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Bowling Together by Bowling Alone: Social Capital and COVID-19

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Introduction

In Bowling Alone Putnam mapped the decline in social capital in the United States and traced such decline to changes in how individuals employ their time. Rather than spending this time with others, negotiating a shared and common way forward, in communities with little social capital, individuals do and experience activities alone. By contrast, in communities with high social capital, individuals do things together, from consequential things like being members of organizations, political parties and the church, to seemingly trivial things like going bowling (Putnam, 2000).

Many definitions of social capital exist (Coleman, 1998; Putnam, 1993; Fukuyama, 2000). Social capital reflects the resources and benefits that individuals and groups acquire through connections with others and involves both shared norms and values that promote cooperation as well as actual social relationships (Kawachi, Subramanian, & Kim, 2008).

Research has identified a positive association between social capital and health (Ehsan, et al., 2019; Kawachi, Subramanian, & Kim, 2008; Rodgers, et al., 2019) although recent evidence suggests that such association may be small (Xue, Reed, & Menclova, 2020). Most of the research is correlational in nature, some studies suggest that associations may be causal (D'Hombres, et al., 2010; Folland, 2007). Research has also identified a positive association between social capital and health behaviors: social capital is associated with healthier behaviors, as measured through smoking, alcohol use, physical activity, vegetable consumption and sleep (Poortinga, 2006; Nieminen et al., 2013).

Few of the studies that examine the association between social capital and health examined the contribution of social capital for infectious and communicable diseases and those that did, generally focused on sexually transmitted diseases (Rodgers, et al., 2019).

Such studies reveal mixed results: out of the seven studies included in the review conducted by Rodgers and colleagues, one identified a strictly positive association, one a strictly negative association and five a positive, negative or no association depending on the measures of social capital used, the range of controls introduced, and the subpopulation examined.

What can be expected on the association between social capital and individuals' capacity to change their behaviors in order to halt the spread of the COVID-19 disease through social distancing? Are communities who bowl together in normal time better at bowling alone when COVID-19 required them to do so?

Social capital and behavioral change in response to COVID-19

Social interactions can foster the spread of infectious diseases. However, social relations determine other key factors that are important in shaping the course of the COVID-19 pandemic. In particular, social capital can change individuals' awareness of the costs and benefits associated with behaviors that can contribute to or reduce the spread of the Sars-CoV-2 virus. It can also contribute to change individuals' evaluations of the costs and benefits associated with such behaviors, given personal disease susceptibility and how wide the net is cast in the number of individuals whose welfare is considered relevant.

We examine data from US counties to identify how different communities responded to the threat posed by COVID-19 by changing behaviors that can protect health by promoting social distancing such as reducing mobility and staying at home. We are interested in examining if social capital was implicated in how fast, how profoundly and how consistently communities changed their behaviors in the early phase of the COVID-19 pandemic. Furthermore, we are interested in identifying if social capital altered behavioral responses to the implementation of shelter-in-place regulations, local level transmission dynamics and how pleasant going outside was because of weather conditions.

Social capital and mobility reductions: direct pathways

Because COVID-19 is caused by a viral infection that can be passed on during an asymptomatic or peri-symptomatic phase (Bai et al., 2020), communities with high levels of interpersonal relations might be, other things being equal, more likely to experience sustained clusters of local infections and to do so earlier than other communities (Borgonovi, Andrieu & Subramanian, 2020). However, beyond this initial phase, the evolution of the COVID-19 pandemic is determined by the extent to which communities are able to adopt behaviors that reduce transmission. Furthermore, since scientific understanding of the virus and how it spreads is evolving rapidly, adopting health protective behavior depends on communities being able to ensure that members are able to acquire, interpret, act upon and share sound medical advice, filtering between trustworthy scientific information, unfounded theories and dangerous and discredited news. Research indicates that individuals who have accurate information are more likely to adopt health protective behaviors such as wearing a face mask in public, washing hands frequently, and avoiding unnecessary social contacts (Niepel, et al., 2020; Sheeran, Harris and Epton, 2014; Bish and Michie, 2010).

Social capital could therefore influence the likelihood that individuals will adopt health protective behaviors by shaping how quickly community members acquire accurate information (Stephens et al., 2004, Viswanath et al., 2006). Individuals expose others to COVID-19 when they catch the SArs-CoV-2 virus and fail to self-isolate. A high level of social capital could alter behaviors because individuals in communities with strong norms for reciprocity and social solidarity would suffer a high psychological prize if they infected others (Alfaro, et al., 2020). Finally, in areas with high levels of social capital, community members can increase the cost of engaging in dangerous behaviors by enforcing social monitoring and stigmatizing lack of adoption of health protective behaviors (Coleman, 1990, Putnam, 1993).

Evidence on the extent to which social capital shapes mobility reductions is emerging (Bargain & Aminjonov, 2020; Durante, Guiso & Gulino, 2020): communities with high levels of social capital socially distanced more than communities with low levels of social capital. This evidence is in line with evidence on prior pandemics. For example, data from Taiwan suggest that social capital was associated with other forms of health protective behaviors such as the intention to receive vaccination against the flu, to wash hands more frequently, and with the intention to wear face masks (Chuang, et al., 2015). Similarly, in Sweden and the United States, social capital was associated with the intention to receive the vaccination against the H1N1 pandemic in 2009 (Rönnerstrand, 2014; 2016).

We hypothesize that, other things being equal, communities with high levels of social capital will reduce their mobility faster and more markedly than communities with low levels of social capital.

