Civic Capital and Social Distancing during the Covid-19 Pandemic*

John M. Barrios
Washington University St. Louis

Efraim Benmelech
Northwestern University & NBER

Yael V. Hochberg
Rice University & NBER

Paola Sapienza
Northwestern University and NBER

Luigi Zingales
University of Chicago & NBER

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Using mobile phone and survey data, we show that during the early phases of COVID-19, voluntary social distancing was greater in areas with higher civic capital and amongst individuals exhibiting a higher sense of civic duty. This effect is robust to including controls for political ideology, income, age, education, and other local-level characteristics. This result is present for U.S. individuals and U.S. counties as well as European regions. Moreover, we show that after U.S. states began re-opening, high civic capital counties maintained a more sustained level of social distancing, while low civic capital counties did not. Finally, we show that U.S. individuals report a higher tendency to use protective face masks in high civic capital counties. Our evidence points to the importance of considering the level of civic capital in designing public policies not only in response to pandemics, but also more generally.

*Correspondence to: luigi.zingales@chicagobooth.edu, The University of Chicago Booth School of Business, 5807 S Woodlawn Ave, Chicago, IL 60637.

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I. Introduction

In their fight against COVID-19, governments around the world face technological and social constraints. Initially, technological constraints, such as how many tests could be administered per day, were the primary concern. As the fight against Covid-19 has moved from the acute phase to trench warfare, ensuring adequate compliance with public health recommendations has become extremely important for the success of containment strategies until a vaccine is developed and distributed.

Individuals may comply with public health containment measures (such as wearing a mask or maintaining adequate social distance) simply out of fear of contagion. However, such fear is often not enough to obtain the efficient level of precaution, given that an important externality is imposed on others (Callum et al., 2020). For example, in the absence of any punishment, an infected individual derives no personal benefit from complying with public health recommendations, despite the potentially large social benefits. An infected individual will comply only if he cares about the collective's welfare, and if he expects that most other people will also comply (if they do not, his action will have no marginal benefit). Thus, his behavior does not reflect solely the tendency of some people to internalize externalities as a matter of personal conscience, but also their expectation that other people in the community would do so. This combination of "values and beliefs that help a group overcome the free-rider problem in the pursuit of socially valuable activities" is what Guiso et al. (2011) define as civic capital. We use the term civic capital to identify the civic engagement component of "social capital" and to distinguish it from other elements (e.g., the value of networks) embedded in alternative broader definitions.[1] Historically, scholars have measured this civic component by looking at the frequency of voting (Putnam 1993), donating blood (Guiso et al., 2004), donating organs (Guiso et al., 2016), or the propensity to coordinate with other players in experimental games (Herrmann et al., 2008).

In this article, we analyze how differences in civic capital—across individuals, U.S. counties, and European regions—can account for varying degrees of voluntary compliance with public health recommendations—such as social distancing rules—during the early phase of the COVID-19 pandemic, and mask-wearing in the later phases of the pandemic. Our paper adds to the emerging literature on compliance with social distancing instructions during the COVID-19 pandemic (Alcott

[1] The definition of social capital varies in the literature and it is not our intention to review this literature here. To illustrate the range of interpretations, Bourdieu (1986) defines social capital as a resource possessed by an individual, while Putnam (1993) focuses more (but not entirely) on "sturdy norms of generalized reciprocity" (Putnam, 1993b, pp. 36-37), which captures the civic dimension.

et al., 2020; Barrios and Hochberg, 2020, Dasgupta et al., 2020, Wright et al., 2020). Our paper has the merit of testing the role that civic capital plays in a new situation, completely different than the ones in which it was initially elaborated. It thus represents a powerful out-of-sample test of civic capital's predictive power as a concept, and more generally illustrates the important potential role of civic capital in shaping public policy.

Using cell phone data and novel survey data, we find that U.S. counties, U.S. individuals, and European regions with more civic capital socially distance more during the early phase of the epidemic and are more likely to wear masks during its later stages. This is true even after controlling for ideology (Alcott et al., 2020; Barrios and Hochberg, 2020), income as a proxy for the fraction of essential workers (Dasgupta et al., 2020, Wright et al., 2020), as well as age, education, and other local-level characteristics.

Several contemporaneous papers exhibit similar themes, with complementary results. In the United States, Ding et al. (2020) show that social distancing increases more in counties where individuals historically demonstrated greater willingness to incur individual costs to contribute to social objectives. In Europe, Bargain and Aminjonov (2020) find that regions that trust the government more comply more. Durante et al. (2020) show that mobility declined more in Italian provinces with higher civic capital, both before and after a mandatory national lockdown. Our results not only encapsulate all of this evidence, but they also demonstrate the robustness of the findings across different environments. Moreover, our study adds unique survey evidence, in which we correlate individual civicness with social distancing behavior, in order to rule out the hypothesis that the results are driven by unobserved geographic heterogeneity that correlates with the level of civic capital in the area.

II. Data

Social Distancing Measures

We use two different sources of data to measure people's mobility at the county level. Our first two measures, used for our U.S. analysis, come from Unacast. This company combines granular location data from tens of millions of anonymous mobile phones and their interactions with each other each day. These interactions are then extrapolated to the population level. The Unacast data span the period of February 24th to April 9th, 2020. They provide us with two social distancing behavior measures: 1) the change in average daily distance traveled and 2) the change in visits to non-essential retail and services.[2] The changes are calculated relative to a baseline measure, which is the average for the same day of the week and county for the pre-COVID-19 period (January 1, 2020, to March 8th, 2020). [3] By always comparing Saturdays to Saturdays, Tuesdays to Tuesdays, and so forth, the social distancing measures capture deviations from the regular visitation rhythm of the 7-day week during the pandemic. Appendix Figure A1 (Panel A) maps the average daily level of the Unacast mobility measures geospatially. On the left, we plot the daily average of the percentage change in distance traveled in the county relative to the pre-COVID period, while on the right, we plot the daily average of the percentage change in the number of visits to non-essential businesses in the county relative to the pre-COVID-period.

Our second source of social distancing data, used for our European analysis, is from the Google COVID-19 Community Mobility Report, which aggregates location data from users who have opted-in to Location History for their Google account. Similar to the Unacast measures, the Google data are measured as changes vis-à-vis a baseline: in this case, the median value for the corresponding day of the week during the period of Jan 3–Feb 6, 2020. The data contain information on community mobility based on the type of location: Retail and Recreation, Grocery and Pharmacy, Parks, Transit stations, Workplaces, and Residential. Residential and Parks have trends opposite to all the other measures, since people are more likely to spend time in parks and be in their residence when a social distancing norm is in place. We use two of these community mobility measures: "Retail and Recreation" and "Residential." For any given day, Retail and Recreation is defined as the percent change between that day and the baseline in time cellular phones spent near places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. In contrast, the Residential measure is defined as the percent change vis-à-vis the baseline in individuals' time at their place of residence. Appendix Figure A1 (Panel B) maps the two Google mobility-based measures used geospatially. While the Google measures are available for both the U.S. and Europe, in the U.S., Google's county coverage is more limited than Unacast. For this reason, in the U.S., we use Unacast for the main specification and show the robustness of our inferences to the use of Google measures in the Appendix.

