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Stay-at-home orders, social distancing, and trust

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Abstract

A clear understanding of community response to government decisions is crucial for policy makers and health officials during the COVID-19 pandemic. In this study, we document the determinants of implementation and compliance with stay-at-home orders in the USA, focusing on trust and social capital. Using cell phone data measuring changes in non-essential trips and average distance traveled, we find that mobility decreases significantly more in high-trust counties than in low-trust counties after the stay-at-home orders are implemented, with larger effects for more stringent orders. We also provide evidence that the estimated effect on post-order compliance is especially large for confidence in the press and governmental institutions, and relatively smaller for confidence in medicine and in science.

Keywords COVID-19 · Stay-at-home orders · Social distancing · Trust

JEL Classification H12 · I12 · I18

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1 Introduction

As of mid-December 2020, the outbreak of COVID-19 has claimed more than 1,600,000 lives worldwide and caused unprecedented disruption in many areas of our lives. In most countries hit by the pandemic, authorities adopted measures to impose lockdowns and different forms of social (or physical) distancing to stem the uncontrolled spread of the virus, limit infections and deaths, and ease the pressure on the healthcare system and health service providers. In the USA, county and state officials started implementing stay-at-home policies during the second half of March 2020. Studies so far have shown that governmental actions along with public cooperation can indeed slow down the spread of the disease (Abouk and Heydari Forthcoming; Anderson et al. 2020; Bai et al. 2020; Hsiang et al. 2020; Viner et al. 2020).

As the effectiveness of stay-at-home orders relies on public compliance, understanding whether and how communities respond to government decisions is crucial for policy makers and health officials to choose appropriate measures to contain the COVID-19 pandemic. This is especially true given that stay-at-home orders have been shown to increase domestic violence incidents, mental health distress, and the unemployment rate (e.g., Beland et al. 2020; Brodeur et al. 2021; Leslie and Wilson 2020), making it hard to maintain these policies for a long period of time.

In this paper, we study the determinants of implementation and compliance with stay-at-home orders in the USA, focusing on trust and social capital. We test whether counties with higher levels of trust and social capital were more likely to implement stay-at-home orders, and whether their citizens reduced their mobility more than others following the implementation of these policies. These hypotheses are motivated by a growing number of studies showing a positive relationship between social capital and cooperation, necessary for the efficient provision of public goods (e.g., Gächter et al. 2004; Herrmann et al. 2008). 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 and non-essential visitation. We also rely on Google Community Mobility reports as an additional measure of mobility.[1]

We first document the determinants of implementation (and timing) of stay-at-home orders. We find that stay-at-home orders are more likely to be implemented in counties and states with a Democratic governor, confirming the results presented in Baccini and Brodeur (2021). We also find that key determinants of orders' timing (i.e., the time elapsed between the first confirmed COVID-19 case and the order enactment) are the presence of an airport, coast, county seats, population, and COVID-19 incidence. In contrast, our results suggest that trust in others and alternative measures of trust and confidence are not significantly related to the likelihood (or the timing) of implementing a stay-at-home order.

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[1]Google cell phone data indicates percent change in visits to the following six categories of places: (1) grocery stores and pharmacies, (2) parks, (3) transit stations, (4) retail and recreation, (5) residential, and (6) workplaces.

Second, we turn our attention to the determinants of compliance with stay-at-home orders. In our empirical model, we include county and calendar day fixed effects and document social mobility changes by county social capital and trust levels before and after the implementation of stay-at-home orders in a double difference framework. Our findings suggest that individuals living in counties with relatively more trust in others decrease their mobility significantly more once a stay-at-home 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 other relevant policies, such as mask mandates, school closures, business closures, cancellation of public events, restrictions on gatherings, closure of public transportation, and international travel. Exploiting different trust and confidence measures in the GSS, we show that the estimated effect on post-order compliance is especially large for confidence in the press, congress, and federal government, and relatively small for trust in medicine and science.

We also test the importance of additional plausible determinants of compliance: religion, crime, and political affiliation. For crime, we rely on data from the GSS on whether the respondent is afraid to walk alone at night. We do not find any evidence that religiosity and neighborhood fear affect the county's level of compliance to governmental orders. However, we find that counties with relatively more self-declared Democrats decrease significantly more their mobility post-order.

Our study contributes to a growing literature documenting 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 2021; Engle et al. 2020), poverty and economic dislocation (Wright et al. 2020)), belief and trust in science (Briscese et al. 2020), access to high-speed internet (Chiou and Tucker 2020), political affiliation (Allcott et al. 2020; Painter and Qiu 2020), and attitudes about the virus's severity (Oosterhoff and Palmer 2020). See Brodeur et al. (2022) for a literature review.

The most relevant studies are possibly Engle et al. (2020) and Bargain and Ulugbek (2020) and Durante et al. (2021). 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,[2] higher population density, and relatively more people over the age of 65.[3] Bargain and Ulugbek (2020) rely on human mobility data in Europe and provide evidence that regions with high political trust decrease their mobility relatively more than those with low political trust after the implementation of a lockdown. Last, Durante et al. (2021) provide evidence that mobility decreased

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

[3]Canning et al. (2020) conducted an online survey in the USA 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.

significantly more in provinces with relatively higher civic capital in Italy and Germany.

We contribute to the existing literature by focusing on a major set of mechanisms that might have shaped compliance with public health orders in the USA. More precisely, we examine the relationship between compliance and many different trust indicators, local norms, and political and religious engagement. With the way the virus spreads, social distancing might not be 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 also contribute to the literature by looking at the intensity of stay-at-home orders, splitting orders into two categories: (1) a recommendation for individuals to stay home and (2) a strict requirement to stay home with few exceptions. We find that the stringency of orders is of particular importance, with much larger effects on mobility when requiring to stay at home than for less stringent orders. We also find that the decrease in mobility for high-trust (in comparison to low-trust) counties post-order is larger when requiring to stay at home than when only recommending to stay home.

We explore the heterogeneous effects of stay-at-home orders and conduct subsample analyses to test whether the determinants of compliance with stay-at-home orders vary for counties with specific characteristics. We find that the decrease in mobility after the implementation of an order is remarkably larger in urban counties and counties above median poverty and education. While the differential effect of these orders is quite homogeneous across counties for religion and neighborhood fear, we find that in counties with relatively more self-declared Democrats, people reduced their mobility significantly more after stay-at-home orders were issued.

Last, our study contributes to a larger literature on policy responses and social distancing in other countries, such as China and Italy (Qiu et al. 2020; Bonacini et al. 2021; Milani 2021), and to the growing literature documenting the socioeconomic consequences of the pandemic in the USA (e.g., Baccini et al. 2021).

We structure the remainder of the paper as follows. In Section 2, we present the data sources and descriptive statistics. Sections 3 and 4 present the methodology and determinants of stay-at-home orders implementation. In Section 5, we document the determinants of compliance to stay-at-home orders. The last section concludes.

2 Data

2.1 COVID-19 known cases and deaths

Data on COVID-19-related deaths and cases are collected by the John Hopkins Coronavirus Research Center on a daily basis at the county level.[4] The num-

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[4]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.

ber of confirmed cases is updated on a daily basis. Note that confirmed cases include presumptive positive cases.[5] 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.

2.2 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.

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 variation in mobility over time. In other words, a given county is compared to itself over time (before and after the implementation of stay-at-home orders), 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 "non-essential visitation," the percent change in average distance traveled, and the change in "human encounters." We rely on the first two metrics for our analysis.[6] 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 policy makers in the USA.

For our analysis, we rely on daily data from February 24th to August 5th at the county level. See Table 1 for summary statistics. As of August 5th, for instance, data showed that average non-essential visits' mobility in the nation as a whole

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[5]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.

[6]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 stay-at-home policies nor county COVID-19 death rate. Results available upon request.

Table 1 Summary statistics — within 30 days of order

	Mean	Median	Std. Dev.	Min	Max
Unacast variables:					
Non-essential visits	–0.33	–0.37	0.26	–1.00	1.68
Travel distance	–0.21	–0.22	0.20	–0.95	2.43
Google variables:					
Residential	9.80	11.00	8.77	–7	38
Work	–23.50	–28.00	19.29	–81	43
Transit	–17.75	–16.00	24.71	–91	222
Parks	7.76	4.00	42.00	–91	308
Groceries	0.95	1.00	16.91	–81	171
Retail	–16.88	–20.00	25.00	–100	187
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	0.12	0.00	0.66	0.00	28.03
COVID-19 cases per 10K	3.42	2.57	13.01	0.00	846.64

Data for Unacast variables is from February 24th to August 5th at the county level. For Google variables, data is from Google Community Mobility reports for the period between February 15th and August 5th. We restrict the sample to within 30 days of a stay-at-home order. Both sets of measures show the change in mobility compared to a baseline for the same areas and same day of the week prior to the virus spread. Trust measures are from the General Social Survey (GSS). Based on repeated questions from 2000 to 2014 in 436 counties, each variable is computed as weighted shares from respondents' answers

was approximately 33% lower than during the pre-pandemic reference time period. Of course, these figures conceal the uneven geography of social distancing and tremendous variation in behavior change across the US states, and across counties within the same state.