Social capital and mobility reductions: indirect pathways

A number of studies have modelled individuals' behavioral decisions to stay at home, engage in social contacts, work and any other out-of-the-home activity during the COVID-19 pandemic (Atkenson, 2020, Glover et al., 2020). The COVID-19 pandemic dramatically changed the opportunity cost of sheltering vs. moving, especially among those with the highest likelihood of suffering negative health consequences if infected. At the community level, the utility associated with moving can be expected to be lower the higher COVID-19 transmission is within the community, since greater transmission increases individuals' likelihood of becoming infected or infecting others. Such utility however is also idiosyncratically influenced by how enjoyable going outside is: other things being equal, on a rainy day, such enjoyment is lower and on a sunny day it is higher. Finally, shelter-in-place regulations altered the utility individuals derived from moving (Hale et al., 2020). Advising, prohibiting and imposing fines to individuals who leave their home without a valid motive are ways to reduce the utility of moving through the imposition of financial or social penalties for those who do (Ainslie et al., 2020; Hale, et al., 2020; Imai et al., 2020; Memish et al., 2019).

We expect that communities with high levels of social capital will reduce mobility faster as regulations on shelter-in-place initiatives are enacted (Alfaro, et al., 2020; Dave et al., 2020). We also expect that communities with high levels of social capital will be better prepared to adapt to the new 'COVID-19' normal and reduce mobility if epidemiological data indicate increasing COVID-19 infections. Finally, we expect that weather conditions will be associated with greater behavioral changes in high social capital communities. When weather conditions are poor, more activities are conducted indoors and are thus at a higher risk of viral transmission. Moreover, when weather conditions are poor, leaving home becomes less enjoyable and thus the opportunity cost of staying home decreases. To the extent that individuals living in high social capital communities have greater information on transmission risks, we expect them to recognize this and reduce their mobility in the presence of poor weather conditions.

Data and measures

A description of all variables and data sources is available in Table 1. Descriptive statistics are presented in Supplementary Online Table A1.

TABLE 1

Dependent variables: Mobility and Shelter-in-place patterns

We identify mobility patterns at the county level using Cuebiq's Mobility Index (CMI) and Google Community Mobility reports and the percentage of people who remained at home using data from the Cuebiq Shelter-in-place index.

The CMI is a publicly accessible resource made available by Cuebiq and provides the level of movement for each week and in each county in the United States. The index is based on de-identified, geo-located information on smartphone users. The CMI for each county is the median of the aggregated movements of all users within a county. A detailed description of the Cuebiq dataset can be found at https://help.cuebiq.com/hc/en-us/articles/360041285051-Reading-Cuebiq-s-COVID-19-Mobility-Insights. Our database contains movement from the first week in January 2020 until the week of May 4.

We complement analyses based on Cuebiq data using data from the Community Mobility Reports released by Google which cover the period 15 February 2020 to 10 May 2020. Google data indicate the percent change in visits to a number of activities. Data released by Google classified mobility into visits conducted towards the following high-level categories: grocery and pharmacy; parks; transit stations; retail and recreation; residential; workplaces. Because of space limitations, in the main body of the manuscript we provide graphical representations on the differential trends in mobility across counties with different levels of social capital for all categories with sufficient observations. However, we present detailed results only for retail and recreational activities in the main text (other results are available in Supplementary Online Annex B) which include places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters but results for the other categories are available from the authors upon request. We chose this category because it covers non-essential activities (as opposed to, for example, visits to workplaces, grocery and pharmacies for which individuals had less discretionary choice because they might have been obliged to undertake such activities by their employers, by financial needs and/or because they needed to buy food, medications or other essentials). Furthermore, visits to retail and recreation activities, as defined by Google, may have posed an especially high risk of viral transmission because they generate large indoor gatherings (as opposed to visits to parks).

The baseline for the calculation of the change in visits is the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. Data are based on information from users who have opted-in to Location History for their Google Account, so the data represents a sample of Google map users.

Finally, we use the shelter-in-place index from Cuebiq as an additional measure of behavior. Cuebiq's Shelter-in-Place Analysis uses the percentage of users staying at home in a given county to gather weekly level data at the county level. The share of users staying at home is calculated daily by measuring how many users moved less than 330 feet (100 meters) from their home. Our database contains shelter-in-place data from the first week in January 2020 until the week of May 4.

All the mobility and shelter-in-place indices are based on the behavior of samples of the population residing in the different counties. As with all samples, this may or may not represent the exact behavior of the overall population. A discussion of this, as well as other limitations is reported in the limitations section of this manuscript.

Key independent variables:

We use the Social Capital (PSU-SC) index developed by the Penn State University (Rupasingha et al. (2006 with updates)) to identify social capital at the county level. Data are available for 3141 US counties and cover the entire American population ($\mu=0$; $\sigma=1$). The social capital index that we use in our models was calculated on 2014 data, and is an aggregate index constructed using the following indicators: the number of establishments in Religious organizations; the number of establishments in Civic and social associations; the number of establishments in Business associations; the number of establishments in political organizations; the number of establishments in professional organizations; the number of establishments in labor organization; the number of establishments in bowling center; the number of establishments in fitness and recreational sports centers; the number of establishments in golf courses and country clubs; the number of establishments in sports teams and clubs; voter turnout; census response rate; the number of non-profit organizations without including those with an international approach. A summary of data sources used to construct the social capital indicator is available in Annex Table A5. Details on the index construction and studies using it can be found at https://aese.psu.edu/nercrd/community/social-capital-resources. All results were also computed using alterative indicators of social capital and are in line with those presented. For example, we developed the same set of analyses presented using an alternative social capital indicator that emphasizes informal participation in activities supporting the local community as well as the number of registered non-religious and religious non-profits available in the county. Details of the alternative social capital index used for robustness are available in Annex Table A6 and results can be requested from the authors.

We compile state-wide and county-wide shelter-in-place orders (SIPOs) using information from Mervosh et al. (2020) and the National Association of Counties - County Explorer respectively.

Precipitation data by county and by week were obtained from the GHCN-Daily dataset, which contains daily station level information. Data cover the period starting on February 17 and ending on May 10 2020. We calculate weekly county aggregated precipitation by calculating average weekly precipitation levels across all available stations data within a county.

The weekly number of cumulative confirmed COVID-19 cases from February 16 to May 3 2020 by county come from the USA Facts website.