Civic Capital Measures

[2] In the case of non-essential retail and services, the company uses the guidelines issued by various state governments and policymakers to categorize venues into essential vs. non-essential, with essential locations including venues such as food stores, pet stores, and pharmacies.
[3] The pre-COVID baseline period is defined as January 1, 2020, to March 8th, 2020.

For our U.S. analysis, we use three different measures of civic capital. The first is voter participation, calculated using data from the 2004 to 2016 presidential elections, obtained from the MIT Election Data Science and Lab (MEDSL). Voting is the ultimate example of an activity that is privately costly but socially useful. With respect to other measures, it has the advantage of being observed with precision. For each county and election, we calculate voter participation as the number of votes cast divided by the number of voting-age individuals in the county. We then take the average across the five elections to generate the Civic Capital measure. Appendix Figure A2 maps the measure geospatially across the U.S.

The second measure, used to demonstrate robustness, is a social capital composite index developed by the Social Capital Project from the U.S. Joint Economic Committee. The index is constructed from four sub-indexes at the county level: (1) a family Unity sub-index; (2) a Community health sub-index; (3) an institutional health sub-index; (4) and a collective efficacy sub-index.[4] We denote this measure Social Capital Measure 1. This measure has some limitations, as it does not fully reflect the components of civicness included in the definition of social capital.

Given these limitations, we employ a third measure of social capital, the composite index from Rupasingha et al. (2006). This measure uses a principal component analysis to include four social capital factors: (1) The aggregate of various civic, religious, business, labor, political associations in the county divided by population per 1,000; (2) Voter turnout in the 2012 election; (3) Census response rate; (4) Number of non-profit organizations excluding those with an international approach. The four factors are standardized to have a mean of zero and a standard deviation of one, and the first principal component is considered as the index of social capital. We denote this measure Social Capital Measure 2.

For our European analysis, we perform an analysis within countries that allows us to absorb country-level characteristics using country fixed effects. There are very limited civic capital measures at the regional level within a country that are available for a large enough set of countries. The most comprehensive option is the European Social Value Survey (ESS), which contains data at the regional level for European countries. The ESS is a biennial cross-national survey of attitudes and behavior established in 2001 and conducted in 41 European countries over time. The ESS uses cross-sectional probability samples, representing all persons aged 15 and over residing within private households in

[4] The data is downloaded from https://www.jec.senate.gov/public/_cache/files/e86f09f7-522a-469a-aa89-1e6d7c75628c/1-18-geography-of-social-capital.pdf.

each country. Rather than using voting behavior, which is not appropriate in cross country regressions, we use a measure of generalized trust, averaging all ESS surveys responses to the question, "generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people? Please tell me on a score of 0 to 10, where 0 means you can't be too careful, and 10 means that most people can be trusted." Since high civic capital individuals can be trusted more not to cheat, civic capital and generalized trust are linked theoretically and empirically. This is certainly true at the aggregate level (Putnam, 1993), but also at the personal level (to the extent people project their own behavior onto others), as observed in the literature on trust (Glaeser et al., 2000). Empirically, in the European Social Value Survey, the correlation between voting and generalized trust in others at the individual level is 48%.[5] This measure of cultural attitudes is commonly used to measure subjective social capital (Alesina and Giuliano, 2015).

The ESS contains information on regions using the NUTS system, the Nomenclature of Territorial Units for Statistics, a standardized system for referencing subnational regions within European countries created by the European Union. NUTS is a hierarchical system, with three levels of NUTS defined. Each E.U. Member State is subdivided into several regions at the NUTS 1 level. Each of these regions is then subdivided into subregions at NUTS level 2, and these, in turn, into lower regions at NUTS level 3. To generate a regional measure of civic capital, we face a trade-off. The finer the regional classification, the closer is the match with the mobility data, but the coarser are the civicness measures, as they average fewer responses in each given area. For that reason, we start with NUTS1 classifications for larger macro-regions (92 sub-regions corresponding to 82 unique regions in ESS). We then do additional robustness tests with NUTS2 regions (244 sub-regions corresponding to 114 unique regions in ESS), knowing that our civic capital measure may become noisier in the process. Because France has changed its definition of NUTS regions over time, we exclude France in our main analysis. In a supplementary analysis, we use the average responses from just the last survey administered, allowing us to include France.

Control Variables

To account for COVID exposure risk in our U.S. analysis, we control for the log number of new COVID-19 cases and deaths measured each day in the county. The number of confirmed COVID-19

[5] This result is obtained controlling for country fixed effects. In cross-country studies, it is impossible to use voting attitudes as measures of civic capital because voting behavior across countries is affected by other country level characteristics which can correlate with COVID restrictions. For example, voting in certain countries is mandated by the law.

cases and deaths in a county are obtained from the COVID Tracking Project. The Project collects data on cases and deaths from COVID-19 from state/district/territory public health authorities (or, occasionally, from trusted news reporting, official press conferences, and social media updates from state public health authorities or governors). The data includes the location and date of each case and death, allowing us to geo-assign them to a county-day. To control for differential effects driven by state mandates, we code the information on when each state government-issued "Stay Home" (shelter-in-place) directive. Data is obtained from FINRA (https://www.finra.org/rules-guidance/key-topics/covid-19/shelter-in-place). Data is through April 2, 2020. Appendix Figure A3 maps these mandates geospatially across the U.S. Finally, we include the following socio-economic variables at the county level: population, population density, per capita income, percent of the population older than 60, percent of the population with college, and the percentage of Trump votes in the county obtained in the 2016 election.

For our European analysis, similar to our U.S. analysis, we control for several characteristics at the country and NUTS1 level. To account for different risk factors, we control for exposure to COVID-19 in the country, including the log number of new COVID-19 deaths per million population at the country level measured on each preceding day (source: Johns Hopkins CSSE data https://coronavirus.jhu.edu). At the NUTS1 level, we also control for (log) population density (source: Eurostat) and a measure of political leaning based on the regional average of the answer to ESS question: "In politics people sometimes talk of 'left' and 'right.' Using this card, where would you place yourself on this scale, where 0 means the left and 10 means the right?" Finally, we control for the fraction of the population above 60 and the fraction of the population with a college degree at the NUTS1 level.

Individual-level Survey Data

We augment our analysis with survey level data, where we ask respondents about their specific social distancing behavior and how much they trust people in general. This information comes from a special edition of the Financial Trust Index, a survey of a representative sample of Americans used to study the level of trust in institutions. This wave of the survey was conducted for the Financial Trust Index via telephone by SSRS on April 6th, 2020 – April 12th, 2020, among U.S. adults. A total of 980 interviews were conducted, with a margin of error for total respondents of +/-3.43% at the 95% confidence level. The survey collects information on demographics and various other variables (http://www.financialtrustindex.org/). For the purpose of our study, we focus on the answer to the question “About how many people were you in close physical contact with socially in the past seven days, not including people that live with you? This includes the number of family members, friends, people at religious services, and people at other social gatherings you saw in person. (IF NECESSARY: Please do not include those you saw for work-related reasons.)” As a measure of civic capital, we use a measure of generalized trust, which is the answer to the question “On a scale from 1 to 5 where 1 means "I do not trust them at all” and 5 means “I trust them completely,” Can you please tell me how much do you trust other people?” As proxies for political ideology, we use a measure of trust in the U.S. government (computed in a similar way) and a measure of party leaning: “As of today do you lean more to the Republican Party or more to the Democratic Party?” The survey also contains demographic information (age and education) and a measure of the fear of the virus, which takes higher values if the individual reports being fearful of falling ill from the coronavirus.

