (5) below and (6) above median education (college or more). Socio-Economic controls at the county-level include income per capita, % below poverty, % with higher education, total population and % independent. Epidemiological controls at the county-level include death rate from COVID-19 per 10,000 people, population density, % urban, % old and % male. Geographic controls at the county-level include dummies for an airport in the county, being on the coast and having the state capital city. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Safer-at-Home Policies, Social Distancing: Google Mobility Measures

	Resident	Work	Transit	Parks	Groceries	Retail
	(1)	(2)	(3)	(4)	(5)	(6)
Trust People	-1.530	3.013	6.355	-17.44	8.732**	2.715
	(1.362)	(3.266)	(11.02)	(10.92)	(3.714)	(3.801)
After Lockdown	3.728**	-10.77***	-9.940**	5.789	-12.02**	-9.489**
	(1.567)	(3.514)	(4.849)	(7.353)	(4.887)	(4.359)
After Lockdown	5.111**	-12.88**	-8.323	-3.483	-19.43***	-17.14***
× Trust	(2.512)	(5.364)	(7.160)	(11.99)	(6.742)	(5.834)
Religious	1.050*	-2.105	1.570	2.573	-5.341**	-0.847
	(0.615)	(1.649)	(3.658)	(5.849)	(2.397)	(2.580)
After Lockdown	-0.993	1.836	3.963	3.281	2.155	2.566
× Religious	(1.116)	(2.588)	(3.901)	(4.813)	(3.578)	(3.353)
Fear	1.455	-4.627*	-9.031	2.239	-6.413	-8.963**
	(1.393)	(2.735)	(10.71)	(11.16)	(4.940)	(3.883)
After Lockdown	-4.140	8.293*	9.186	-11.81	13.43**	10.87*
× Fear	(2.518)	(4.803)	(8.347)	(15.09)	(6.278)	(5.897)
Democrats	-1.323	5.339**	-1.402	-2.065	4.301	4.458
	(0.907)	(2.375)	(7.195)	(10.76)	(3.239)	(2.934)
After Lockdown	5.941**	-10.82**	-12.66*	-20.74	-9.108*	-13.85**
× Democrats	(2.275)	(4.615)	(6.794)	(12.31)	(4.759)	(5.132)
COVID-19	1.444	-4.644**	-7.419**	-9.282**	-6.202***	-4.878
Deaths (per 10K)	(1.111)	(2.208)	(2.730)	(3.807)	(2.091)	(2.987)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Day Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Epidemio	Yes	Yes	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes	Yes	Yes
SocioEcon	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,435	8,507	6,429	5,914	8,394	8,407
R-Squared	0.655	0.658	0.518	0.304	0.542	0.508

Notes: Each column shows estimates of separate regressions on six different Google mobility measures: residential (column (1)), workplaces (column (2)), transit stations (column (3)), parks (column (4)), grocery and pharmacy (column (5)), and retail and recreation (column (6)). The sample is restricted to within 10 days (before and after) of the implementation of a safer-at-home order. Standard errors are clustered at the state-level. Socio-Economic controls at the county-level include income per capita, % below poverty, % with higher education, total population and % independent. Epidemiological controls at the county-level include death rate from COVID-19 per 10,000 people, population density, % urban, % old and % male. Geographic controls at the county-level include dummies for an airport in the county, being on the coast and having the state capital city. *** p<0.01, ** p<0.05, * p<0.1

5 Appendix

5.1 Google Inc. Social Distancing Data

Grocery and pharmacy: grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies.

Parks: local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens.

Transit stations: public transport hubs such as subway, bus, and train stations.

Retail and recreation: restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.

Residential: places of residence. Workplaces: places of work.

5.2 GSS Selected Questions:

Political Party Affiliation:

Generally speaking, do you usually think of yourself as a Republican, Democrat, Independent, or what?

Religiousness:

To what extent do you consider yourself a religious person? Are you very religious, moderately religious, slightly religious, or not religious at all?

Trust in others:

Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?

Neighborhood Fear:

Is there any area right around here–that is, within a mile–where you would be afraid to walk alone at night?