Figure 1 and Appendix Fig. 4 highlight the geographic variation in "Non-Essential Visits" and "Travel Distance," respectively, for two dates: one before any stay-home order was announced (March 15th, 2020) and one after all stay-at-home orders were

Date: March 15th, 2020

Visit Metric

-0.856   1.178

Date: April 15th, 2020

Visit Metric

-0.963   0.306
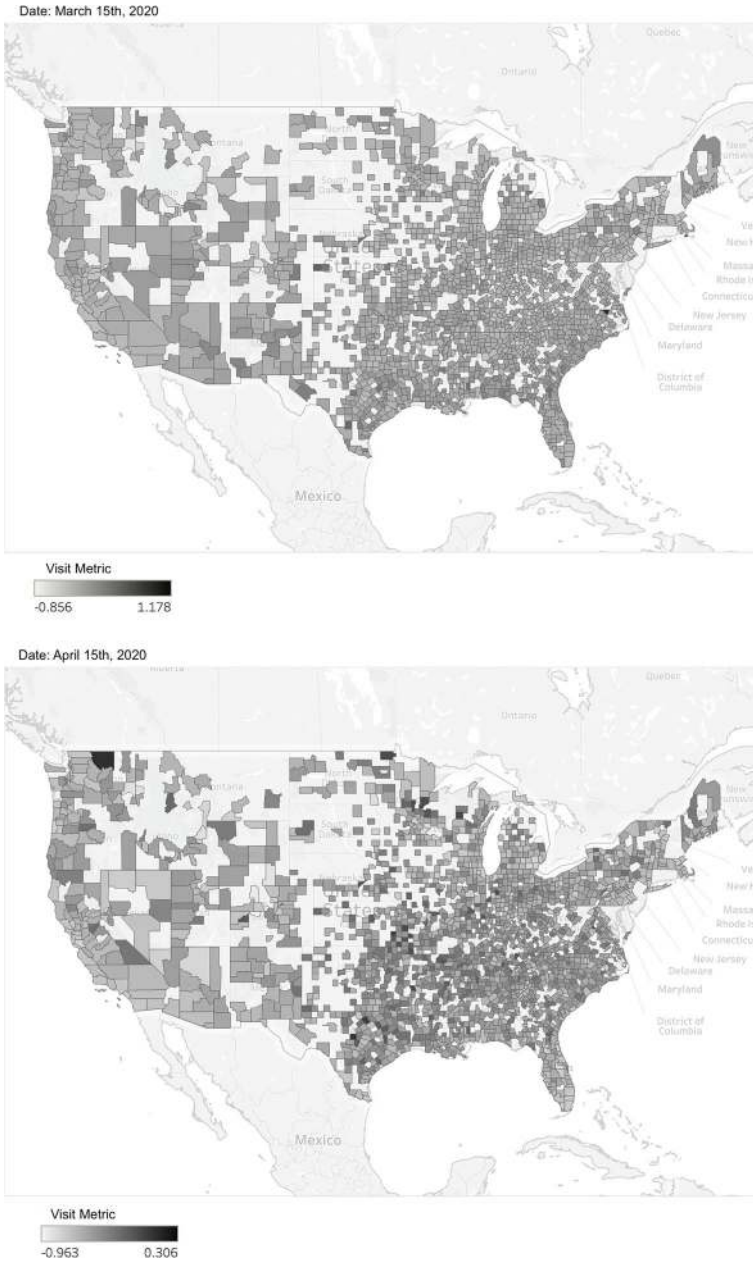
Fig. 1 Percentage change in non-essential visitation on March 15th and April 15th, respectively. Source: Unacast's COVID-19 Toolkit

imposed (April 15th, 2020). While the pre-policy maps show the voluntary community actions against the pandemic's spread,[7] the post-policy figures show the difference in mobility from pre-pandemic to post-order. Despite the obvious national decrease in mobility after governmental actions, these maps reveal clearly that US counties are highly variable in their level of compliance.

We also rely on Google Community Mobility reports to measure compliance with 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 data set is for a specific geographic location and includes the percent change in visits to different places. There are six categories: grocery stores and pharmacies, parks, transit stations, retail and recreation, residential, and workplaces (see the Appendix for the detailed list of places by 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. Table 1 shows change in mobility for six different categories for the period between February 15th and August 5th.

2.3 Stay-at-home orders

We rely on data from the National Association of Counties — County Explorer (NACo) — for the list of county and state stay-at-home orders. This data source provides the date of implementation and the date that the order ended. We use the information on stay-at-home orders both at the state level and at the local level. More precisely, we rely on county-level order for states without statewide orders and for counties and localities that preceded a statewide order with a local order.

For instance, California is the first state in the continental US to implement the statewide order on March 19, 2020. Yet, some counties in California implemented stay-at-home orders even earlier (e.g., Santa Clara County on March 17, 2020).[8] State and county stay-at-home orders would typically require residents in their jurisdiction to only leave their residences for essential activities. For instance, the Santa Clara order specified that people could leave home for activities, such as groceries, exercising outdoors, seeking medical assistance, or providing any of the essential services (supporting "essential infrastructure"). While the specific list of allowed activities vary by state and county (e.g., some would restrict outdoor activities to a certain radius), most orders call on people to stay at their places of residence and not to interact with people outside their household in-person, other than to receive essential services and while maintaining a social distance of at least 6 feet.

The NACo continuously updates its data as new declarations and policies in response to the COVID-19 pandemic are issued across the country. Note that we rely on *the date of implementation* of the order for the analysis, but orders are typically

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[7]See Brzezinski et al. (2020) for more on social distancing in the absence of stay-at-home orders.

[8]Order of the Health Officer of the County of Santa Clara from March 16, 2020: www.sccgov.org/sites/covid19/Pages/order-health-officer-031620.aspx

announced three to five days prior to implementation. We come back to this issue when discussing pre-trends in Section 5.[9]

Additionally, we rely on county-level data on local mask mandates from Wright et al. (2020), and state-level data on school closures, business closures, cancellation of public events, restrictions on gatherings, closure of public transportation, and international travel controls to account for Other policies responses. Data on US states' responses to COVID-19 is from the Oxford COVID-19 Government Response Tracker (OxCGRT). The OxCGRT is based on publicly available information on 13 indicators of government response. Data on containment and closure policies is available from January 1st until August 5th, 2020. We rely on the ordinal scale measurement of these policies to track their enactment and/or removal over our period of study (i.e., between February 24th and August 5th, 2020).[10]

2.4 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, inter-group tolerance, morality, and confidence over the years 1993–2016. We rely on repeated question from 2000 to 2014 to form our pooled sample on 436 counties.[11]

We focus on behavioral and attitudinal questions related to politics and religion, as well as trust in institutions (including 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?" For trust in others, we rely on the following question: "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?"[12] See the Appendix for the exact wording on each selected question.

To build our county-level measures, we rely on respondents' answers to the selected questions and compute weighted shares. As a robustness check, we also split our GSS data into the period including years from 2000 to 2006 (period I) and from

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[9]Another potential issue is that the extent of enforcement of orders could vary across regions. We deal with this issue by accounting for additional restrictions such as business closures and restrictions on gatherings and conducting heterogeneity analyses based on the strictness of the order.

[10]Data on implemented policies in every US state was published on August 6th, 2020 (see Hale et al. (2020) for a detailed data description). Secondary data were retrieved from https://github.com/OxCGRT/USA-COVID-policy.

[11]There are eight General Social Surveys since 2000 (2000, 2002, 2004, 2006, 2008, 2010, 2012, and 2014) covering a total of 436 counties. Appendix Table 10 shows that our sample of counties is quite representative of the USA based on the share of poverty and population with high school or less. However, our GSS sample overrepresents urban counties. Appendix Tables 10 through 30 are available in Brodeur et al. (2021) as Tables A1 through A21.

[12]Glaeser et al. (2020) indicate that perhaps the survey measure of trust, as derived from the GSS, may better pick up trustworthiness rather than trusting behavior. While we believe this might be true, we argue that part of the contribution of this paper is showing that the GSS trust measure might be predictive of compliance behavior.

2008 to 2014 (period II) to examine whether there exist differential trends in the measures of interest. 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 confidence in institutions, we consider that a person has "confidence" if their answer to the abovementioned question is either "a great deal" or "only some." Table 1 provides summary statistic on our variables of interest. In our sample, the county average trust in others is around 20%, trust in medicine and science around 50%, and trust in the press around 30%.

3 Graphical evidence and identification strategy

3.1 Graphical evidence

As the pandemic spreads, individual preventative behavior might change. It is important to document how much of the decrease in mobility is due to the stay-at-home orders per se versus a secular increase in voluntary social distancing.[13] In other words, individuals may limit their mobility and human interaction to protect themselves even in the absence of government interventions. This preventative behavior would be manifested by a voluntary decrease in mobility and could be related to trust, local norms, and political or religious affiliations. Once the stay-at-home orders are implemented, citizens could also comply with orders differently depending on local levels of social capital.

For the purpose of this study, we employ a double difference framework comparing counties' mobility before and after stay-at-home orders based on their social capital and trust levels, i.e., comparing high-trust versus low-trust counties. This will allow us to evaluate how individuals with different trust levels and different community attachments comply with government policies.