Control variables:

In models that do not include county fixed effects, we introduce controls for the following county level characteristics: economic orientation and demographic composition of the county, the political, health and economic profile of residents, and population density.

We control for the economic orientation of the county's economy using data from the Economic Research Service of the USDA using the 2015 classification into one of the following six mutually exclusive categories of economic dependence: nonspecialized counties; farming; mining; manufacturing; federal/state government, and recreation.[1]

Moreover, we control for the population density in the county, expressed in terms of population per square mile. The same data are used to compute the share of the population in the county above the age of 65. We introduce controls for the percentage of the population living in poverty and median income using data from the U.S. Census Bureau, Small Area Income and Poverty Estimates (SAIPE) Program. Data refer to year 2018. We control for the percentage of votes cast that were in favor of Trump in the 2016 presidential elections. Finally, we add a control measuring the share of a county's population suffering from underlying health conditions that have been identified as contributing to a person's risk of suffering severe symptoms if infected with the Sars-CoV-2 virus.

Analytical strategy

[1] For definitions of the county typology codes, visit: https://www.ers.usda.gov/data-products/county-typology-codes/documentation/

In order to examine the direct and indirect association between social capital and behavioral change we develop two sets of analyses: a week-by-week descriptive analysis of the association between social capital and mobility changes during the period starting on February 17 and ending on May 10; and a difference-in-difference analysis of heterogeneity in mobility changes following changes in the opportunity cost of sheltering in place across communities with different levels of social capital.

We start by providing descriptive evidence on overall changes in mobility in US counties between the week starting on February 17 and the week starting in May 4 and the extent to which changes in mobility differ across with different social capital. We do this by estimating a set of regression models described by equation (1):

$$behavior_{y,c,t} = \beta_1\, Social\ Capital_c + \beta_2\, cases_{c,t-1} + \beta_3\, precipitation_{c,t} + \beta_4\, SIPO_{c,t} + \beta_5\, X_{i,c} + \mu_S + \epsilon_c \quad (1)$$

Where c represents counties; t represents a week within the study period (February 17 - May 4 2020); $behavior_{y,c,t}$ represents one of our measures: the index for mobility, the shelter-in-place index, workplace mobility, recreational and grocery mobility from Google observed in county c in week t, $Social\ Capital_c$ represents a time invariant factor that describes the level of social capital in county c; $cases_{c,\ t-1}$ represents the cumulative number of cases diagnosed in county c up to the week preceding the week for which analyses are conducted; $precipitation_{c,t}$ indicates the average weekly precipitation level in county c in week t; $SIPO_{c,t}$ is a dichotomous indicator to mark the presence of shelter-in-place orders in county c in week t, and $X_{i,c}$ is a vector of time-invariant controls, where we include demographic, political, health-related and economic structure of the county (density, percentage of votes cast that were in favor of Trump in the 2016 presidential elections, poverty, share of the population above 65, median household income, share of the population suffering from known health risks for severe COVID-19 consequences and the economic dependency). Finally, we include state fixed effects μ_s, to observe the association between social capital and mobility controlling for all potential sources of unobserved heterogeneity that may vary across states. State fixed effects therefore allow us to account for any unobserved state level characteristic that may shape mobility behaviors and/or that could influence the measurement of indicators used in our analyses such as the download of different apps to determine Cuebiq mobility and shelter-in-place data, and allowing Google to monitor movement for the Google mobility data, protocols for reporting a COVID-19 diagnosis or state regulations that may influence social capital measures but not the underlying social capital latent construct. Therefore, all our models identify within-state between-county variations.

We run models described by equation (1) using alternative mobility measures for robustness, and different ways to examine reductions in mobility (staying at home, reducing overall mobility, reducing mobility directed at performing specific activities). In the main body of the manuscript, we report graphical results for the set of models presented in equation (1) in Figure 3 to illustrate how mobility evolved between the week starting on February 17 2020 and the week starting on May 4 2020. We illustrate how mobility changed, on average, across counties as well as the extent to which mobility changes differed depending on the level of social capital present in a county. We illustrate the difference in mobility patterns that is associated with a one standard deviation difference in social capital. Full model estimates for each week under analysis can be requested from the authors.

We employ a difference-in-difference estimation procedure to examine if the association between mobility and factors that alter the opportunity cost to shelter-in-place depends on the level of social capital present in a community. We do this by fitting equation (2) on the pooled dataset:

$$behavior_{y,c,t} = \beta_1\, cases_{c,t-1} + \beta_2\, precipitation_{c,t} + \beta_3\, SIPO_{c,t} + \beta_4\, cases_{c,t-1} * Social\ capital_c + \beta_5 precipitation_{c,t} * Social\ capital_c + \beta_6 SIPO_{c,t} * Social\ capital_c + \mu_c + \delta_t + \epsilon_{c,t} \tag{2}$$

In equation (2) B_1 represents the change in mobility that can be expected given a change in one unit in the number of cumulative cases diagnosed up to the week preceding the week for which analyses are conducted in areas where social capital equals 0; B_4 represents the *additional* change in mobility that can be expected given a change in one unit in the number of cumulative cases diagnosed up to the week preceding the week for which analyses are conducted in areas when social capital equals 1; B_2 represents the change in mobility that can be expected given a change in one unit in the weekly average precipitation in week t where social capital equals 0; B_5 represents the *additional* change in mobility that can be expected given a change in one unit in the weekly average precipitation in week t where social capital equals 1; B_3 represents the change in mobility that can be expected when shelter-in-place regulations are present in areas where social capital equals 0 and B_6 represents the *additional* change in mobility that can be expected when shelter-in-place regulations are present in areas where social capital equals 1. Because equation (2) includes fixed effects for both weeks and county, the main social capital term cannot be estimated. We do not have additional time varying and county varying controls. Results are presented in Tables 3 and 4.

We run our models using alternative outcome measures (overall mobility trends provided by Google and mobility to specific activities also provided by Google) and present main estimates in the main body of the manuscript and robustness checks in the Supplementary Online Annex.