Trust in Institutions:

I am going to name some institutions in this country. As far as the people running these institutions are concerned, would you say you have a great deal of confidence, only some confidence, or hardly any confidence at all in them?

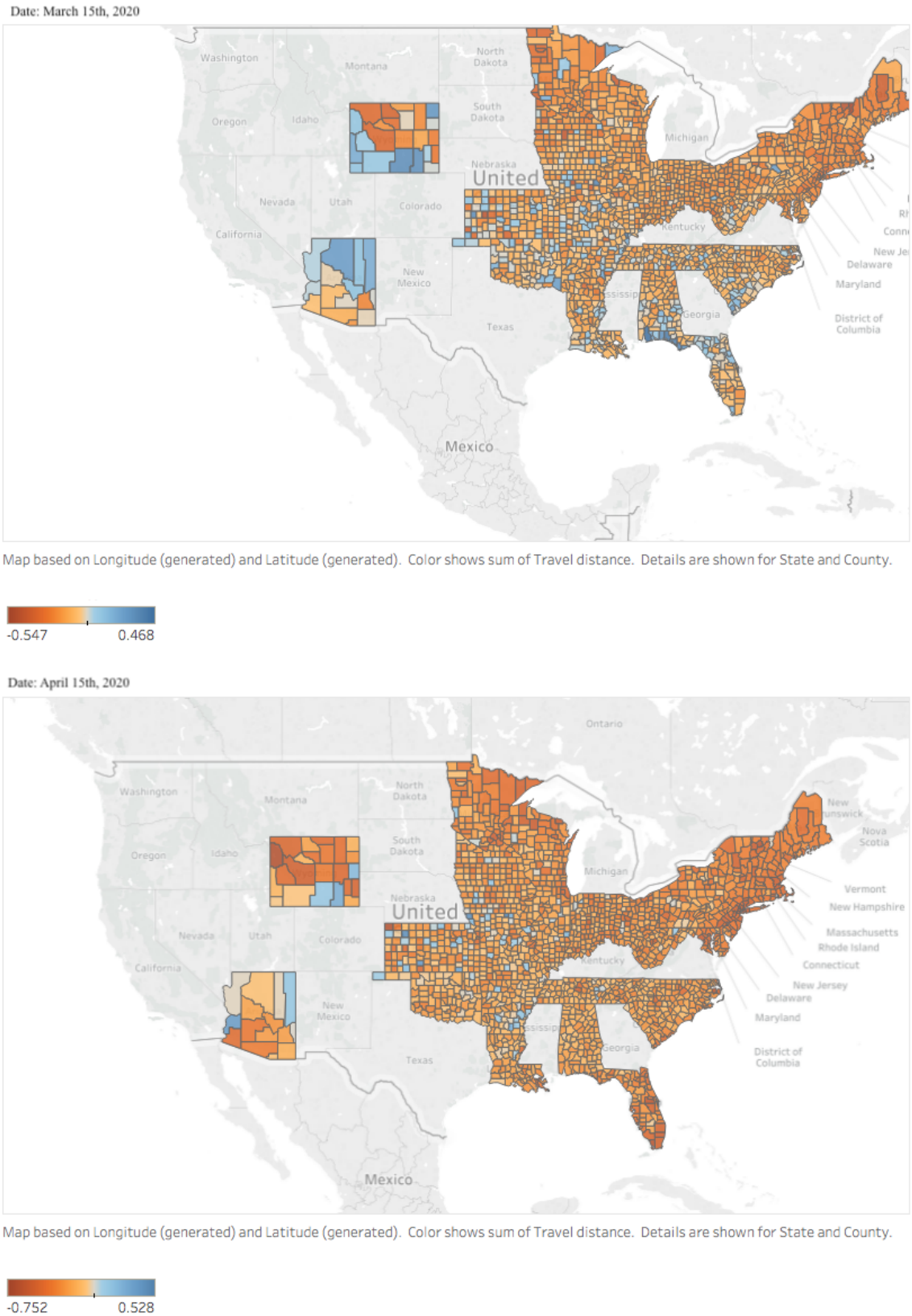

Figure A1: Percentage Change in Average Distance Travelled on March 15th and April 15th respectively *Source*: Unacast's COVID-19 Toolkit.