III. Empirical Results

U.S. County-level Analysis

We begin our analysis by examining the relationship between social distancing behavior and civic capital across U.S. counties. To measure social distancing behavior (SDB), we initially rely on Unacast mobility measures. More precisely, for any given day, we use the change in the daily distance traveled (and in the number of visits to non-essential retail and services) between that day and the pre-COVID baseline. Exhibit 1, Panel A, presents binscatters of the measures of SDB against the county voter participation rate. The left graph uses the daily distance traveled measure, while the right graph uses the number of visits to non-essential businesses. The changes are measured from the baseline period to April 9th. Each plot controls for log 1+ number of new confirmed cases that day, log 1+ number of COVID-19 deaths that day (as proxies for the severity of the pandemic in the area), population density, income per capita, population, and day of the week.

As Exhibit 1, Panel A, shows, higher civic capital counties exhibit more SDB.[6] We investigate the relation between SDB and civic capital formally by estimating the following linear specification:

$$(1)\ Social\ Distancing\ Behavior_{ct} = \beta_t High\ Civic\ Capital_c * Day_t + \alpha\ Health\ Controls_{c,t} + County_{FE} + StateXDay_{FE} + \varepsilon_{c,t}$$

[6] Appendix Figure A4 repeats this exercise for the SDB measures derived from the Google mobility data in the US.

where β_t are time-varying coefficients on High Civic Capital, $Health\ Controls_{c,t}$ is a vector of controls for exposure to COVID-19 in the county, including the log number of new COVID-19 cases and deaths measured on each county day. $High\ Civic\ Capital_c$ is defined as an indicator variable that takes on a value of one if the county is in the top quartile of voter participation and zero otherwise. The specification includes county fixed effects to capture local economics and demographics at the county level and State by Day fixed effects to capture time variation in compliance measures at the state level through the sample period.

We present the results of the estimation graphically in Exhibit 1, Panel B, which plots the β_t from estimating specification (1). The left panel plots the estimates obtained using the percentage change in distance traveled as the dependent variable. The right panel graphs the estimates obtained using the percentage change in the number of visits to non-essential businesses as the dependent variable. We plot the 95 percent confidence intervals for each of the estimates, obtained with standard errors clustered at the county level. Both plots exhibit a larger drop in mobility in high civic-capital counties starting around March 10th, 2020: while overall mobility dropped, it dropped more in high civic capital counties (~5% lower mobility). The graphs also show sharp differences on weekends, as to be expected since people were traveling less during the weekend in a pre-COVID-19 world.

We corroborate our Unacast inferences in Appendix Figure A5 with our two Google Mobility SDB measures. Google Mobility data provides information about the presence of cell phones in Retail & Recreation areas and in Residential areas. We expect the Retail & Recreation measure to go down more vis-à-vis a pre-COVID baseline in high civic capital counties after the pandemic outbreak, while we expect the Residential measure to go up more in high civic capital counties. This is indeed what we observe. Starting around March 10th 2020, the percent changes in mobility around Retail and Recreation (blue line) show a much steeper decline in counties with higher civic capital. In contrast, the red line in Appendix Figure A5 shows that people spend more time in proximity to their residences in high civic capital counties. The graph of presence in residential areas exhibits sharp drops during the weekends. This is not surprising since the difference in time spent at home before and after the pandemic should be smaller during the weekends than during the week. Consequently, even the difference between high civic capital areas and the rest is compressed. Notice, however, that the difference is significantly positive even during the weekends.

In Exhibit 2 Panel A, we estimate a more explicit multivariate model linking the change in mobility between any given day and the pre-COVID baseline to voter participation in presidential elections. The specifications include Day X State fixed effects, log population, log population density, per capita income, Trump 2016 vote share, log(1+number of new COVID-19 cases), log (1+number of new COVID-19 deaths), percentage of people over 60, and percentage of people with at least two years of college. The table reports the estimate for two social distancing measures: change in distance traveled (columns 1-7) and change in the number of non-essentials visits (columns 8-14). The control variables replace the county fixed effect in (1). Substituting these controls does not change the civic capital coefficient's economic magnitude, even though some of these variables may have independent effects on these dependent variables. For example, in areas with higher education, more people can work from home and elderly people are more likely to be retired and not be essential workers. The result further confirms that social distancing is substantially higher in areas with higher civic capital than other areas, even once we account for other characteristics, such as political orientation.[7]

One potential threat to our previous inferences is that social distance behavior may be driven not by voluntary compliance, but by county-specific mandatory orders to close businesses or "stay home." If there are stricter social distancing orders in counties with high civic capital, our civic capital variable may capture local government mandates rather than voluntary behavior. To ease these concerns, in Exhibit 1 Panel A, we controlled for State X Day fixed effects. Yet, these controls do not absorb further possible variation at the county level.

To address this, In Exhibit 2, Panel B, we insert county fixed effects to address these concerns more directly. Doing so prevents us from estimating the direct effect of civic capital—which is measured at the county level—on SDB in general. We can, however, estimate the differential response of High Civic Capital counties to state-level rules and to the national stay at home recommendation (Coronavirus Guideline for America) issued by the White House on March 16[th]. To this purpose, we estimate the following regression:

$$
\begin{aligned}
(2)\ \ & Social\ Distancing\ Behavior_{c.t} \\
&= \beta_1 Post\ State\ Mandating\ Stay\ Home_{s,t} \\
&+ \beta_2 Post\ State\ Mandating\ Stay\ Home_{st} * High\ Civic\ Capital_c \\
&+ \ \beta_3 Post\ National\ Guidelines_t * High\ Civic\ Capital_c \\
&+ \ \alpha\ Health\ Controls_{c,t} + County_{FE} + \ Day_{FE} + \varepsilon_{c,t}
\end{aligned}
$$

[7] Appendix Tables A1, A2 and A3 replicate this analysis using: (1) the alternative Google Mobility data (Table A1), and (2) alternative measures of civic capital (Tables A2, A3).

where $Health\ Controls_{c,t}$ is a vector of controls for exposure to COVID-19 in the county (including the log number of new COVID-19 cases and deaths measured on each county day) and $Post\ State\ Mandating\ Stay\ Home_{s,t}$ is an indicator variable that is set to one in the state-days after a state implements a mandatory stay at home ordinance. $Post\ National\ Guidelines_t$ is an indicator equal to one for the days after March 16th. The direct effect of this variable is subsumed by the inclusion of day fixed effects in the specifications.