Results

Mobility trends across the United States

Figure 1 illustrates trends in mobility across counties in the United States between February 17 and May 10. The first vertical line marks March 17, when announcements were made on the importance to sheltering-in-place. The second vertical line marks the time window when many states introduced SIPOs. A detailed timeline of the adoption of SIPOs across the United States is available in the Supplementary Online Annex Table A2.

The solid black line represented in Figure 1 indicates that, in the second half of February and the first week of March people moved around as they did at the start of February. But after the first week of March, mobility decreased. Interestingly, people's behavior changed both when national announcements were made and when shelter-in-place-orders (SIPOs) legislation were passed. These results are in line with findings from Abouk and Heydari (2020) indicating that reductions in out-of-home social interactions depend both on policy measures and voluntary decisions of individuals. In fact, the intensity of mobility decreased to a larger extent following recommendations than following mandatory requirements, possibly because those who did not commit to behavioral changes following the former were individuals who found it difficult or could not change their behavior for psychological, economic or work-related reasons.

Figure 1 also suggests that mobility begun to converge to the levels observed in February well before the easing of lockdowns was announced in many states: from the week starting on April 6 onwards mobility started to increase even though the first SIPOs were lifted on April 24 (Table A3) (Nguyen, et al., 2020). At the same time, because mobility tends to be higher when days are longer, the weather is warmer and rains less, observing the same levels of mobility in May and in February means that people changed their usual patterns of behaviors because of the pandemic or some of the measures implemented to halt its spread. The major increase in unemployment registered in the United States may have also contributed to this: as many people lost their job, many remained at home more than what they usually do in order to reach their workplace.

Social capital differentials in behavioral responses to COVID-19

Figure 1 reports not only how behavior evolved on average across counties but also illustrates behavioral changes in counties with high (top 25% in social capital) and with low levels of social capital (bottom 25% in social capital – dotted line).

Figure 1 indicates that mobility was lower in areas with higher levels of social capital at baseline, i.e. early February. Figure 1 also shows that while social capital differentials in mobility remained stable in February and in the first week of March, when most individuals underestimated the likelihood of COVID-19 reaching the United States to the degree it did, patterns started to diverge markedly from the week starting on March 9 onwards. Individuals living in high social capital counties reduced their mobility more profoundly than individuals living in low social capital counties. Overall mobility returned close to baseline in both high and low social capital communities.

FIGURE 1

Differences in mobility between counties with high and low social capital could reflect differences across counties other than social capital. In Figure 2 we illustrate the differential trend in mobility that can be expected between two counties that differ by one standard deviation in the social capital index, after controlling for state fixed effects and county level characteristics. We complement analyses based on overall mobility with results on mobility directed at specific activities over which individuals may have a different level of control and that may entail a different level of risk as well as sheltering-in-place behavior.

Results confirm that at the start of the period under analysis, overall mobility did not differ greatly depending on the level of social capital present in a community and any differences observed at baseline remained stable before the COVID-19 pandemic hit. We conducted tests to confirm that trends in the association between social capital and overall mobility were stable in the period before COVID-19 became a concern. We estimated a model with overall mobility as outcome and introduced dichotomous indicators reflecting the week under analysis, with the week of February 17 as the reference period as well as a series of interaction terms obtained by multiplying each of the week variables and social capital. In the pre-treatment weeks the interaction effects were not statistically significant and were close to zero (b= 0.007 p= 0.582 for week of Feb 24; b= 0.004 p= 0.759 for week of March 2; b=-0.013 p= 0.316 for week of March 9).

Figure 2 suggests that individuals living in high social capital counties begun to alter their behavior more than individuals living in low social capital counties once awareness of the threat posed by COVID-19 increased. Individuals in high social capital communities appear to have become aware and to have acted upon such awareness before others (social capital differentials in overall mobility widened already in the week before announcements by the US government were made, i.e. the week starting on March 9). Social capital differentials grew larger in the second part of March (except for the week of March 30 when SIPOs were first introduced in many states and when social capital differentials in overall mobility were closed as a result). Social capital differentials returned to baseline at the end of April and early May.

Analyses of mobility by destination suggest that trends in social capital differentials in overall mobility were primarily due to a steep decline in mobility directed at retail and recreation activities which became pronounced in March and early April, slightly less pronounced in late April and begun to widen again in May. Social capital differentials in mobility towards workplaces and groceries and pharmacies grew in early and mid-March but such difference closed from the end of March onwards. These results suggest that individuals in high social capital counties reduced mobility to non-essential activities compared to individuals in low social capital counties. Analyses of sheltering-in-place data are in line with this finding: before the pandemic, individuals living in high social capital communities were less likely to stay at home than individuals in low social capital communities. Because our social capital indicator reflects participation in activities this is to be expected. However, by early March such negative differential was closed and individuals living in high social capital communities were as likely as individuals within in low social capital communities to shelter-in-place. By end of March gaps in sheltering-in-place widened again, although given insights on changes in mobility by activity, such quantitative return to pre-pandemic levels may have been accompanied by a qualitative change in the types of activities individuals engaged in.

FIGURE 2

The indirect effect of social capital: the role of SIPOs, local transmissions and weather conditions

Estimates presented in Figure 2 identify the within state, between county social capital differential in trends in overall mobility, mobility towards retail and recreation and in shelter-in-place behaviors, net of differences across counties in the economic and social makeup of the county, net of the presence of SIPOs and net of differences in weather conditions. However, estimates presented thus far consider only the direct association between social capital and mobility while ignoring the possible additional indirect associations due to the fact that social capital may change individuals' responses to SIPOs, weather conditions and the number of COVID-19 cases diagnosed in a community.