Table A1: Summary Statistics

	Mean	Median	Std. Dev.	Min	Max
Unacast variables:					
Non-essential visits	-0.43	-0.45	0.20	-1.00	1.68
Travel distance	-0.28	-0.28	0.15	-0.84	1.34
Google variables:					
Residential	10.77	12.00	8.63	-11	38
Work	-24.82	-29.00	18.72	-81	43
Transit	-18.79	-18.00	24.69	-91	103
Parks	7.25	3.00	43.12	-91	308
Groceries	0.46	1.00	17.72	-81	174
Retail	-18.82	-24.00	25.03	-100	226
Trust measures:					
% Trust People	0.19	0.18	0.11	0.00	0.65
% Religious	0.42	0.47	0.26	0.00	0.96
% Neighborhood Fear	0.17	0.16	0.11	0.00	0.74
% Democrats	0.31	0.30	0.15	0.00	1.00
% Independent	0.39	0.39	0.14	0.00	1.00
% Trust Congress	0.32	0.32	0.11	0.00	1.00
% Trust Fed	0.33	0.33	0.11	0.00	0.83
% Trust Medicine	0.49	0.48	0.13	0.00	1.00
% Trust Press	0.31	0.29	0.12	0.00	1.00
% Trust Science	0.49	0.47	0.13	0.00	1.00
COVID-19:					
COVID-19 deaths per 10K	0.04	0.00	0.27	0.00	11.72
COVID-19 cases per 10K	1.39	0.17	4.56	0.00	236.17

Table A2: Comparison of our Sample with all U.S. Counties

	All Counties:	**Our Sample**
Share of	0.827	0.847
White Population	(0.170)	(0.189)
Income	26648	26607
Per Capita	(6915)	(6646)
Share of Individuals	0.164	0.154
Below Poverty	(0.082)	(0.075)
Share of Individuals	0.071	0.064
in Severe Poverty	(0.046)	(0.039)
Share of Individuals	0.581	0.571
in Labor Force	(0.084)	(0.092)
Share of Individuals	0.483	0.500
with High-school or Less	(0.105)	(0.102)
N	3,217	1,139

Notes: Means and standard deviations in parentheses.

Table A3: Safer-at-Home Policies, Social Distancing and Alternative Measures of Trust

	Travel Distance				
	(1)	(2)	(3)	(4)	(5)
After Lockdown	-0.139***	-0.134***	-0.154***	-0.133***	-0.178***
	(0.012)	(0.014)	(0.017)	(0.014)	(0.022)
Trust Congress	0.061***				
	(0.021)				
After Lockdown	-0.045				
× Trust Congress	(0.039)				
Trust Fed		-0.018			
		(0.039)			
After Lockdown		-0.059			
× Trust Fed		(0.040)			
Trust Medicine			-0.023		
			(0.024)		
After Lockdown			0.004		
× Trust Medicine			(0.027)		
Trust Press				0.018	
				(0.024)	
After Lockdown				-0.063	
× Trust Press				(0.039)	
Trust Science					-0.046*
					(0.027)
After Lockdown					0.051
× Trust Science					(0.033)
State FE	Yes	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Epidemio controls	Yes	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes
Socio-Econ controls	Yes	Yes	Yes	Yes	Yes
Observations	5,355	5,355	5,355	5,355	5,355
R-Squared	0.65	0.65	0.65	0.65	0.65

Notes: The dependent variable is our index for total travel distance. The sample is restricted to within 10 days (before and after) of the implementation of a safer-at-home order. Standard errors are clustered at the state-level. Socio-Economic controls at the county-level include income per capita, % below poverty, % with higher education, total population and % independent. Epidemiological controls at the county-level include death rate from COVID-19 per 10,000 people, population density, % urban, % old and % male. Geographic controls at the county-level include dummies for an airport in the county, being on the coast and having the state capital city. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Social Distance & Lockdown – Subsamples