Before turning to our double difference framework, we first employ a local polynomial fit to document the daily variation in "Non-essential Visits" and "Travel Distance" across different trust-group counties in Fig. 2 and Appendix Fig. 5. We divide our GSS sample by the average share of trust in others and use the binary measure of trust for ease of interpretation. We rely on March 1 as day 0 (first reference line). The second reference line marks the date of the first official stay-at-home order enactment on March 16.[14] There is a sharp reduction in mobility starting as early as February 26, with similar trends for low- and high-trust counties. After the virus outbreak, we see a differential decrease in mobility between the two groups, suggesting that people who live in counties with higher share of trust adopt a stronger response with a more prevalent preventative behavior.

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[13]Brzezinski et al. (2020) rely on an instrumental variables approach and show that lockdowns in the USA increased time spent at home by as much as 39%.

[14]Between February 26 and March 1, only nine counties in our sample had confirmed positive cases. After March 1, this number started to increase exponentially reaching 226 counties on March 16, which motivates choosing March 1st as day 0.
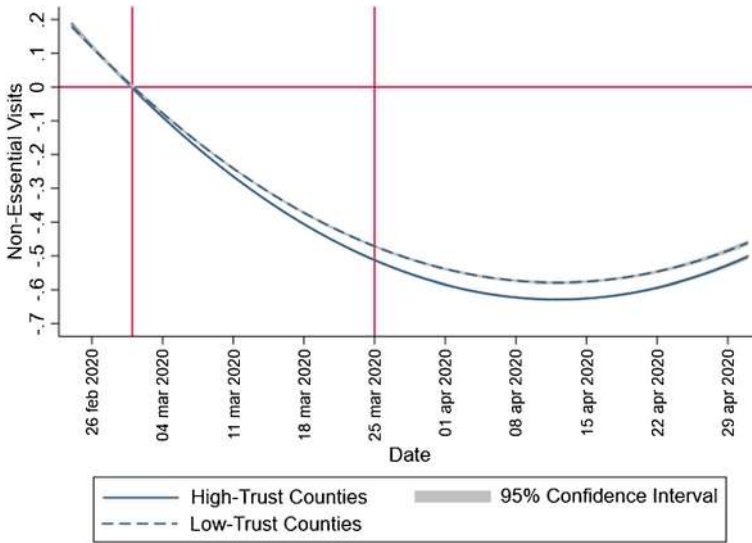
Fig. 2 Polynomial fit of the daily variation in "Non-essential Visits" for the two trust-group counties and its 95% confidence interval. Source: Unacast's COVID-19 Toolkit

Most importantly, the gap continues to widen following the announcement of (local and statewide) stay-at-home orders, and persists until the last date of observation. These results provide suggestive evidence that people in counties with higher share of trust tend to comply more with public orders.

3.2 Model specification

We now turn to our double difference framework. Our objective is to investigate the causal effect of stay-at-home orders on social distancing patterns for counties with different socio-political norms, such as trust and affiliations.

In our analysis, we rely on day of the week and county fixed effects to control for county time-invariant and day-specific characteristics. The inclusion of county fixed effects allows us to account for unobservable county level characteristics that could potentially be correlated with trust and social capital and to analyze changes in mobility measures within areas over time.[15]

More precisely, we estimate the following specification:

$$
\begin{aligned}
y_{ctd} = \lambda_c &+ \gamma_d + \kappa StayHome_{ct} + \beta Trust_c \times StayHome_{ct} \\
&+ \delta Deaths_{ct-1} \times StayHome_{ct} + \eta OtherPolicies_{ct} \times StayHome_{ct} + \varepsilon_{ctd}, \quad (1)
\end{aligned}
$$

where y_{ctd} is one of our metrics measuring social distancing: percent change in average distance traveled and percent change in non-essential visitation in county c

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[15]There are potential measurement issues with the cell-based tracking data in terms of comparisons across areas. It is thus very important to analyze changes in mobility measures within areas over time rather than across areas.

on calendar day t and day of the week d. The sample is restricted to within 30 days (before and after) of the implementation of a stay-at-home order, unless the order in a specific state ends before 30 days.

We include a full set of county dummies λ_c to control for time-invariant county characteristics. County fixed effects allow us to account for local differences in the overall contagion level within the study period and different local healthcare systems. More importantly, by controlling for county time-invariant characteristics, we account for persistent cultural differences that may affect both our trust measures and mobility. We also add day of the week dummies γ_d to capture differential mobility during week days. The dummy variable $Stay\ Home_{ct}$ equals one if the day is after the date of policy implementation in county c. 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. Our main coefficient of interest is β, corresponding to the interaction term between trust and the stay-at-home order dummy. In the model including the share of trust in others, we add interaction terms with other social capital indicators such as the share of religious individuals, share of those afraid to go out in their neighborhood at night, and share of Democrats.

Additionally, we control for COVID-19-related death rates in county c on the previous day $t - 1$. We interact the variable $Deaths_{ct-1}$ with the $Stay\ Home_{ct}$ dummy to account for any structural change or "jump" at the treatment date. The inclusion of this interaction term serves to control for voluntarily reduction in mobility related to a higher perceived risk of infection. The non-interacted term is also included to account for contagion level pre-trends. In addition, a decrease in mobility could be driven by other government policy responses such as mask mandates, school closures, business closures, cancellation of public events, restrictions on gatherings, closure of public transportation, and international travel. We control for these policies using a vector of dummy variables, $Other\ policies_{ct}$. We interact these policies with the $Stay\ Home_{ct}$ dummy to account for any overlap or simultaneous implementation with the stay-at-home orders. Our standard errors are clustered at the county level.

In some models, we also rely on the following trust-related measures instead of trust in others: confidence in the congress, the federal government, the press, medicine and science. 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 might tend to adopt a more preventative behavior and obey the authorities more.

As a robustness check, we add a second interaction term to our main specification in order to account for change in mobility due to voluntary preventative behavior. This identification strategy thus allows us to assess the independent actions and compliance levels separately. More precisely, our modified specification is:

$$
\begin{aligned}
y_{ctd} = {} & \lambda_c + \gamma_d + \kappa\, StayHome_{ct} + \eta\, COVID_{ct} + \delta\, Trust_c \times COVID_{ct} \\
& + \beta\, Trust_c \times StayHome_{ct} + \delta\, Deaths_{ct-1} \times StayHome_{ct} + \varepsilon_{ctd}, \quad (2)
\end{aligned}
$$

where the dummy variable $COVID_{ct}$ equals one if the day is after the date of first confirmed positive COVID-19 case in county c. The coefficient δ corresponds to the interaction term between trust (or other social capital indicators) and the COVID

dummy, the latter being our proxy to capture voluntary change in our outcome variables due to the COVID-19 spread.

Last, to examine the heterogeneous effects of community attachments on social distancing, we split the counties' sample based on several socioeconomic characteristics such as poverty, urban population, and education. In other words, we look at how citizens' compliance with social distancing guidelines varies in counties with varied average level of social capital and trust.

4 Determinants of implementation of stay-at-home orders

Our ultimate aim is to examine the effect of trust and community attachments on change in mobility before and after stay-at-home orders. For our double difference approach, the identification assumption would be violated if the levels of social capital or trust affect the likelihood (and timing) of implementing stay-at-home orders. To examine the determinants of this decision, we relate the likelihood of stay-at-home order implementation in our GSS sample on an extended set of socioeconomic, geographic, and epidemiological variables, including our main trust variable. The estimates are reported in Table 2. We also report similar estimates for our alternative measures of trust in Appendix Table 11. In column 1, we include counties' geographic characteristics. We gradually add demographic, economic, epidemiological, and political variables to our model in columns 2–5.

Our results suggest that trust in others, as well as alternative measures of trust, is not significantly related to the likelihood of implementing a stay-at-home order. The negative and significant coefficients on "religious" and "capital county" variables suggest that counties with higher share of religious people, and counties where the state government is located, were less likely to enact a stay-at-home order. In contrast, these orders were more likely to be implemented in counties with higher population. Income per capita and educational attainment are not correlated with the implementation of stay-at-home orders, while there is a borderline (positive) significant coefficient for poverty. We also find that stay-at-home orders are more likely to be implemented in counties with a Democratic governor, confirming the results presented in Baccini and Brodeur (2021). In Appendix Table 12, we show that relying on the full set of US counties yields similar findings.

In addition to the likelihood of implementation, it is important to examine the determinants of the timing of stay-at-home order implementation. We generate a variable capturing the number of days between the date of first COVID-19 case and date of order implementation in each county. Our sample is restricted to counties that implemented a stay-at-home order.[16] Our results are shown in Table 3 and Appendix Table 13.

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[16]We rely solely on the positive values of days between first case and stay-at-home order. This restriction allows us to examine more precisely the decisions of stay-at-home orders made at the county level as negative values might indicate that the order was implemented at the state-level before the county had any positive confirmed cases. However, our findings are robust to including the negative values of days.