We interact both the Post State Stay Home Mandate and the Post National Guideline with an indicator variable for high civic capital counties ($High\ Civic\ Capital_c$), allowing us to see the differential response in SDB for these counties relative to others.[8] This allows us to look directly at the differential effect of the national-level guidelines on compliance ($Post\ National\ Guidelines_t * High\ Civic\ Capital_c$). The specifications also include county fixed effects and day fixed effects to capture time-invariant county characteristics (such as the county's political orientation) and time-varying changes in responses to the pandemic.

When we use changes in distance traveled as our dependent variable, both the coefficient on $Post\ State\ Mandating\ Stay\ Home_{s,t}$ (-0.018) and the coefficient on the interaction between this variable and the indicator for High Civic Capital counties (-0.014), are negative and statistically significant (column (1)). Put differently, when a state issues an order to stay home, all counties reduce the distance traveled relative to the pre-COVID period (by approximately 2%), but high civic capital counties even more so (an additional 1.3%). Even the interaction coefficient between the National Guidelines and the high civic-capital counties is negative and statistically significant. In fact, the coefficient is almost three times that of the interaction of the high civic-capital dummy with the Post Stay-Home mandate, implying that high civic capital counties respond more to the national guidelines as well. To put the magnitude of the association in context, on top of the overall 15% reduction in distance traveled in the sample due to COVID, the overall decrease in distance traveled for counties in the bottom three quartiles of civic capital when stay at home mandates are issued is an incremental 2%. In comparison, in high civic capital counties the overall incremental decrease is approximately 7%. The results' pattern is identical when we use changes in the number of visits to non-essential businesses as the dependent variable (column 3).

[8] Here we again define High Civic Capital$_c$ as an indicator variable equal to one if the county is in the highest quarter of voter participation and zero otherwise.

While county fixed effects absorb all differences in political leaning, these differences might still impact mandatory rules' response (e.g. Barrios and Hochberg, 2020). For this reason, in columns (2) and (4), we add an interaction between $Post\ State\ Mandating\ Stay\ Home_{s,t}$ and a county's share of votes for President Donald J. Trump in the 2016 presidential election. Similarly, we interact Trump's vote share with the $Post\ National\ Guidelines_t$ dummy. Both these interactions exhibit a positive coefficient (i.e., compliance is lower in counties where Trump obtained a higher share of votes). When the change in distance traveled is used as the dependent variable, these coefficients are not statistically different from zero at conventional levels. In contrast, when the dependent variable is a change in the number of visits to non-essential businesses, the coefficients are statistically significant. Most importantly, both the economic magnitude and the statistical significance of the interactions between the introduction of state and national rules and the High Civic Capital dummy are unchanged by introducing the interactions with Trump's vote share. This result confirms that the civic capital explanation of voluntary compliance is orthogonal to the "political affiliation" explanation. It also suggests that Civic Capital acts in two ways: it increases voluntary social distancing and compliance with government rules when government rules are welfare-enhancing.[9]

In the Appendix, we repeat this analysis using the alternative Google measures (Appendix Table A4) and alternative measures of civic capital (Appendix Table A5). Our results remain robust to these alternative specifications.

Robustness

We can further confirm the predictive ability of civic capital for SDB by looking at the changes in mobility around the time U.S. states began to loosen their restrictions. The figure plots the changes in event time, where time zero is the date in which a state loosens restrictions. Each data point is obtained by regressing the percent change in the mobility measure between that specific event day and the baseline level, set at 14 days before the state lifts the restrictions. The specification includes calendar day fixed effects and controls for COVID-19 cases, population density, Trump 2016 voter share, and per capita income in the counties.

Exhibit 3 Panel A plots these changes in the Google measure of mobility near Retail & Recreation for high civic capital counties (in blue) and low civic capital counties (in red) around a state's opening

[9] Our results are moot on whether high civic capital areas will comply more or less with hideous government rules (like racial segregation).

date. As before, the high civic capital counties are defined as those in the top quartile of voter participation, and the low civic capital ones are those in the bottom quartile.

As Panel A of the figure shows, even as states begin loosening restrictions, social distancing compliance remained steady in high civic capital counties (blue line)—even when the law did not mandate it. By contrast, in low civil capital counties (red line), mobility around Retail & Recreation increased steadily even before the loosening of restrictions and continued to increase afterward. In Appendix Figure A6, we perform the same analysis for mobility near residences, with symmetric results. We also perform the same analysis with Unacast data, with similar results.

All the compliance measures we used thus far relate to social distancing. For additional robustness, we present evidence on the effects of civic capital on mask usage. The New York Times published a large (250,000 people) survey on the self-reported use of masks administered between July 2nd and July 14th by an independent firm (Dynata). In Exhibit 3, Panels B and C, as a dependent variable, we use the county-level answers to this survey. Panel B reports the percentage of survey respondents that use a mask: the percentage that always or frequently use a mask (left panel) and the percentage that never use a mask (right panel). These measures are plotted against our civic capital measure (the county voter participation rate). Each plot controls for population density, income per capita, population, Trump 2016 vote share, the log 1+ number of confirmed cases at the time of the survey, log 1+ number of COVID-19 deaths, and state fixed effects.

As can be seen from Panel B, in high civic capital counties, people are more likely to answer that they always wear a mask, and are less likely to answer that they never wear a mask. Panel C shows this more formally. It presents estimates from multi-variable regression where we regress the percentage of respondents who say "always use a mask" or "never use a mask" at the county level on our measure of civic capital (average voter participation rate). Each of the specifications includes controls for county characteristics that may affect mask usage: log population, log population density, per capita income, and the 2016 presidential election vote share for Donald J. Trump. We also include controls for COVID exposure in the county, by including the log of 1+ number of COVID-19 cases and log 1+ number of COVID-19 deaths in the county. The inferences remain the same, with the estimates demonstrating a positive association between mask usage and civic capital.

Individual-level Survey Evidence

While our county-based regressions account for most of the variation (R^2 between 87% and 95%), it is still possible, at least theoretically, that there could be some unobserved variable at the county level that is correlated with High Civic Capital, and which drives our results. For example, it is possible that more restrictive stay at home mandates are issued in counties with higher civic capital or that high civic capital counties are counties with a smaller proportion of essential workers. To address this potential limitation, in Exhibit 4, we examine individual-level survey data. Since data on individual cell phones is not available, we rely on a self-reported social interaction measure obtained in the survey. The question we use is, "how many people were you in close physical contact with socially in the past seven days, not including people that live with you?" The possible answers were "None" (35% of the respondents), "Less than 3" (26%), "3 to 5" (19%), "6 to 10" (8%), and "more than 10" (12%).

The survey does not contain questions on civic capital directly. However, it does contain a question on generalized trust in others: "On a scale from 1 to 5 where 1 means 'I do not trust them at all' and 5 means 'I trust them completely,' Can you please tell me how much do you trust other people in general?" 14% choose 1, 16% 2, 41% 3, 20% 4 and 9% 5. The survey also includes a question about trust in the government (where 30% respond either 4 or 5) and a question about political leaning (where 30% lean Republican, 41% Democrat, and 29% neither), which we also employ in the analysis.