	Total Travel Distance					
	(1)	(2)	(3)	(4)	(5)	(6)
Trust People	0.031	0.017	0.017	0.058*	-0.108	0.056*
	(0.036)	(0.133)	(0.088)	(0.032)	(0.151)	(0.031)
After Lockdown	-0.127***	-0.044	-0.181***	-0.090***	-0.087**	-0.116***
	(0.031)	(0.027)	(0.048)	(0.032)	(0.040)	(0.025)
After Lockdown	-0.019	-0.222***	-0.064	-0.087*	0.026	-0.080*
× Trust	(0.039)	(0.072)	(0.051)	(0.047)	(0.081)	(0.044)
Religious	-0.032	0.000	-0.094	-0.001	-0.046	-0.002
	(0.024)	(0.039)	(0.075)	(0.021)	(0.044)	(0.018)
After Lockdown	-0.010	0.014	0.051	-0.007	0.001	-0.000
× Religious	(0.021)	(0.018)	(0.030)	(0.014)	(0.016)	(0.018)
Fear	-0.040	-0.025	0.160***	-0.070*	0.009	-0.052
	(0.046)	(0.081)	(0.048)	(0.036)	(0.059)	(0.036)
After Lockdown	0.070	0.053	-0.047	0.108**	-0.053	0.111**
× Fear	(0.058)	(0.053)	(0.038)	(0.045)	(0.047)	(0.043)
Democrats	0.042	0.091	-0.022	0.072*	0.066	0.076**
	(0.028)	(0.060)	(0.171)	(0.037)	(0.134)	(0.030)
After Lockdown	-0.048	-0.144**	0.152*	-0.115*	-0.070	-0.080
× Democrats	(0.044)	(0.069)	(0.079)	(0.066)	(0.080)	(0.050)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,402	1,953	1,071	4,284	1,239	4,116
R-Squared	0.70	0.60	0.58	0.68	0.51	0.68

Notes: The dependent variable is our index for total travel distance. The sample is restricted to within 10 days (before and after) of the implementation of a safer-at-home order. Standard errors are clustered at the state-level. Columns have restricted subsamples: (1) below and (2) above median poverty; (3) rural (4) urban counties; (5) below and (6) above median education (college or more). Socio-Economic controls at the county-level include income per capita, % below poverty, % with higher education, total population and % independent. Epidemiological controls at the county-level include death rate from COVID-19 per 10,000 people, population density, % urban, % old and % male. Geographic controls at the county-level include dummies for an airport in the county, being on the coast and having the state capital city. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Social Distance & Lockdown – Governor Affiliation

	Non-Essential Visits		Travel Distance	
	(1)	(2)	(3)	(4)
Trust People	-0.036	0.011	0.022	0.052
	(0.099)	(0.047)	(0.046)	(0.037)
After Lockdown	-0.072	-0.103***	-0.118***	-0.078
	(0.078)	(0.033)	(0.031)	(0.047)
After Lockdown	-0.176	-0.049	-0.047	-0.065
× Trust	(0.133)	(0.048)	(0.066)	(0.052)
Religious	0.028	-0.030	-0.003	-0.021
	(0.034)	(0.029)	(0.027)	(0.044)
After Lockdown	-0.039	0.033	-0.006	-0.005
× Religious	(0.043)	(0.021)	(0.021)	(0.016)
Fear	-0.012	-0.120	0.006	0.004
	(0.057)	(0.069)	(0.039)	(0.046)
After Lockdown	0.036	0.077	0.013	0.070
× Fear	(0.085)	(0.047)	(0.048)	(0.040)
State FE	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	4,200	3,423	2,772	2,562
R-Squared	0.52	0.46	0.70	0.64

Notes: The dependent variable is our index for non-essential visits in columns 1–2 and total travel distance in columns 3–4, respectively. The sample is restricted to within 10 days (before and after) of the implementation of a safer-at-home order. Standard errors are clustered at the state-level. Odd columns (1 and 3) are for counties in states with a democratic governor, while even columns (2 and 4) correspond to counties with a republican governor. Socio-Economic controls at the county-level include income per capita, % below poverty, % with higher education, total population and % independent. Epidemiological controls at the county-level include death rate from COVID-19 per 10,000 people, population density, % urban, % old and % male. Geographic controls at the county-level include dummies for an airport in the county, being on the coast and having the state capital city. *** p<0.01, ** p<0.05, * p<0.1