Table 2 Likelihood of stay-at-home order implementation — main trust variable

	Likelihood of implementing a stay-at-home order				
	(1)	(2)	(3)	(4)	(5)
Panel A: Trust variables					
Trust people	–0.054	–0.079	–0.045	–0.043	–0.054
	(0.094)	(0.094)	(0.098)	(0.097)	(0.096)
Religious	–0.080**	–0.093**	–0.095**	–0.100***	–0.077**
	(0.038)	(0.037)	(0.038)	(0.038)	(0.037)
Neighborhood fear	0.158*	0.138	0.081	0.081	0.056
	(0.094)	(0.094)	(0.099)	(0.100)	(0.099)
Democrats	–0.066	–0.080	–0.104	–0.114	–0.118
	(0.080)	(0.080)	(0.081)	(0.081)	(0.080)
Independent	–0.029	–0.037	–0.044	–0.047	–0.039
	(0.083)	(0.082)	(0.082)	(0.082)	(0.080)
Panel B: Geographic variables					
With airport	0.059**	-0.003	-0.008	0.004	0.014
	(0.028)	(0.032)	(0.032)	(0.032)	(0.032)
Coastal county	0.065***	0.040*	0.036	0.039*	0.022
	(0.021)	(0.023)	(0.024)	(0.024)	(0.024)
Capital county	–0.111**	–0.140***	–0.145***	–0.148***	–0.131***
	(0.048)	(0.048)	(0.048)	(0.047)	(0.047)
Panel C: Demographic variables					
Population		0.048***	0.050***	0.050***	0.049***
		(0.015)	(0.015)	(0.015)	(0.015)
Population density		–0.012	–0.028	–0.048*	–0.069**
(per 10K)		(0.024)	(0.026)	(0.029)	(0.029)
Urban share		–0.056	–0.049	–0.036	–0.028
		(0.075)	(0.077)	(0.077)	(0.076)
Elderly share		–0.212	–0.238	–0.212	–0.214
		(0.275)	(0.281)	(0.280)	(0.275)
Male share		0.368	0.483	0.468	0.158
		(0.493)	(0.504)	(0.501)	(0.499)
Panel D: Economic variables					
Per capita income			0.116	0.105	0.096
			(0.106)	(0.106)	(0.106)
Share below poverty			0.588*	0.625*	0.578*
			(0.346)	(0.347)	(0.345)
Share above college			–0.162	–0.146	–0.243
			(0.193)	(0.192)	(0.190)

Table 2 (continued)

	Likelihood of implementing a stay-at-home order				
	(1)	(2)	(3)	(4)	(5)
Panel E: Epidemiological variables					
Cases per population				0.011	0.018**
(per 10K)				(0.008)	(0.008)
Panel F: Political variables					
Democrat governor					0.086***
					(0.021)
Observations	434	432	432	432	431
R-squared	0.071	0.115	0.122	0.137	0.169

The dependent variable is a dummy that takes the value of one if a county implemented a stay-at-home order and zero otherwise. A total of 20 counties (in our GSS sample) did not implement a stay-at-home order. Coefficients in all columns are derived from ordinary least squares regressions. In column 1, we include a set of demographic variables. We sequentially add our sets of economic, epidemiological, and political variables in columns 2–5. Panel E includes COVID-19 cases per 10,000 one day prior order implementation. For counties that did not implement a stay-at-home order, we proxy this variable by the average number of cases (one day prior implementation) of other counties

Robust standard errors in parentheses: *** $p<0.01$; ** $p<0.05$; * $p<0.1$

We find that none of the trust or confidence measures is correlated with the timing of stay-at-home orders. Our estimates suggest that the major determinants of order timing are geographic (i.e., presence of an airport and coastal and capital counties), demographic (e.g., population and population density), and epidemiological characteristics. The time elapsed between the first case and order enactment was longer in counties with higher share of individuals above college education. These policies also seem to be implemented faster in counties with a Democratic governor. These findings are robust to relying on the full sample of US counties (Appendix Table 14).

To sum up, we do not find evidence that counties with more trust were more likely (or faster) to implement stay-at-home orders.

5 Determinants of compliance with stay-at-home orders

We now turn to our analysis of the determinants of compliance with stay-at-home orders. We first present our main double difference estimates and then conduct subsample analyses.

5.1 Double difference

Table 4 presents estimates of Eq. 1. The dependent variable is the index of non-essential visits in columns 1–3 and total travel distance index in columns 4–6. Only

Table 3 Timing of stay-at-home order implementation – main trust variable

	Timing of stay-at-home order implementation				
	(1)	(2)	(3)	(4)	(5)
Panel A: Trust variables					
Trust people	0.661	0.0202	–2.793	–1.846	–1.025
	(3.119)	(2.999)	(3.097)	(2.700)	(2.656)
Religious	1.689	0.906	1.395	0.248	–0.175
	(1.270)	(1.219)	(1.213)	(1.068)	(1.054)
Neighborhood fear	8.604***	7.728**	9.131***	4.309	4.563*
	(3.126)	(3.001)	(3.082)	(2.726)	(2.675)
Democrats	–3.695	–4.704*	–4.515*	–2.793	–2.121
	(2.648)	(2.584)	(2.595)	(2.270)	(2.235)
Independent	–4.232	–3.828	–3.248	–1.801	–1.700
	(2.836)	(2.702)	(2.676)	(2.336)	(2.291)
Panel B: Geographic variables					
With airport	4.229***	1.480	1.356	1.127	0.888
	(0.850)	(0.939)	(0.937)	(0.822)	(0.811)
Coastal county	1.372**	0.183	0.154	0.231	0.593
	(0.662)	(0.693)	(0.727)	(0.635)	(0.630)
Capital county	4.720***	3.718**	3.449**	3.703***	3.306***
	(1.507)	(1.444)	(1.433)	(1.249)	(1.230)
Panel C: Demographic variables					
Population		1.813***	1.701***	2.286***	2.290***
		(0.485)	(0.490)	(0.431)	(0.423)
Population density		0.613	0.476	-4.607***	-4.080***
		(0.796)	(0.884)	(0.913)	(0.908)
Urban share		0.572	–1.382	–1.437	–1.427
		(2.547)	(2.602)	(2.273)	(2.228)
Elderly share		–4.823	1.196	1.610	0.651
		(8.686)	(8.806)	(7.673)	(7.535)
Male share		–24.38	–23.23	–5.151	6.038
		(25.099)	(25.042)	(21.888)	(21.683)
Panel D: Economic variables					
Per capita income			–0.140	–2.024	–1.441
			(3.255)	(2.841)	(2.816)
Share below poverty			2.525	–4.691	–2.648
			(10.634)	(9.318)	(9.212)
Share above college			14.480**	11.450**	13.180**
			(5.990)	(5.227)	(5.157)

Table 3 (continued)

	Timing of stay-at-home order implementation				
	(1)	(2)	(3)	(4)	(5)
Panel E: Epidemiological variables					
Cases per population				1.701***	1.515***
(per 10K)				(0.215)	(0.216)
Panel F: Political variables					
Democratic governor					–2.202***
					(0.573)
Observations	348	347	347	347	346
R-squared	0.173	0.267	0.292	0.466	0.489

The dependent variable is the number of days between the date of the first COVID-19 case and the date of order implementation. We restrict our analysis on the positive values of this measure. Coefficients in all columns are derived from ordinary least squares regressions. In column 1, we include a set of demographic variables. We sequentially add our sets of economic, epidemiological, and political variables in columns 2–5. Panel E includes COVID-19 cases per 10,000 one day prior order implementation

Robust standard errors in parentheses: *** $p<0.01$; ** $p<0.05$; * $p<0.1$

county-day observations up to 30 days prior to the implementation of the stay-at-home order and 30 days after the implementation are included, unless the order in a specific state and/or county ends before 30 days.[17] In columns 1 and 4, we only include county and day of the week fixed effects. We are thus comparing within-county mobility, before and after a stay-at-home order. We control for the lagged COVID-19-related death rate per 10,000 in columns 2 and 5. Columns 3 and 6 present our preferred specification, in which we extend our controls to include Other policies: making masks mandatory (county level), and statewide schools closing, business closing, cancellation of public events, gathering restrictions, closure of public transportation, and international travel control.

The estimates for our stay-at-home order suggest that the introduction of an order reduces non-essential visits and total travel distance by about 25 and 17 percentage points, respectively. This effect decreases in magnitude but remains robust to the inclusion of controls for other governmental implemented policies.

We now turn to our main results. We find that individuals in counties with a higher trust in other people reduce their mobility significantly more during stay-at-home orders in comparison to low-trust counties. Our estimates are statistically significant at the 1% level, and suggest that higher trust in others is associated with a significant larger decrease in non-essential visits and travel distance once stay-at-home orders are implemented.

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[17]Extending the time period to include all dates in our sample (i.e., from February 24th to August 5th, unless the stay-at-home order in a specific state and/or county ends prior to August 5th) has no effect on our conclusions. Appendix Table 15 shows that our main results in Table 4 are robust to the use of this time period rather than the within 30 days period.