Exhibit 4 reports the estimates from an ordered probit, where our dependent variable is the response to the question on the number of people outside your household you were in contact with during the previous week. We report marginal effects computed at the mean value of the covariates. In column (1), our explanatory variables are the degree of trust in others (proxy for civic capital) and the degree of trust in government. Consistent with our county-level results, more civic people see fewer people outside of their family, i.e., they self-distance more. An increase from the median level of trust (category 2) to a complete level of trust (category 5) reduces the probability of interacting with 10 people or more by 6 percentage points (60% of the sample probability). In contrast, people who trust the government more tend to socialize *more* with people outside their family. This effect, however, is a proxy for political leaning. When we add a dummy equal to 1 if a respondent declares that they lean Republican (column 2), the effect of trust in government disappears, while the effect of trust in others remains virtually unchanged. As was the case for the county data, there seem to be two sources of variation in SDB: one related to political affiliation, and the other to civic capital, with the two orthogonal to each other. These results are unchanged when we control for fear of getting killed by the virus as self-reported in the survey, and for other regional conditions (number of COVID-19 cases in the country, population density, income per capita, age, degree of education), as we report in columns (3) to (6). Thus, the individual survey results confirm the cell-phone based results at the county level.

European Analysis

Is the effect of civic capital just a U.S. phenomenon, or does it apply to other countries as well? To answer this question, we turn next to European data. Because national guidelines and shopping habits differ widely across countries, making a comparison across countries is difficult. We therefore conduct a within-country analysis, much as we have done for the U.S. above. To do so, we cannot use a national measure of civic capital similar to what is done in Coen et al. (2019). Rather, we need sub-national measures of civic capital. The European Social Survey (ESS) provides such a measure at the sub-regional level. For the 41 countries participating in the survey, the ESS asks the question, "generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people? Please tell me on a score of 0 to 10, where 0 means you can't be too careful, and 10 means that most people can be trusted."

The ESS countries are divided into sub-regions with different levels of coarseness. The NUTS 1 classification includes 82 sub-regions, while NUTS 2 includes 114. Since the number of observations per country remains the same, there is a trade-off between going deeper into the sub-region classification and more noisy civic capital measures. This noise is due to the sparsity of respondents as we go deeper into sub-region classifications. In Exhibit 5, Panel A and B, we use ESS data at the NUTS 1 level, utilizing the last eight waves of the ESS. Due to a change in the NUTS classification system for France, we can only utilize the last wave of the ESS survey for France. (In Appendix Table A6, we present the robustness to using the more noisy NUTS2 level classifications.) To measure SDB, we use the Google mobility data.

Exhibit 5 Panel A plots the estimated coefficient β_t of a specification similar to (1) based on the European data, where the dependent variables are (1) the changes in time cell phones spent around Retail and Recreation locations (blue line) in any given day vis-à-vis the pre-COVID baseline; and (2) the similar change for time cell phones spent around Residences (red line). High Civic Capital areas are defined based on the average level of generalized trust of an area vis-à-vis the national average (top quartile in the country). As expected, and consistent with our U.S. county and individual-level findings, mobility around retail and recreation locations declines after the beginning of March 2020, and more so in high civic capital areas. In contrast, the mobility in the residential areas goes up, and, similarly, more so in high civic capital areas.

In Panel B, we report the estimates from richer multivariate regressions in the spirit of the models estimated in Exhibit 2 Panel A. For each of the dependent variables, the first specification (columns (1) and (6) contains our measure of civic capital (average trust in the region), the log number of COVID-19 deaths per million inhabitants (as a proxy for the severity of the pandemic in the area), and population density. We also include country fixed effects and calendar-day fixed effects. Even after controlling for the severity of the disease in the region and population density, we observe that more civic areas experience a steeper decline in mobility around retailing and a steeper rise in mobility in residential areas. A one standard deviation increase in the average trust is associated with a 0.1 standard deviation change in mobility near retailing. This effect, which is statistically significant at the conventional level, is unchanged in columns (2) and (7) where we control for the average share of votes to right-wing parties (as defined by the ESS). The same is true in columns (3) and (8), where we control for the percentage of people in the region trusting the politician more than the country average, as in Bargain and Aminjonov (2020). While the generalized trust coefficient is slightly reduced, it remains of similar magnitude and statistically different from zero at the conventional level. Consistent with our U.S. survey data results, ‘trust in others’ and ‘trust in politicians’ capture two separate effects.

When we also control for the fraction of population over 60 (columns 4 and 9), the effect of generalized trust is unchanged. When we control for education level (columns 5 and 10), the effect of generalized trust is unchanged when we use the changes in mobility around Retail and Recreation as the dependent variable. In contrast, the coefficient drops by more than two thirds and loses statistical significance when we use mobility around Residences as the dependent variable. This is hardly surprising, since the decision to stay home is greatly affected by the type of job a person does, which is highly correlated with education. This effect appears to dominate the effect of generalized trust.

Overall, our findings show that civic capital is significantly associated with more voluntary social distancing behavior and more compliance to social distancing legal norms across individuals, European regions, and U.S. counties.

IV. Discussion and Conclusion

Starting with Thaler and Sunstein (2008), a growing literature examines how psychological insights can be used to improve public policy. For example, Chetty (2015) proposes incorporating behavioral economics into public policy to improve policy decisions. Yet there is no similar literature focusing on how sociological insights can improve public policy, despite the fact that such insights might be very important. Japan was able to contain COVID-19 with voluntary social distancing and without either large-scale testing or rigid lockdowns. As of September 2020, Spain is struggling with a massive second wave, despite a period of rigid lockdown. Sociological insights may be useful in explaining such discrepancies. Our paper shows that the concept of civic capital can be useful in understanding differences in voluntary compliance and behavioral responses to government guidelines during the COVID-19 pandemic. Areas with high civic capital follow social distancing guidelines more, not only across U.S. counties, but also across regions of Europe, and even across individuals.

While helpful in designing a response to COVID-19, our results have implications beyond pandemics. It is almost tautological that when people internalize the externalities they generate more, the provision of public goods can be provided at a lower cost. For example, a waste recycling program is cheaper when people voluntarily sort their garbage, regardless of the government's penalties. Our results suggest that the concept of civic capital is a useful way to measure these prosocial attitudes. Thus, they confirm the idea that a region's civic capital is a source of collective capital, enabling societies to improve policy interventions. Interestingly, successful policy interventions can, in turn, increase a region's civic capital (Guiso et al., 2016). This creates the possibility of a virtuous cycle. To what extent this virtuous cycle can explain persistent economic development differences is an important question for future research.