In Table 2 we present OLS and difference-in-difference estimates (models that include both county and time fixed effects) of models described in equation (3) where we consider the possibility that the effect of SIPOs, COVID-19 cases and weather on mobility decisions is not homogeneous across communities but depends on the level of social capital present in a community. Table 3 presents detailed results for mobility directed at retail and recreation activities while Table 4 presents the same set of estimates for shelter-in-place behaviors. In the Supplementary Online Annex B we report estimates for alternative outcome measures derived from the Google Mobility Report. For each factor – SIPOs, number of cases and precipitation – the model presents the estimated effect when social capital equals 0 (main effect) and the additional effect for a one-unit difference in social capital (interaction effect).

Results presented in Table 2 indicate that individuals tend to move less in the presence of SIPOs, when the number of diagnosed COVID-19 cases is larger and when it rains (negative main effects coefficients). Estimates are highly statistically significant in both OLS and in the difference-in-difference specification in the case of weather and presence of SIPOs and in the difference-in-difference specification in the case of number of COVID-19 cases. The within-county across weeks estimates indicate that compared to when SIPOs are not in place, the adoption of SIPOs is associated with a reduction of around 0.48 in the mobility index which corresponds to around one standard deviation (model 4). However, the extent to which individuals reduce their mobility in response to the adoption of a SIPO differs depending on the level of social capital in a community.

Estimates presented in model 4 indicate that individuals living in a community with a social capital value one standard deviation above the mean can be expected to reduce mobility by 0.56 index points after the introduction of a SIPO. By contrast, individuals living in a community with a social capital value one standard deviation below the mean can be expected to reduce mobility by only 0.39 index points after the introduction of a SIPO. Similarly, while a difference of 1000 COVID-19 cases is associated with an average decline within a county of 0.02 in the mobility index, the effect is larger when individuals live in counties with social capital values one standard deviation above the mean (0.03 index point reduction). Finally, a difference of 10 centimeters in rain in a week is associated with a decline in mobility within a county of 0.3 index point. The effect becomes larger when the county has a high level of social capital (0.4).

Results presented in Table 3 on mobility towards retail and recreation paint a very similar picture: the presence of SIPOs, a higher number of COVID-19 diagnoses and a rainy weather were all associated with lower mobility towards retail and recreation activities. According to the fixed effects specifications presented in models (2), (4) and (6) of Table 3, the associations between weather condition and mobility reductions, between the number of COVID-19 cases and mobility reductions and between the presence of SIPOs and mobility reductions were amplified by social capital.

TABLE 2

TABLE 3

Table 4 illustrates associations between weather condition, SIPOs and number of COVID-19 diagnoses and sheltering in place behavior. Results reveal that people remained home more when the weather was poor, when SIPOs were introduced and when the number of COVID-19 diagnoses was larger. In line with analyses presented in Tables 2 and 3 social capital amplified the association between weather conditions and the likelihood of remaining home and of the number of COVID-19 diagnoses and remaining home. By contrast, SIPOs appear to be less effective in high social capital communities in the model not including fixed effects, a potential reflection of the fact that individuals living in communities with high social capital already changed their behavior prior to the introduction of SIPOs. However, results reported in model (4) indicate that the effect of SIPOs across counties with different levels of social capital is imprecisely estimated (result not statistically significant at the 5% level).

TABLE 4

Social capital differentials and COVID-19 vulnerability across the United States

In order to evaluate the likely risk different communities face because of COVID-19 we combine information on community level social capital and how vulnerable local residents are to suffer severe health consequences because they suffer from conditions such as diabetes, obesity, high blood pressure, lung disease and heart disease.

We consider counties with a high prevalence of chronic conditions and low levels of social capital to be very vulnerable while counties with a low prevalence of chronic conditions and high levels of social capital to have low levels of vulnerability. Annex A4 in the Supplementary Annex details how the vulnerability index was calculated while Figure 3 plots the vulnerability index for each county with available data. Results indicate that many counties, particularly in the Southeast face a very high level of vulnerability because they combine high rates of chronic conditions and low levels of social capital. This result is consistent with a wealth of evidence indicating that community level social capital is associated with lower rates of cardiovascular diseases, obesity, diabetes and cancer (Ehsan, Klaas, Bastianen, & Spini, 2019; Kawachi, Subramanian, & Kim, 2008; Rodgers, Valuev, Hswen, & Subramanian, 2019 for comprehensive reviews). These findings help identify communities that should be closely monitored if a high health toll because of COVID-19 is to be prevented and where mandatory efforts to protect local populations such as SIPOs may be especially valuable.

FIGURE 3

Limitations

The quality and properties of the data that have been made available by Cuebiq and Google remain hard to assess given that the raw underlying data are not made public. In particular, we cannot determine if mobility patterns detected by Cuebiq and Google are representative of the overall patterns undertaken by populations in different counties. No information on the number of users or on the number of people who turned on their location history setting in Google is provided and no information can be identified on the extent to which the demographics of individuals used to construct Cuebiq mobility index or the Google mobility trends match the underlying demographics of underlying populations in different counties. We use mobility data derived using two methodologies for cross-validation. However, both methodologies reflect mobile usage and therefore could lead to biased estimates if patterns of smartphone use differ across counties with low and high social capital and with a different propensity to change behavior at the beginning of the pandemic. Data from the 2016 American Community Survey (Ryan, 2018) reveal that there are important demographic and geographic differences in smartphone use: individuals over the age of 65 and individuals living in rural areas in some states are significantly less likely to own and use a smartphone. We control for socio-economic and demographic characteristics of populations in different counties, population density, and state fixed effects to ensure that differences in smartphone penetration and use will bias our findings through sample selection. Nonetheless it is impossible to guarantee that no such sample selection bias exists.

Finally, we only evaluate two types of behavior, reduced mobility and to shelter-in-place. Further research could attempt to identify the role social capital played in promoting other types of behavioral responses during the COVID-19 pandemic, such as wearing face masks.