Table 4 Stay-at-home policies, social distancing and trust – within 30 days of order

	Non-essential visits			Travel distance		
	(1)	(2)	(3)	(4)	(5)	(6)
After order	−0.245***	−0.248***	−0.219***	−0.167***	−0.169***	−0.120***
	(0.034)	(0.033)	(0.039)	(0.025)	(0.024)	(0.037)
After order	−0.264***	−0.257***	−0.183***	−0.191***	−0.188***	−0.188***
× Trust	(0.058)	(0.057)	(0.041)	(0.042)	(0.041)	(0.031)
After order	0.018	0.018	−0.003	0.006	0.008	0.008
× Religious	(0.021)	(0.021)	(0.016)	(0.015)	(0.015)	(0.013)
After order	−0.001	0.007	−0.060	−0.007	−0.000	−0.037
× Fear	(0.055)	(0.054)	(0.041)	(0.041)	(0.039)	(0.033)
After order	−0.212***	−0.202***	−0.156***	−0.178***	−0.170***	−0.145***
× Democrats	(0.044)	(0.043)	(0.033)	(0.038)	(0.036)	(0.031)
After order		−0.024***	−0.008***		−0.021***	−0.012***
× Deaths$_{(t-1)}$		(0.002)	(0.002)		(0.003)	(0.003)
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Other policies	No	No	Yes	No	No	Yes
Observations	23,395	23,395	23,395	24,347	24,347	24,347
R-squared	0.619	0.620	0.873	0.684	0.686	0.852

The dependent variables are our indexes of non-essential visits and total travel distance in columns 1–3 and 4–6, respectively. The sample is restricted to within 30 days (before and after) of the implementation of a stay-at-home order unless the order in a specific state ends before 30 days. The analysis includes 398 and 414 counties for non-essential visits and travel distance, respectively. All specifications include day and county fixed effects. Columns 2, 3, 5, and 6 include a variable for the lagged daily COVID-19-related death rates at the county level interacted with the *After order* dummy. Additionally, in columns 3 and 6, we control for other implemented policies interacted with the *After order* dummy: making masks mandatory (county level), school closures, business closure, cancellation of public events, gathering restrictions, closure of public transportation, and international travel control (state level)

Standard errors clustered at the county level. *** $p<0.01$; ** $p<0.05$; * $p<0.1$

We confirm the robustness of this result by adding to the model lagged COVID-19-related death rates per 10,000 in columns 2, 3, 5, and 6 and our set of Other policies controls in columns 3 and 6.[18] The inclusion of these additional control variables has no effect on the significance of our estimates. The magnitude of our *After order* variable and the interaction term with our trust measure suggests that

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[18] We show that our results are robust to replacing our COVID-19-related deaths control by the confirmed number of positive cases in Appendix Table 16.

a one percentage point increase in trust is associated with a decrease of about 0.2 percentage point in non-essential visits and travel distance.

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 nor neighborhood fear is related to post-order mobility. Of note, these variables are significantly related to the implementation (and timing) of stay-at-home orders, which makes it hard to interpret the causal effect of these variables on mobility.

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 people in counties with a lower share of votes for Republicans demonstrate higher compliance with stay-at-home orders. Our estimates suggest that a one percentage point increase in the share of Democrats in a specific county is associated with around 0.15 percentage point decrease in non-essential visits and in distance traveled, conditional on counties' COVID-19-related deaths and other implemented policies. Again, caution is required in interpreting these estimates causally since Republican counties/states were slower at implementing stay-at-home orders.

To establish that the treatment effects are driven by the orders and not just some continuation of pre-existing trends, we present event study graphs on pre-trends and post-treatment dynamics. We generate dummies for leads and lags of the interaction term between trust and stay-at-home orders implementation for 30 days before and 100 days after the passage of order. We illustrate our results by plotting the daily estimated coefficients of interest on "Non-Essential Visits" in Fig. 3 and on "Distance Traveled" in Appendix Fig. 6. We omit the first day of our analysis, i.e., 30th day before the stay-at-home order implementation *(t-30)*. The reference vertical lines on day *(t+80)* indicate the date by which all counties had ended their stay-at-home orders.

The estimates are not significantly different from 0 in the weeks prior to the order implementation in Fig. 3, suggesting that the trends were parallel. (Only one lead is borderline statistically significant in Appendix Fig. 6.) Interestingly, we find that residents of high-trust counties in comparison to low-trust counties started reducing their non-essential visits few days prior to the implementation of the stay-at-home order. This may reflect people's anticipation of the impending order date since *state* orders are typically announced few days prior to implementation.[19] Note that this anticipation has a downward bias on our estimated interaction coefficients.[20]

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[19]We unfortunately are unable to collect data on announcements for *county*-level orders. But we did manage to collect information for all statewide stay-at-home orders and find that orders were usually announced three to five days prior to implementation.

[20]We replicate our results of Table 4 by removing the five days prior order implementation in Appendix Table 17. The size of the coefficients on the effect of trust becomes larger in magnitude in all specifications.
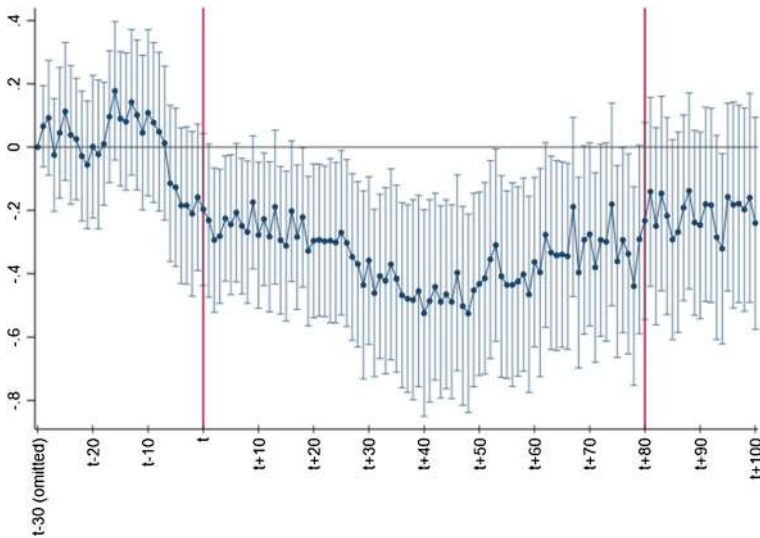
Fig. 3 Leads and lags analysis for non-essential visits: We plot leads and lags estimates for the interaction term between trust and stay-at-home order for 30 days pre- and post-implementation. We control for lagged COVID-19-related death rate (deaths by 10,000) and our usual set of fixed effects

In the post-order enactment period, we see that the differential effect of trust on compliance is statistically significant and persists as long as stay-at-home orders are in place. Once orders start to be lifted (i.e., all lifted after day *t+80*), the effect of trust on "Non-Essential Visits" loses its significance and slowly decreases in magnitude on the "Travel Distance" variable.

In Table 5 and Appendix Table 18, we show the estimates of Eq. 1 using different trust and confidence measures as explanatory variables. Each column in these tables represents a separate regression on "Non-essential Visits" and "Travel Distance," respectively. We find that residents in counties with higher confidence in governmental institutions (congress and federal government) decrease significantly more their non-essential visits and distance traveled following the implementation of an order. With the press constantly reporting updates and details on the order adoption measures, it is also plausible that people who put more confidence in the press adjust their behavior more than those who do not. We find that the effect of confidence in press on post-order is also significantly negative and large in magnitude. In contrast, we do not find strong evidence that confidence in medicine and science affects compliance with orders.

5.2 Simple counterfactual

So far, our findings suggest that trust in governmental institutions, such as the congress and federal government, increases citizens' compliance with governmental stay-at-home orders. Levels of trust in government differ widely across countries. Based on an international COVID-19 Tracker report published by YouGov late May 2020, around 40% of individuals in the USA had somewhat or complete

Table 5 Stay-at-home policies, social distancing, and alternative measures of trust — within 30 days of order

| | Non-essential visits | | | | |
	(1)	(2)	(3)	(4)	(5)
After order	–0.318***	–0.309***	–0.337***	–0.323***	–0.327***
	(0.032)	(0.034)	(0.036)	(0.031)	(0.038)
After order	–0.071**				
× Confidence congress	(0.034)				
After order		–0.093**			
× Confidence FED		(0.037)			
After order			–0.013		
× Confidence medicine			(0.034)		
After order				–0.075**	
× Confidence press				(0.033)	
After order					–0.027
× Confidence science					(0.036)
Observations	23,395	23,395	23,395	23,395	23,395
R-squared	0.866	0.866	0.866	0.866	0.866

The dependent variable is our index for non-essential visits. The sample is restricted to within 30 days (before and after) of the implementation of a stay-at-home order unless the order in a specific state ends before 30 days. All specifications include day and county fixed effects and a variable for the lagged daily COVID-19-related death rates interacted with the "After order" dummy at the county level. We also control for other implemented policies interacted with the *After order* dummy: making masks mandatory (county-level), school closures, business closure, cancellation of public events, gathering restrictions, closure of public transportation, and international travel control (state level)

Standard errors clustered at the county level. *** $p<0.01$; ** $p<0.05$; * $p<0.1$

trust in their government during the pandemic.[21] This level is among the lowest among OECD countries, with about 70% of individuals surveyed answering that they somewhat or completely trust their government.[22]

In what follows, we conduct a simple counterfactual exercise to determine how higher trust in governmental institutions would have affected the magnitude of compliance with orders.[23] These results are of interest given the current political context

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[21] YouGov is a global public opinion organization. It gathers information about COVID-19 by asking people to share their experiences of the global pandemic. We rely on the International COVID-19 tracker update published on May 18th: https://today.yougov.com/topics/international/articles-reports/2020/05/18/international-covid-19-tracker-update-18-may.