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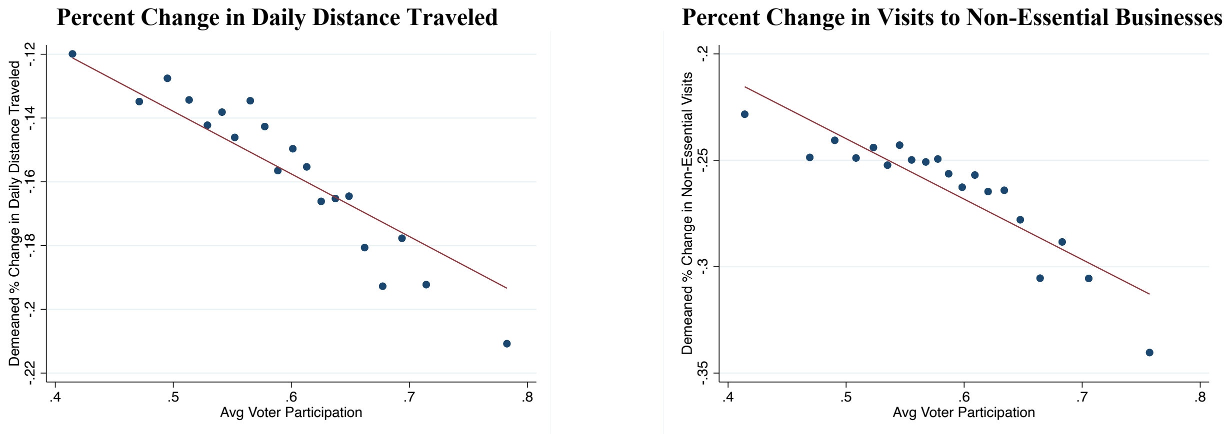
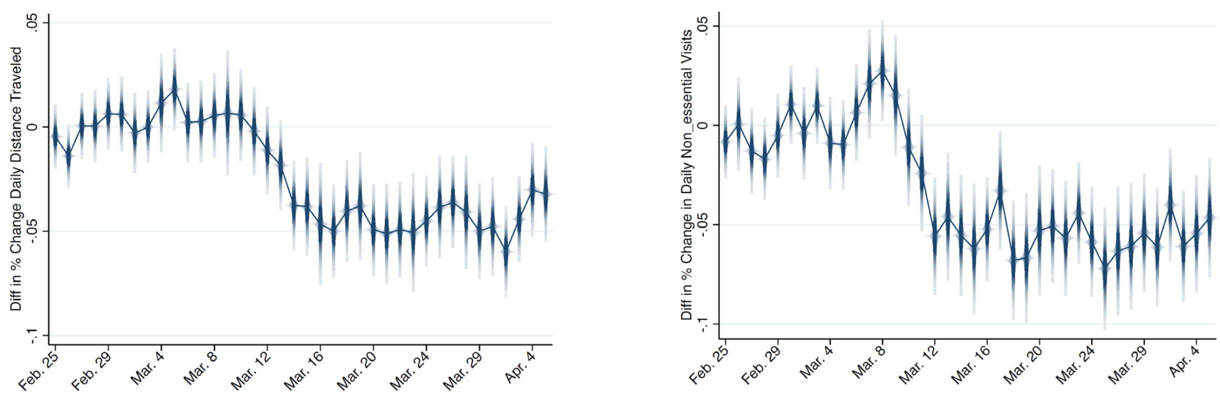
Exhibit 1. Civic Capital and Mobility

Panel A: Bin-scatters of Social Distancing versus Civic Capital



This panel plots our two measures of Social Distancing Behavior (SDB) against the county voter participation rate. As a measure of SDB, the left graph uses the percentage change in daily distance traveled between April 9, 2020 and the pre-COVID baseline, as estimated by Unacast using cellular phone data. The right graph uses instead the percent change in visits to non-essential businesses during the same period. Each of these measures has been demeaned. Each plot controls for log 1+ number of new confirmed cases that day, log 1+ number of COVID-19 deaths that day, population density, and income per capita, population.

Panel B: Social Distancing Behavior and High Civic Capital (U.S.)



The panel plots the differential changes in mobility (the difference in Social Distancing Behavior (SDB)) between High Voter Participation counties and all other counties by calendar time (day). SDB is measured as percentage changes in distance traveled daily (left panel) and in number of visits to non-essential businesses (right panel). Each day the change is computed vis-à-vis the pre-COVID baseline for the same day of the week, as estimated by Unacast. The plotted estimates are obtained by regressing these changes on the interaction between a High Voter Participation county-dummy and the day indicator. Thus, they should be interpreted as the difference between High Voter Participation counties and all others. The specification includes county fixed effects, state by day fixed effects, and controls for COVID-19 cases and deaths. Each of the estimates includes 95 percent confidence intervals. Standard errors are clustered at the county level. The lower the coefficient, the higher the social distancing compliance in the high vote participation counties (Q4) vs. the counties in the bottom three quartiles of voter participation. The graph shows sharp differences on weekends.

Exhibit 2:

Panel A: Civic Capital and Social Distancing Behavior (U.S.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES					Chg. Dist				
Voter Participation	-0.138***	-0.133***	-0.242***	-0.233***	-0.217***	-0.218***	-0.183***	-0.152***	-0.152***
	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Trump Vote Share		0.091***	0.026**	0.022	0.011	0.009	0.017	0.010	0.010
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lop Population			-0.014***	-0.012***	0.005	0.005	0.002	0.006**	0.006**
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Income Per Cap				-0.000**	-0.000**	-0.000**	-0.000**	-0.000	-0.000
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pop Density					-0.018***	-0.018***	-0.019***	-0.018***	-0.018***
					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Perc of Pop at Least Some College						0.013	0.039	0.026	0.026
						(0.04)	(0.04)	(0.04)	(0.04)
Per of Pop Above 60							-0.304***	-0.327***	-0.327***
							(0.07)	(0.07)	(0.07)
Log(New COVID Cases +1)								-0.024***	-0.024***
								(0.00)	(0.00)
Log (New Death +1)									0.003
									(0.00)
Observations	101,252	101,252	97,994	97,994	97,994	97,994	97,994	97,910	97,901
Adjusted R-squared	0.646	0.649	0.658	0.658	0.660	0.660	0.661	0.665	0.665
DayXState FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
VARIABLES					Chg. NE Visits				
Voter Participation	-0.270***	-0.149***	-0.116***	-0.121***	-0.101***	-0.102***	-0.148***	-0.117***	-0.116***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Trump Vote Share		0.330***	0.173***	0.179***	0.167***	0.163***	0.152***	0.144***	0.144***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Lop Population			-0.038***	-0.044***	-0.032***	-0.032***	-0.029***	-0.023***	-0.023***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Income Per Cap				0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pop Density					-0.014***	-0.014***	-0.013***	-0.013***	-0.013***
					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Perc of Pop at Least Some College						0.041	0.007	-0.017	-0.017
						(0.06)	(0.06)	(0.06)	(0.06)
Per of Pop Above 60							0.371***	0.341***	0.340***
							(0.11)	(0.11)	(0.11)
Log(New COVID Cases +1)								-0.024***	-0.024***
								(0.00)	(0.00)
Log (New Death +1)									0.002
									(0.00)
Observations	64,722	64,722	62,033	62,033	62,033	62,033	62,033	61,960	61,951
Adjusted R-squared	0.713	0.740	0.759	0.760	0.761	0.761	0.762	0.765	0.765
DayXState FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel A provides a multivariate analysis of social distancing behavior at the county level. The sample period is February 25th to April 9. For each day in that sample period, the dependent variable is the percentage change in distance traveled (column 1-7) and number of non-essential visits (columns 8-15) between that day and a pre-COVID baseline for the same day of the week, as measured by Unacast. In each specification, we regress the SDB on voter participation (average of voter participation from presidential elections ‘08-‘16). Each of the specifications includes Day X State fixed effects. The second column of each set begins to add controls for county characteristics that may affect SDB: Trump 2016 vote share, log population, per capita income, log population density, percentage of people with at least some college, percentage of population above 60. Additionally, we add COVID-19 risk-related controls: log one plus the number of new COVID-19 cases and log one plus the number of new COVID-19 deaths. Standard errors are reported in parenthesis and are clustered at the county level. *p<0.10. **p<0.05, ***p<0.01.