Discussion and Implications

In the absence of vaccines or effective pharmacological treatments, it is expected that communities will have to coexist with the health threat posed by COVID-19 for a prolonged period lasting months, possibly years. However, social distancing has major economic and social consequences (Glover et al., 2020; Coibion et al., 2020). Therefore, coexisting with the virus is most likely to entail a tightening and easing of restrictions rapidly to avoid exponential increases in cases (Dave, Friedson, Matsuzawa, & Sabia, 2020) while minimizing economic and social costs.

Although it is impossible to know how different populations will react to this or alternative scenarios, we provide evidence on the extent to which community level social capital was associated with mobility reductions in the United States in the early phases of the COVID-19 pandemic. Our results indicate that before the COVID-19 pandemic individuals living in high social capital communities moved less than individuals living in low social capital communities. Individuals living in high social capital communities reduced mobility to a larger extent than individuals living in low social capital communities and behavioral changes pre-dated the imposition of mandatory requirements to shelter-in-place. To the extent that these results reflect a causal effect of social capital on behavioral changes, they suggest that social capital played a direct role in shaping behavioral responses to the pandemic by ensuring that individuals in such communities had better information on the Sars-Cov-2 virus and/or better ability to act on such information than individuals in other communities, that they modified their behaviors to protect themselves and others rather than to respect legal requirements either because of norms of reciprocity or social sanctioning.

We also found that in communities with greater social capital, increases in the number of diagnosed cases and poor weather conditions led to larger reductions in mobility and larger increases in the percentage of people who remained home than in low social capital communities. We also found that shelter-in-place regulations more effectively promoted mobility reductions in communities with higher levels of social capital but no differential association across communities with different levels of social capital was identified for remaining at home. This result could reflect the fact that in high social capital communities individuals changed their staying at home behavior before the pandemic hit. The fact that the number of COVID-19 cases appears to be more associated with behavioral changes in high social capital communities is in line with the hypothesis that social capital promotes information acquisition and the ability and willingness to act on such information. Social distancing is especially important when viral transmission is more prevalent. Finally, the observation that poor weather conditions were associated with a greater reduction in mobility in high social capital communities could indicate that when individuals in such communities left their home, they were more likely to do so to engage in outdoor activities or that they evaluated the attractiveness of leaving their home given the potential health cost associated with doing so. Taken together these findings suggest that social capital led to better information on COVID-19 risks, ways to reduce such risks and an ability and willingness to act on such information. Our analyses suggest that in the initial phases of the spread of infectious diseases such as COVID-19, communities that have a tight web of social relationships and strong norms of reciprocity are better prepared and are more willing to change their behaviors to protect community members. Communities that ***'bowl together'*** in normal times, are able to ***'bowl alone'*** to a greater degree than other communities when social distancing is needed to protect the community in general and its most vulnerable in particular.

We complement analyses of the association between social capital and behavioral changes in mobility and staying at home with descriptive analyses on the vulnerability to COVID-19 of counties in the United States given their level of social capital and prevalence of populations with chronic health conditions. We find that a large number of counties are highly vulnerable to COVID-19, combining a large number of residents with chronic health conditions and low levels of community social capital. This is not surprising since the literature highlights an effect between community level social capital and the incidence of diabetes, obesity, and hypertension.

Our findings may be important not only to evaluate what happened in the early phase of the COVID-19 pandemic in the US, but also to consider where efforts should be put as legal barriers to the SARS-CoV-2 virus are relaxed. Our work suggests that the stock of social capital in a community is a crucial factor. Reinforcing the social capital available in a community when this is present and supporting communities when social capital is lacking should be just as much of a priority as sourcing stocks of face masks or testing kits to protect population health.

Social capital generally arises through spontaneous sociability (Fukuyama, 1995). Therefore, explicit efforts designed to create social capital can be challenging in normal circumstances but especially so during a pandemic, when individuals' physical relationships and interactions are discouraged to reduce viral transmission. Moreover, it has been argued that governmental actors are inherently ill equipped to promote the development of social capital (Etzioni, 1993; Fukuyama, 1995). Although other authors maintain that governmental actors can play a central role in social capital formation (Evans, 1996), they warn that governmental efforts designed to create social capital must involve the decentralization of power and tailor actions to different local circumstances (Warner, 2001).

Programs that have been effective in promoting social capital have not involved large-scale social engineering but, rather, stakeholder participation to facilitate incremental connectedness and shared responsibility of local populations (Fukuyama, 1995; Senge, 1990; Wilson, 1997). Therefore, programs designed to promote norms of trust and reciprocity require local governments to trust citizens, sharing responsibility and guaranteeing autonomous decision-making. Fearon, Humphreys and Weinstein (2009) demonstrated that even a brief exposure to participatory politics, i.e. through the organization of community committee structures and supporting those structures to help meet community needs, can increase social capital in a meaningful and lasting way.