[22] Our GSS data suggest that the average confidence in congress and the federal government in the period prior the COVID-19 spread was between 30 and 35%.

[23] See https://www.pewresearch.org/politics/2020/10/09/perceptions-of-donald-trump-and-joe-biden/ .

of the upcoming post-election changes in the USA as they hint at possible effects for compliance with stay-at-home orders under the new government from January 2021 onwards. Changes in public compliance may occur given the sharp difference in approach to addressing the COVID-19 pandemic by the incumbent President and President-Elect.

In sharp contrast to most world leaders and to his political opponent Joe Biden, Trump sought to downplay the threat of the pandemic. This strategy had limited political success, with nearly 60% of people in the USA disapproving the way the government has been handling the COVID-19 crisis.[24] In contrast, the new Biden administration considers combating the COVID-19 pandemic as their number one priority. The Biden plan calls for restoring trust, credibility, and accountability of the federal government, as communication with the public is believed to be key to building trust in governmental institutions.

As a part of their plan, the Biden-Harris team will create a "Nationwide Pandemic Dashboard" to display transmission rates of the virus in regions across the country. The CDC will also oversee announcing recommendations for when it is safe to open or close restaurants, schools, and businesses, according to the updated plan. Furthermore, in an effort to boost public confidence, Biden received the COVID-19 vaccine before it became widely available to the public. This shift in the federal government treatment of the pandemic could potentially affect the level of trust in the institutions, consequently shaping the behavioral response to the mobility restrictions by the general public. The results of the counterfactual exercise could then help shed some light on the expected compliance with further restrictions should they be put in place.

The computation of the counterfactual is based on the effect of confidence in congress and the federal government on the change in non-essential visits and distance traveled. For this counterfactual, we rely on point estimates from Table 5 and Appendix Table 18 to compute the level of decrease in mobility that would have taken place After order implementation if confidence was of X percentage points higher. To allow for a margin of error in our counterfactual calculations, we provide lower and upper bounds using the 95% confidence interval from our estimates.

Table 6 shows the results of this counterfactual analysis. We report the decrease in mobility due to stay-at-home orders implementation (i.e., our coefficients on the *After order* dummy) in column 2. In columns 3–5, we show counterfactual outcomes in mobility decrease if trust in governmental institutions had been of 10 p.p. or 20 p.p. or 30 p.p. higher. Our results suggest that a level of confidence in congress and federal government of around 60% would be associated with a 3 p.p. further decrease in non-essential visits and a further 2 p.p. decrease in distance traveled for counties under a stay-at-home order. With a large literature documenting the correlation between mobility patterns and decreased COVID-19 case growth in the USA (see Badr et al. (2020), for instance), these findings suggest that a higher trust

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[24]See Baccini et al. (2021) for more details on Trump's response to the pandemic. See https://projects.fivethirtyeight.com/coronavirus-polls/ and https://www.pewresearch.org/politics/2020/10/09/perceptions-of-donald-trump-and-joe-biden/ for surveys of Americans.

Table 6 Counterfactual outcomes for higher trust in governmental institutions

Mobility outcomes	Decrease upon stay-at-home order	10 p.p. higher	20 p.p. higher	30 p.p. higher
Panel A: Confidence in FED				
Non-essential visits	–30.91%	–31.84%	–32.77%	–33.70%
		(-31.11; -32.57)	(-31.31; -34.24)	(-31.50; -35.91)
Travel Distance	–19.47%	–20.49%	–21.52%	–22.54%
		(–19.89; –21.10)	(–20.31; –22.73)	(–20.73; –24.36)
Panel B: Confidence in congress				
Non-essential visits	–31.84%	–32.55%	–33.27%	–33.98%
		(–31.89; –33.22)	(–31.93; –35.60)	(–31.98; –35.98)
Travel distance	–21.00%	–21.64%	–22.27%	–22.91%
		(–21.13; –22.15)	(–21.25; –23.29)	(–21.38; –24.44)

The computation of the counterfactual is based on our estimates in Table 5 for change in non-essential visits and Appendix Table 18 for change in distance traveled. Column 2 reports our coefficients on the *After order* dummy. The reported values in columns 3–5 are estimated margins of total change in mobility in the counterfactual scenarios of higher confidence in the federal government (panel A) and higher confidence in the congress (panel B). We present 95% confidence intervals as lower and upper bound on these calculations (in parentheses)

in governmental institutions could have led to lower confirmed cases and lower COVID-19-related deaths.

5.3 Subgroup analyses

Table 7 and Appendix Table 19 provide subgroup analyses on non-essential visits and distance traveled, respectively. We investigate the effect of trust and social capital on social distancing after the orders for the following subsamples (columns in parentheses): (1) below and (2) above median poverty; (3) rural and (4) urban counties; (5) below and (6) above median education. Note that data on socioeconomic variables is from the American Community Survey (ACS-5 years estimates) for the latest available years (2014 to 2018).[25] We find that the differential effect of stay-at-home orders by trust level on our mobility measures is remarkably larger in urban counties and counties above median poverty and education.

The differential effects of stay-at-home orders are fairly homogeneous across the different subgroups for religion and fear of walking outside at night. In contrast, we find that people who live in counties with relatively more self-declared Democrats were significantly more likely to follow guidelines to stay home in urban and relatively more educated counties.

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[25] Data on the share of urban population is based on the last census (2010) before the pandemic outbreak.

Table 7 Stay-at-home policies, social distancing, and trust — heterogeneous effect — within 30 days of order

	Non-essential visits					
	Poverty		Urbanism		Education	
	Below median	Above median	Rural	Urban	Below median	Above median
	(1)	(2)	(3)	(4)	(5)	(6)
After order	−0.181***	−0.240***	−0.189*	−0.239***	0.006	−0.215***
	(0.040)	(0.064)	(0.111)	(0.040)	(0.072)	(0.039)
After order	−0.113**	−0.309***	−0.168	−0.158***	−0.129	−0.109***
× Trust	(0.049)	(0.078)	(0.106)	(0.041)	(0.090)	(0.039)
After order	−0.026	0.013	0.021	0.006	−0.046	0.017
× Religion	(0.019)	(0.025)	(0.033)	(0.016)	(0.029)	(0.016)
After order	−0.084*	−0.050	0.002	−0.013	−0.104	−0.063
× Fear	(0.045)	(0.073)	(0.072)	(0.044)	(0.070)	(0.040)
After order	−0.158***	−0.139**	0.064	−0.147***	0.011	−0.180***
× Democrats	(0.034)	(0.066)	(0.154)	(0.032)	(0.095)	(0.029)
Observations	13,783	9673	3630	19,826	5040	18,416
R-squared	0.622	0.620	0.500	0.631	0.561	0.626

The dependent variable is our index for non-essential visits. The sample is restricted to within 30 days (before and after) of the implementation of a stay-at-home order unless the order in a specific state ends before 30 days. All specifications include day and county fixed effects and a variable for the daily COVID-19-related death rates at the county level. We also control for other implemented policies interacted with the *After order* dummy: making masks mandatory (county level), school closures, business closure, cancellation of public events, gathering restrictions, closure of public transportation, and international travel control (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)
Standard errors clustered at the county level. *** $p<0.01$; ** $p<0.05$; * $p<0.1$

5.4 Intensity of stay-at-home orders

In this subsection, we investigate heterogeneous effects of orders depending on their "strictness." For this exercise, we use data on policy intensity from the Oxford COVID-19 Government Response Tracker (OxCGRT) implemented by the University of Oxford's Blavatnik School of Government. The OxCGRT has released data measuring policy responses to the pandemic across all 50 US states on August 6th, 2020. To capture counties' heterogeneity in the strictness of orders, we rely on the ordinal scale measure of stay-at-home requirements policy. This variable takes the value of zero if no stay-at-home measures were taken, one if governmental authorities recommended to the public to not leave their house ("low" stay-at-home intensity), and two if staying-at-home was required with exceptions for daily exercise, grocery shopping, and essential trips ("high" stay-at-home intensity).

In Table 8, we estimate Eq. 1 and show the differential effect of stay-at-home strictness by trust in people on changes in non-essential visits and total travel distance. Our variables of interest are dummies for "low" stay-at-home intensity and "high" stay-at-home intensity. Our estimates show that higher intensity orders are associated with a large and significant decrease in mobility, while lower intensity orders are related to a much smaller (and insignificant) decrease in mobility. Our coefficients on the interaction term for trust in all specifications suggest that the effect of trust is slightly larger for "high" than for "low" intensity orders.

We find that religiosity has no differential impact on mobility regardless of the implemented orders being more or less strict. In contrast, people in counties with a higher share of Democrats seem to comply more with governmental orders that are strictly implemented.

In Appendix Tables 20 and 21, we repeat this exercise using alternative measures of trust on "Non-Essential Visits" and "Travel Distance," respectively. Our results on both mobility measures are similar, suggesting that trust in governmental institutions and press has a larger effect on compliance when "high" intensity stay-at-home orders are implemented. For instance, our estimates suggest that a one percentage point increase in a county's share of confidence in congress leads to a 0.09 percentage point decrease in non-essential visits once a strict stay-at-home order is enacted (conditional on county level COVID-19-related deaths and other implemented policies).