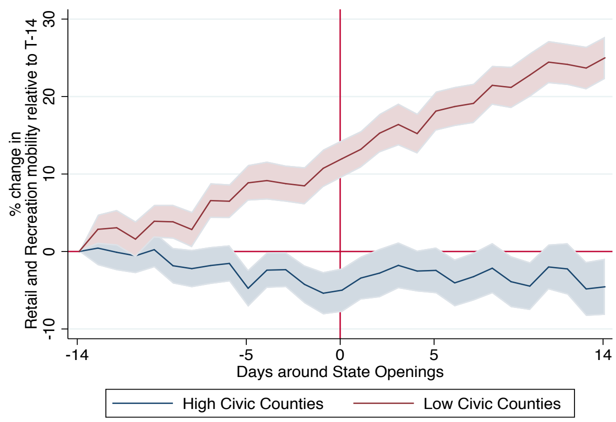
Panel B: Civic Capital, SDB and Stay at Home Mandates

	(1)	(2)	(3)	(4)
VARIABLES	Chg. Dist	Chg. Dist	Chg. NE Visits	Chg. NE Visits
Post Stay Home Order	-0.018***	-0.019***	-0.021***	-0.022***
	(0.00)	(0.00)	(0.00)	(0.00)
High Civic Capital X Post National Guideline	-0.039***	-0.038***	-0.047***	-0.043***
	(0.01)	(0.01)	(0.01)	(0.01)
High Civic Capital X Post Stay Home	-0.014***	-0.013***	-0.009**	-0.008*
	(0.00)	(0.00)	(0.00)	(0.00)
High Trump X Post National Guideline		0.008		0.028***
		(0.00)		(0.01)
High Trump X Post Stay Home		0.009*		0.021***
		(0.00)		(0.01)
Observations	101,927	101,927	64,936	64,936
Adjusted R-squared	0.711	0.711	0.839	0.839
Day FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Health Controls	Yes	Yes	Yes	Yes

Panel B presents a variation of the analysis conducted in Panel A. The sample period is February 25th to April 9th, 2020. The dependent variable is the same, i.e., daily percentage change in distance traveled (column 1-7) and in number of non-essential visits (columns 8-15), where the changes are measured with respect to a pre-COVID baseline for the same day of the week. We control for county fixed effects, day fixed effects, and the log number of confirmed cases in each specification. To examine the differential social distancing behavior, we interact Post Stay Home Order and Post National Guidelines with an indicator for high voter participation (county being in the top quartile of voter participation). Post National Guidelines is an indicator variable for days after March 16th, when the White House issued a national stay at home recommendation (Coronavirus Guideline for America). We also control the interaction between Trump voters' share in 2016 and Post Stay Home Order and Post National Guidelines to separate the potential confounding effect of civicness and political leaning. Standard errors are clustered by county. *p<0.10. **p<0.05, ***p<0.01.

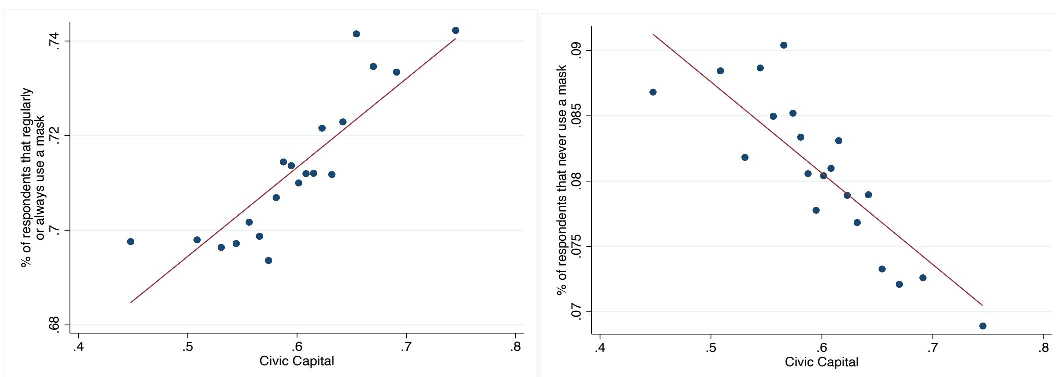
Exhibit 3.

Panel A: Mobility Around State Reopenings (U.S.)



This panel analyzes the variations in Social Distancing Behavior (SDB) from 14 days before a state lifts its COVID restrictions to 14 days after. The SDB is phone mobility near Retail and Recreation as measured by Google. The figure plots the changes in event time for high civic capital counties (top quartile of voter participation, in blue) vs. low civic capital counties (lowest quartile of voter participation, in red). Each data point is obtained by regressing the percent change in the mobility measure between that specific event day and the baseline level, set at 14 days before the state lift the restrictions. The specification includes calendar day fixed effects and controls for COVID-19 cases, population density, Trump 2016 voter share, and per capita income in the counties. Each of the estimates includes 95 percent confidence intervals. Standard errors are clustered at the county level. The graph shows that phone mobility near Retail and Recreation does not change much after the mandatory restrictions are lifted in high civic areas, while it increases sharply in low civic capital areas.

Panel B: Civic Capital and Mask Usage



This panel plots the percentage of respondents to the New York Times survey who use a mask (the percentage that always or frequently use a mask (left panel) and the percentage that never use a mask (right panel)) against our civic capital measure (the county voter participation rate). Each plot controls for population density, income per capita, population, Trump 2016 vote share, the log 1+ number of confirmed cases at the time of the survey, log 1+ number of COVID-19 deaths, and state fixed effects.