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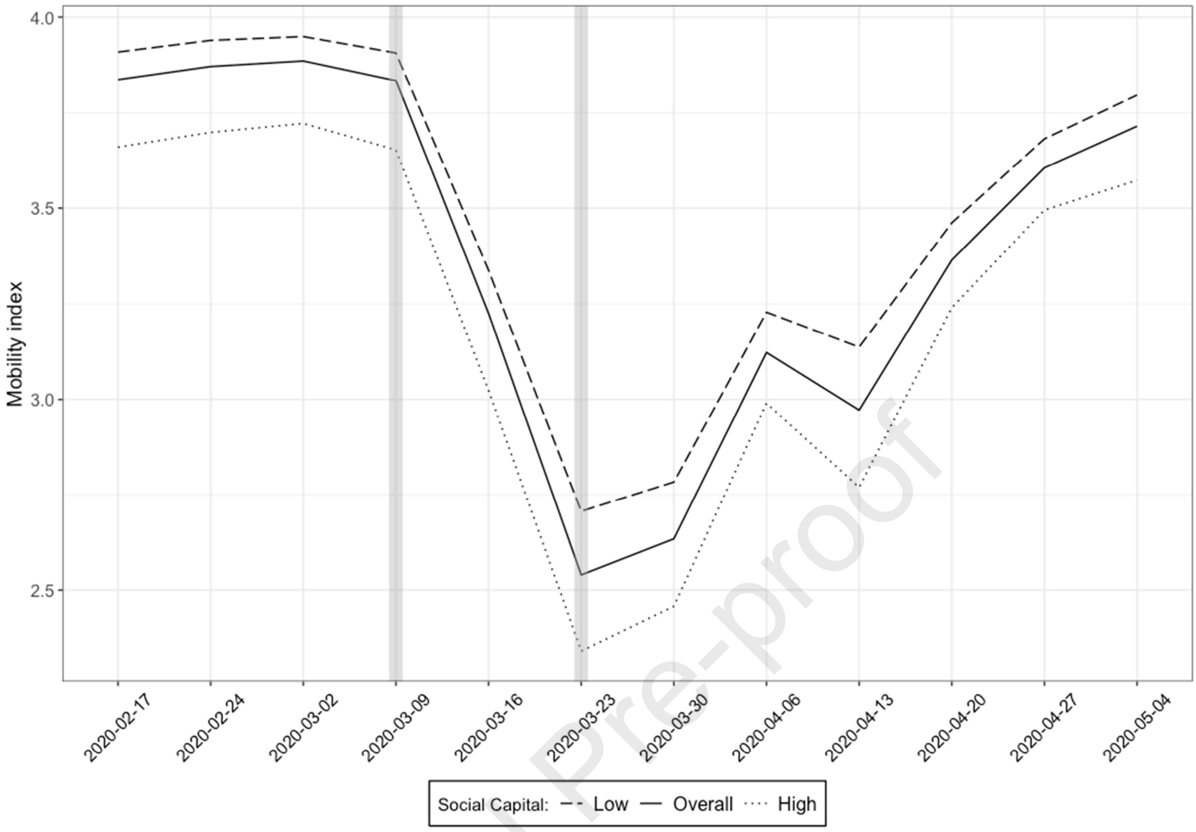
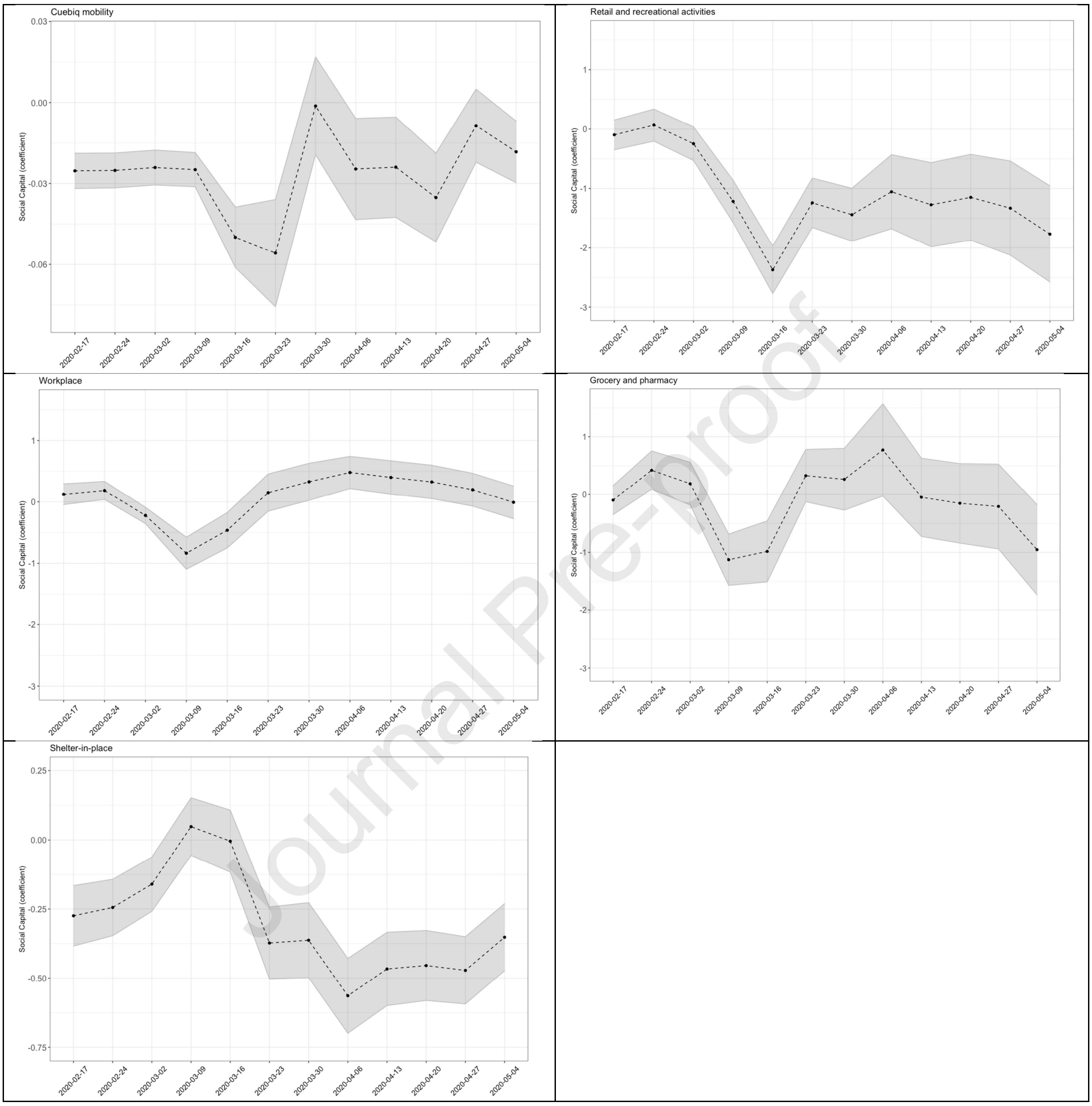
Figure 1. *Social capital differentials in trends in mobility, February 17 – May 10*



Source: Cuebiq mobility data and the Penn State University-Social Capital (PSU-SC) Index.