Overall, our results suggest that the strictness of orders and its interaction effect with trust are important predictors of compliance. These results have important policy implications since the strictness of lockdowns has been shown to be related to economic losses and happiness of citizens, among other variables (e.g., Brodeur et al. (2021)).

5.5 Robustness check

So far, our results provide suggestive evidence that higher-trust counties are more likely to comply with stay-at-home orders. We check the robustness of our results in this subsection.

We first examine whether our model is capturing an effect of the stay-at-home order or a general response to the higher risk associated with COVID-19. In other words, we want to examine whether our main result that individuals in counties with a higher share of trust comply more with government orders is robust to taking into account voluntary preventative behavior. We provide estimates of Eq. 2 in Table 9 and Appendix Table 22. We restrict the sample to 30 days within the stay-at-home order implementation, unless the order in a specific state and/or county ends before 30 days. Our estimates suggest that controlling for the impact of COVID-19 has no effect on our main finding that residents of high-trust counties reduced their non-essential visits and distance traveled significantly more upon stay-at-home order declaration. In other words, we find that people who live in counties with a higher share of trust in others demonstrate stronger adherence to the stay-at-home orders in addition to their larger voluntary decrease in mobility. Our results also suggest that the differential effects of stay-at-home orders by confidence in press and governmental institutions on obedience remain statistically significant.

Table 8 Intensity of stay-at-home policies, social distancing and trust — within 30 days of order

	Non-essential visits			Travel distance		
	(1)	(2)	(3)	(4)	(5)	(6)
Low intensity	–0.117*	–0.123**	0.030	–0.044	–0.049	0.017
	(0.061)	(0.056)	(0.039)	(0.034)	(0.041)	(0.030)
High intensity	–0.260***	–0.267***	–0.115**	–0.162***	–0.167***	0.004
	(0.042)	(0.041)	(0.046)	(0.031)	(0.030)	(0.036)
Low intensity	–0.239**	–0.211**	–0.123**	–0.213***	–0.189***	–0.131***
× Trust	(0.099)	(0.090)	(0.052)	(0.074)	(0.064)	(0.048)
High intensity	–0.287***	–0.277***	–0.209***	–0.228***	–0.221***	–0.173***
× Trust	(0.075)	(0.073)	(0.048)	(0.056)	(0.054)	(0.038)
Low intensity	0.019	0.013	0.009	0.016	0.011	0.004
× Religious	(0.041)	(0.022)	(0.024)	(0.027)	(0.025)	(0.019)
High intensity	–0.001	–0.001	–0.004	–0.007	–0.005	–0.011
× Religious	(0.025)	(0.025)	(0.017)	(0.019)	(0.019)	(0.014)
Low intensity	0.005	0.019	–0.070	–0.088	–0.075	–0.114**
× Fear	(0.116)	(0.107)	(0.059)	(0.088)	(0.079)	(0.056)
High intensity	0.068	0.077	–0.069	0.023	0.031	–0.051
× Fear	(0.065)	(0.064)	(0.049)	(0.048)	(0.046)	(0.039)
Low intensity	–0.106	–0.111	–0.149***	–0.065	–0.069	–0.083*
× Democrats	(0.085)	(0.078)	(0.044)	(0.075)	(0.068)	(0.047)
High intensity	–0.245***	–0.233***	–0.172***	–0.212***	–0.201***	–0.159***
× Democrats	(0.059)	(0.058)	(0.037)	(0.049)	(0.047)	(0.036)
Death rate$_{(t-1)}$	No	Yes	Yes	No	Yes	Yes
Other policies	No	No	Yes	No	No	Yes
Observations	23,395	23,395	23,395	24,347	24,347	24,347
R-squared	0.675	0.678	0.869	0.719	0.722	0.845

The dependent variables are our indexes of non-essential visits and total travel distance in columns 1–3 and 4–6, respectively. The sample is restricted to within 30 days (before and after) of the implementation of a stay-at-home order unless the order in a specific state ends before 30 days. The analysis includes 398 and 414 counties for non-essential visits and travel distance, respectively. All specifications include day and county fixed effects. *Low intensity* is a dummy for whether the order is implemented with Low intensity, while *High intensity* is a dummy for whether the order is implemented with High intensity. Columns 2, 3, 5, and 6 include a variable for the lagged daily COVID-19-related death rates at the county level interacted with the *After order* dummy. Additionally, in columns 3 and 6, we control for other implemented policies interacted with the *After order* dummy: making masks mandatory (county level), school closures, business closure, cancellation of public events, gathering restrictions, closure of public transportation, and international travel control (state level)

Standard errors clustered at the county level. *** $p<0.01$; ** $p<0.05$; * $p<0.1$

Table 9 Stay-at-home policies, COVID-19, and trust — within 30 days of order

| | Non-essential visits | | | | | |
	(1)	(2)	(3)	(4)	(5)	(6)
After COVID	–0.273***	–0.299***	–0.280***	–0.314***	–0.297***	–0.204***
	(0.018)	(0.022)	(0.023)	(0.031)	(0.020)	(0.046)
After order	–0.178***	–0.165***	–0.166***	–0.186***	–0.172***	–0.254***
	(0.018)	(0.023)	(0.023)	(0.030)	(0.021)	(0.034)
After order × Trust people	–0.166*** (0.081)					
After COVID × Trust people	–0.132* (0.076)					
After order × Conf. congress		–0.141** (0.067)				
After COVID × Conf. congress		0.001 (0.066)				
After order × Conf. FED			–0.136** (0.065)			
After COVID × Conf. FED			–0.053 (0.067)			
After order × Conf. medicine				–0.049 (0.056)		
After COVID × Conf. medicine				0.033 (0.062)		
After order × Conf. press					–0.124** (0.062)	
After COVID × Conf. press					–0.002 (0.061)	
After order × Conf. science						0.022 (0.060)
After COVID × Conf. science						–0.090 (0.064)

Table 9 (continued)

| | Non-essential visits | | | | | |
	(1)	(2)	(3)	(4)	(5)	(6)
Observations	23,395	23,395	23,395	23,395	23,395	23,395
R-squared	0.736	0.734	0.735	0.734	0.734	0.734

The dependent variable is our index for non-essential visits. The sample is restricted to within 30 days (before and after) of the implementation of a stay-at-home order unless the order in a specific state ends before 30 days. The analysis thus includes 413 counties until April 24, 2020. Each column shows a separate regression including interactions of trust measures with $After\ COVID$ dummy and $After\ order$ dummy, respectively. The $After\ COVID$ dummy takes the value of zero if the county has no confirmed positive COVID-19 case, and one starting the day when the first positive case is confirmed in a specific county. All specifications include day and county fixed effects and a variable for the daily COVID-19-related death rates at the county level

Standard errors clustered at the county level. *** $p<0.01$; ** $p<0.05$; * $p<0.1$

Another potential issue is that trust may be related to the economic environment, which in turn is related to mobility patterns. To account for this potential omitted variable bias, we interact our $After\ order$ dummy with two socioeconomic variables: share of urban population and share of individuals below poverty. The estimates are presented in Appendix Table 23. Our results are robust to the inclusion of these additional interaction terms and our Other policies controls.

We also examine whether there are differential trends in our GSS trust measure across counties. Recall that for the main analysis we built our trust and confidence measures based on GSS data from 2000 to 2014. Appendix Table 24 shows our main results based on two different GSS subsamples: subsample I including survey years between 2000 and 2006 in columns 1–2 and subsample II including survey years between 2008 and 2014 in columns 3–4. Estimates confirm our previous findings in both samples, with slightly higher (lower) magnitude in the first (second) pooled sample.

Another potential issue is measurement error for the variables created from collapsing the GSS self-reported data. We check whether our findings are robust to relying on observed data rather than self-reported indicators. We proxy for neighborhood fear using average county level crime rate between 2000 and 2014 from the Uniform Crime Reporting Program Data (US Department of Justice, federal Bureau of Investigation). We rely on counties' average rate of adherents for 236 religious groups in 2000 and 2010 from the US Religion Census to substitute for the share of religious individuals. Finally, we replace the share of self-declared Democrats by the counties' average share of votes won by Democratic party in presidential election years 2000, 2004, 2008, and 2012.

Overall, we find similar results for our objective and subjective measures of political affiliation and religion. The estimates are reported in Appendix Table 25. In contrast, despite a positive raw correlation between neighborhood fear and crime rate (correlation coefficient of 0.40), our estimates for the interacted crime variable are different for our subjective and objective crime variables. We document a positive differential effect on mobility for the objective measure of crime, while we do not find any evidence that social mobility during the orders was related to neighborhood fear.

We now present robustness checks for our mobility data. For these specification checks, we rely on the Google COVID-19 Community Mobility Reports to measure social mobility. Appendix Table 26 shows estimates on changes in people's activities for the six different categories.[26] The estimates in this table confirm the robustness of our previous findings; we find that individuals in counties with more trust in others are more likely to comply with stay-at-home 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 terms are statistically significant for all the categories mentioned above.