Panel C: Civic Capital and Mask Usage

	(1)	(2)	(3)	(4)
VARIABLES	**% Use Masks Freq or Always**	**% Use Mask Never**	**% Use Mask Sometimes**	**% Use Mask Always**
Civic Capital	0.145***	-0.058***	-0.057***	0.114***
	(0.02)	(0.01)	(0.01)	(0.03)
Observations	3,005	3,005	3,005	3,005
Adjusted R-squared	0.646	0.427	0.333	0.711
State FE	Yes	Yes	Yes	Yes
Soc-Econ Controls	Yes	Yes	Yes	Yes
Health Controls	Yes	Yes	Yes	Yes

This panel presents estimates from multi-variable regression, where we regress the percentage of respondents' usage of masks at the county level on our measure of civic capital (average voter participation rate). Each of the specifications includes controls for county characteristics that may affect mask usage: log population, log population density, per capita income, and Trump 2016 vote share. We also include controls for COVID exposure in the county by including the log of 1+ number of COVID-19 cases and log 1+ number of COVID-19 deaths in the county. Each specification also includes State fixed effects. Robust standard errors are reported in parenthesis. *p<0.10. **p<0.05, ***p<0.01

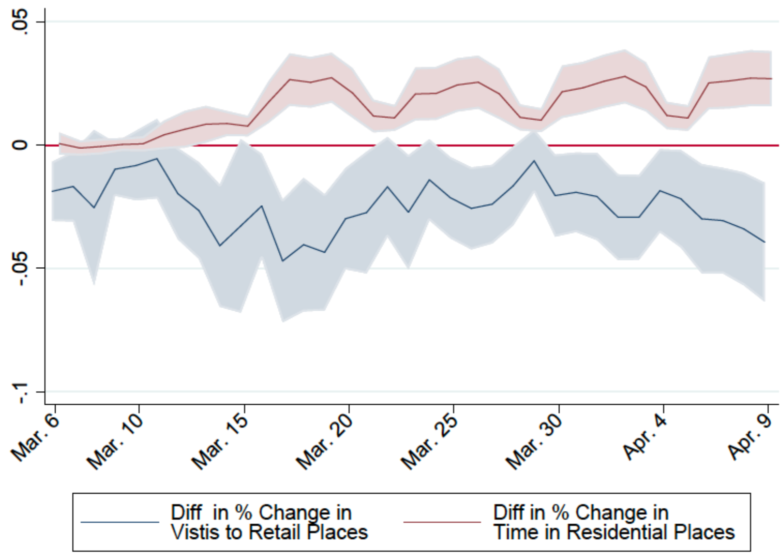
Exhibit 4. Trust Toward Others and Social Distancing Behavior (U.S.)

	# people you meet socially (excluding people living with)					
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Trust in other people	-0.082**	-0.081**	-0.086**	-0.067*	-0.064*	-0.063*
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Trust the US Government	0.059**	0.028	0.031	0.030	0.025	0.023
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Lean Republican		0.331***	0.306***	0.337***	0.333***	0.338***
		(0.07)	(0.08)	(0.08)	(0.08)	(0.08)
Fearful of getting sick			0.041	0.036	0.038	0.038
			(0.04)	(0.04)	(0.04)	(0.04)
Log of population density in county			-0.029	-0.034	-0.031	-0.011
			(0.02)	(0.02)	(0.02)	(0.03)
Income per capita in the county			0.000	-0.000	-0.000	0.000
			(0.00)	(0.00)	(0.00)	(0.00)
Age				-0.007***	-0.007***	-0.007***
				(0.00)	(0.00)	(0.00)
Has College					-0.098	-0.094
					(0.08)	(0.08)
Number of cases in the county						-0.027
						(0.02)
Observations	940	940	871	871	871	871

The exhibit presents estimates from multivariate ordered probit regressions where the dependent variable is the answer to the question: "About how many people were you in close physical contact with socially in the past seven days not including people that live with you? This includes the number of family members, friends, people at religious services, and people at other social gatherings you saw in person." The main variable of interest is "trust in other people," which is the answer to the question: "On a scale from 1 to 5 where 1 means 'I do not trust them at all' and 5 means 'I trust them completely,' Can you please tell me how much do you trust other people?" "Trust in the U.S. government" is a variable similar to trust in other people, but only referred to the U.S. government. "Lean Republican" is a dummy variable equal to one if respondents answer Republican to the question, "As of today do you lean more to the Republican Party or more to the Democratic Party?" "Fearful of getting sick" is a variable that takes higher values if individual reports to be fearful of getting sick from coronavirus. We also control for county-level measures of population density, income per capita, age, a dummy equal to one if the person has a college degree, and the number of cases. The answers are from a questionnaire fielded between April 6th and April 12th, 2020. The coefficients reported are computed at the mean value of the covariates. *p<0.10. **p<0.05, ***p<0.01.

Exhibit 5

Panel A: High Trust and Social Distancing Behavior (Europe)



Panel A plots the estimates obtained by regressing Social Distancing Behavior measures on the interaction between high trust regions and the day indicator. The two SDB measures are changes in the number of visits and the time spent in residential places between the day reported and the pre-COVID baseline for the same day of the week, as computed by Google. We define regions at the NUTS level 1. The specification includes country by day fixed effects. Each of the estimates includes 95 percent confidence intervals. Standard errors are clustered at the regional level. The plot captures the difference in social distance behavior between high trust regions and the rest of the regions. We plot the change in mobility in retail (excluding groceries and pharmacies) and recreation in blue, while the change in time in Residential Places in red. We find that high trust regions reduce their visits to retail locations to a larger extent than low trust regions. Moreover, when practicing social distancing, people tend to move more in the proximity of their residence. In areas with high civic capital, the percentage change in residential mobility is greater than in areas with low civic capital.

Panel B: Trust Toward Others and Social Distancing Behavior (Europe)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Chg. Retail	Chg. Retail	Chg. Retail	Chg. Retail	Chg. Retail	Chg. Resident	Chg. Resident	Chg. Resident	Chg. Resident	Chg. Resident
Avg. Trust	-0.034***	-0.031***	-0.023**	-0.024**	-0.023**	0.018***	0.018***	0.013***	0.014***	0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lag Num of Death per million	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(Population Density)	-0.018***	-0.018***	-0.016***	-0.013***	-0.013***	0.009***	0.008***	0.007***	0.007***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Avg. Political Leaning		-0.012	-0.009	-0.008	-0.009		-0.001	-0.003	-0.004	0.001
		(0.01)	(0.01)	(0.01)	(0.01)		(0.00)	(0.00)	(0.00)	(0.00)
Trust in Politicans			-0.013	-0.009	-0.009			0.008**	0.006*	0.005
			(0.01)	(0.01)	(0.01)			(0.00)	(0.00)	(0.00)
Fraction of Pop Over 60				0.179	0.179				-0.046	-0.044
				(0.12)	(0.12)				(0.04)	(0.04)
Fraction of Pop Attain College					-0.000					0.001***
					(0.00)					(0.00)
Observations	4,404	4,404	4,404	4,348	4,348	4,404	4,404	4,404	4,348	4,348
Adjusted R-squared	0.888	0.888	0.888	0.888	0.888	0.892	0.892	0.892	0.892	0.893
Mean. Outcome	-0.41	-0.41	-0.41	-0.41	-0.41	0.13	0.13	0.13	0.13	0.13
Date Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B presents estimates from multi-variable regressions of the same SDB measures used in Panel A, i.e., the percentage difference between the number of visits and the time spent in residential places of a specific day and a pre-COVID baseline for the same day of the week, as computed by Google. The sample period is March 6th to April 9th. We define regions at the NUTS level 1. To measure trust, we averaged ESS data over eight waves, including France only in the last survey, because NUTS classifications have changed over time in France. We control for the lag number of deaths in the region, population density, the average voting preferences, trust in politicians in the NUTS region, fraction of population over 60, and fraction of population with a college degree, country fixed effects, and day fixed effects. Standard errors are clustered at the NUTS 1 Level. *p<0.10. **p<0.05, ***p<0.01.