Similar to our previous results, the estimates for the interaction term between the post-order dummy and religiosity suggest that religiosity has no effect on compliance with social distancing orders. For crime perception, the estimates are mostly imprecise and statistically insignificant in four out of six columns. Last, our estimates suggest that an increase with the share of Democrats is associated with a decrease in mobility for all categories (and an increase in time spent at home).

Last, we examine the effect of stay-at-home orders on different trust and confidence measures using Google mobility indices in Appendix Tables 27 and 28. We confirm our main findings that higher confidence in governmental institutions and press is associated with higher compliance.[27]

6 Conclusion

The uneven geography of social distancing observed from cell phone location tracking data in the USA suggests that not all Americans altered their behavior in the same way 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 Program, 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 regarding the role of trust in shaping people's preventative behavior and compliance with government orders in the midst of the pandemic. By relying on county-level variation in the USA and employing a double difference framework, we find that in areas with higher individual trust in others, people 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 tends to be higher in counties with relatively more self-declared Democrats.

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[26]See Section 2 for more details on the outcome variables.

[27]We also estimate (2) using Google measures on changes in residential and retail visits in Appendix Tables 29 and 30, respectively. As suggested in our previous findings, results show that the higher mobility reduction in counties with higher shares of trust in others, in governmental institutions, and in press is mainly driven by a direct response to legal orders.

Furthermore, we examine the effect of different trust measures such as trust in public institutions, medicine, and press. We find that people who live in counties with a higher share of citizens trusting the press and the government are more likely to adjust their behavior to orders following their announcement. This result could be driven by the fact that the novel virus and the stay-at-home orders are dominating the news.

While our findings refer to behavioral changes during the early months of the pandemic, they provide suggestive evidence that trust and social capital likely played important roles throughout the pandemic in shaping the public response and adherence to the restrictions. Our results, therefore, suggest that building trust, combined with strategic controls and clear communication by the government, could provide a successful tool for authorities to promote pro-social public behavior of social distancing during mass immunization campaigns (Eichengreen et al. 2021).

Appendix

A.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.

A.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?
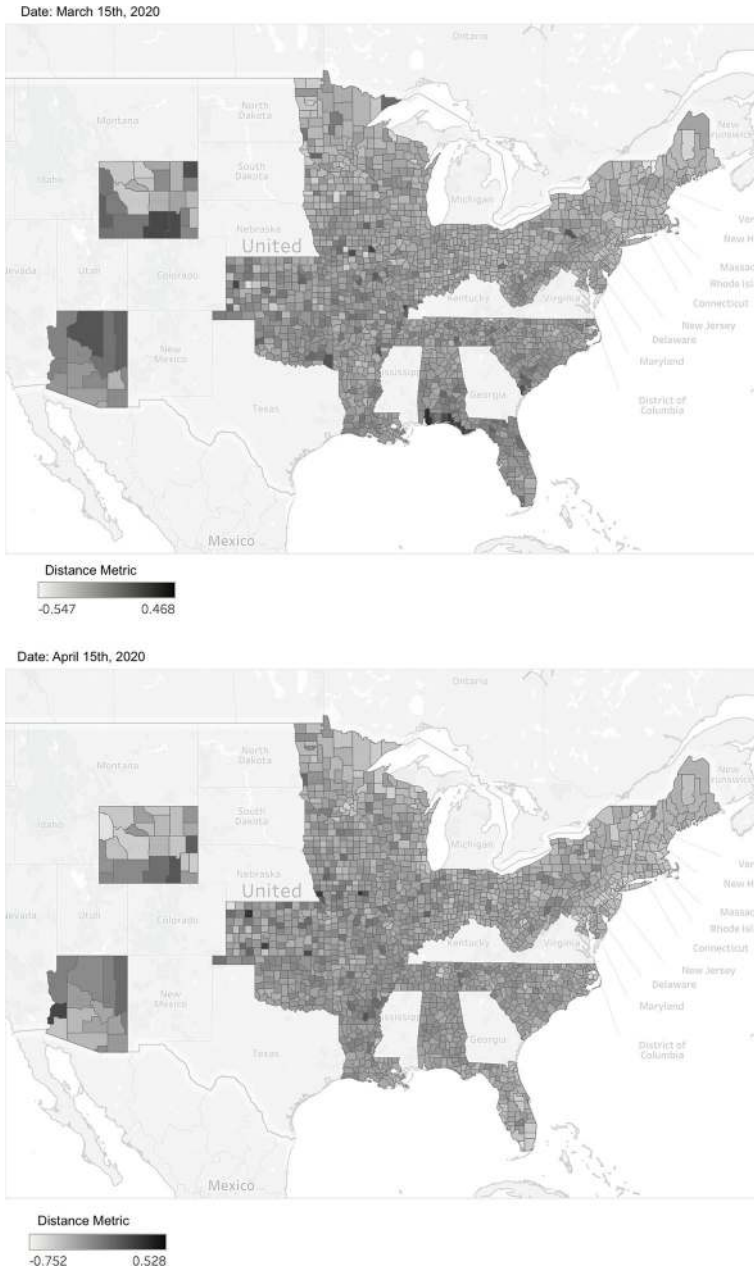Trust in others:
Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?
Neighborhood Fear:
Is there any area right around here–that is, within a mile–where you would be afraid to walk alone at night?
Trust in Institutions:
I am going 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?

Date: March 15th, 2020

Distance Metric

-0.547   0.468

Date: April 15th, 2020

Distance Metric

-0.752   0.528

Fig. 4 Percentage change in average distance traveled on March 15th and April 15th, respectively. Source: Unacast's COVID-19 Toolkit. Note the differential coverage by state of travel distance compared to visitation, which affects the sample size in the different specifications depending on the outcome variable
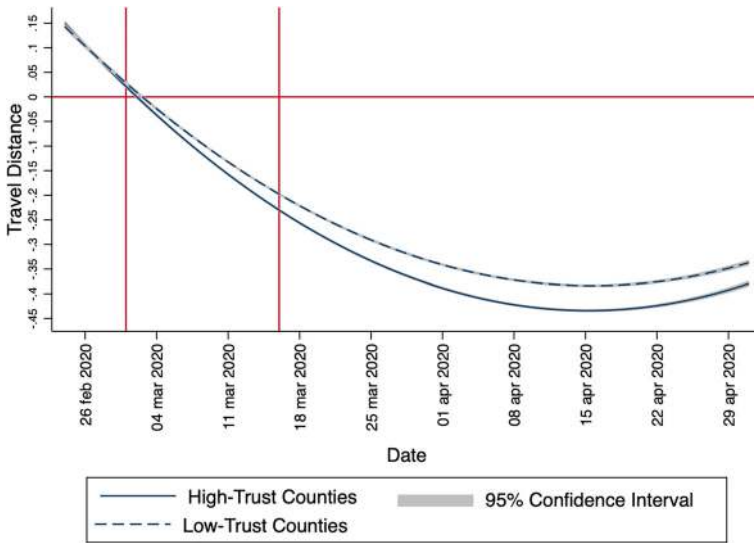
Fig. 5 Polynomial fit of the daily variation in "Travel Distance" across different trust-group counties and its 95% confidence interval. Source: Unacast's COVID-19 Toolkit
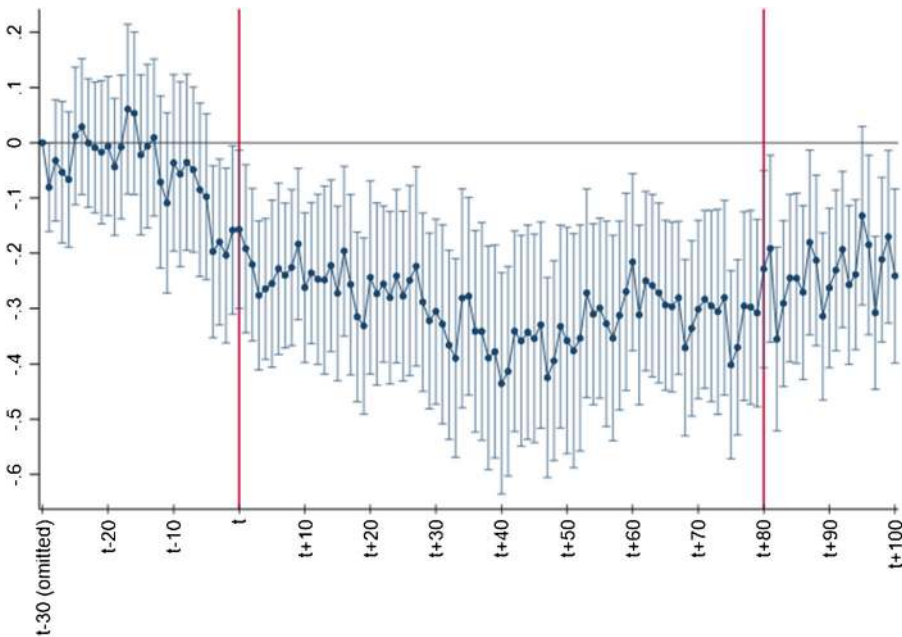
Fig. 6 Leads and lags analysis for distance traveled: We plot leads and lags estimates for the interaction term between trust and stay-at-home order for 30 days pre- and post-implementation. We control for lagged COVID-19-related death rate (deaths by 10,000) and our usual set of fixed effects

Declarations

Conflict of interest The authors declare no competing interests.

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