Figure 2. *Social capital differentials in mobility and shelter-in-place across US counties, February 17 - May 10*



Notes: Mobility towards parks and transit stations is not reported because too few counties are covered. Estimates based on week-specific regression (1) coefficients and including controls for: COVID-19 cases, precipitation, lockdown, votes for Trump, economic dependence, population density, share of people over 65, median household income, health risk and the share of people in poverty, state fixed effects. Estimates from a pooled model with time fixed effects displaying estimates for all controls is available in Supplementary Annex Table B1.

Source: Cuebiq, Google Mobility trends and Penn State University-Social Capital (PSU-SC) Index.

Table 1. *List of variables and sources*

Data	Unit	Resource/website
Outcome variables:		
- Cuebiq's Mobility Index (CMI)	Index	https://help.cuebiq.com/hc/en-us/articles/360041285051-Reading-Cuebiq-s-COVID-19-Mobility-Insights
- Cuebiq's Shelter-in-place analysis	% of users at home	https://help.cuebiq.com/hc/en-us/articles/360041285051-Reading-Cuebiq-s-COVID-19-Mobility-Insights
- Community Mobility by Google	% change from baseline	https://www.google.com/covid19/mobility/
Control variables:		
- Penn State University-Social Capital (PSU-SC) Index	Std (mean 0 and SD of 1)	https://aese.psu.edu/nercrd/community/social-capital-resources/social-capital-variables-for-2014
- Total population *(weights in models)*	Counts	https://www2.census.gov/programs-surveys/popest/technical-documentation/file-layouts/2010-2018/cc-est2018-alldata.pdf
- Number of cases	Counts	https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/
- Economic dependence of counties	Factor	https://www.ers.usda.gov/data-products/county-typology-codes/
- Poverty	Percentage	U.S. Census Bureau, Small Area Income and Poverty Estimates (SAIPE) Program
- Weather *(precipitation)*	Counts (cms by 10)	Menne, M.J., I. Durre, B. Korzeniewski, S. McNeal, K. Thomas, X. Yin, S. Anthony, R. Ray, R.S. Vose, B.E.Gleason, and T.G. Houston, 2012: Global Historical Climatology Network - Daily (GHCN-Daily), Version 3]. NOAA National Climatic Data Center. http://doi.org/10.7289/V5D21VHZ [15-04-2020].
- Demographic structure *(share of people above 65)*	Percentage	https://www2.census.gov/programs-surveys/popest/technical-documentation/file-layouts/2010-2018/cc-est2018-alldata.pdf
- Density	Population per square mile	U.S. Census Bureau, Census of Population and Housing (https://www.census.gov/library/publications/2011/compendia/usa-counties-2011.html#LND)

- SIPO	Dummy	Mervosh et al. (2020) and "The National Association of Counties - County Explorer" (https://ce.naco.org/?dset=COVID-19&ind=Emergency%20Declaration%20Types)
- Political	Percentage	https://github.com/tonmcg/US_County_Level_Election_Results_08-16/blob/master/2016_US_County_Level_Presidential_Results.csv
- Median income	Thousands	U.S. Census Bureau, Small Area Income and Poverty Estimates (SAIPE) Program
- Health risk index*	Factor	www.policymap.com
Risk map:		
- Health risk index*	Index	www.policymap.com

Notes: (*): "COVID-19 risk index normalized by adult population in 2020. PolicyMap created this index for the New York Times. It represents the relative risk for a high proportion of residents in a given area to develop serious health complications from COVID-19 because of underlying health conditions identified by the CDC as contributing to a person's risk of developing severe symptoms from the virus. These conditions include COPD, heart disease, high blood pressure, diabetes, and obesity. Estimates of COPD, heart disease, and high blood pressure prevalence are from PolicyMap's Health Outcome Estimates. Estimates of diabetes and obesity prevalence are from the CDC's U.S. Diabetes Surveillance System"

Table 2. *Estimated indirect effect of social capital on overall mobility through SIPOs, weather conditions and number of COVID-19 cases, February 17 – May 10 2020.*

	Dependent variable:					
	Mobility Index					
	OLS	FE	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	4.031^{***}		4.030^{***}		4.033^{***}	
	(0.011)		(0.011)		(0.011)	
Weather*Social Capital	-0.028	-0.055^{***}				
	(0.019)	(0.015)				
SIPO*Social Capital			-0.019^{**}	-0.085^{***}		
			(0.008)	(0.006)		
COVID cases*Social Capital					0.011^{***}	-0.005^{***}
					(0.001)	(0.001)
Weather (precipitation)	-0.381^{***}	-0.331^{***}	-0.361^{***}	-0.286^{***}	-0.370^{***}	-0.293^{***}
	(0.020)	(0.014)	(0.017)	(0.010)	(0.017)	(0.010)
SIPO	-0.864^{***}	-0.425^{***}	-0.875^{***}	-0.478^{***}	-0.870^{***}	-0.425^{***}
	(0.008)	(0.010)	(0.009)	(0.011)	(0.008)	(0.010)
COVID cases	0.008^{***}	-0.018^{***}	0.007^{***}	-0.020^{***}	0.020^{***}	-0.024^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Share of Republican votes in 2016 presidential elections	1.056^{***}		1.052^{***}		1.069^{***}	
	(0.031)		(0.031)		(0.031)	
Population density (1000 people per sqmile)	-0.014^{***}		-0.014^{***}		-0.015^{***}	
	(0.001)		(0.001)		(0.001)	
% people in poverty	-0.013^{***}		-0.014^{***}		-0.014^{***}	
	(0.002)		(0.002)		(0.002)	
% of people above 65	-1.808^{***}		-1.779^{***}		-1.874^{***}	
	(0.098)		(0.099)		(0.095)	
Median income (thousands)	-0.014^{***}		-0.014^{***}		-0.014^{***}	
	(0.0004)		(0.0004)		(0.0004)	
Health risk	-0.178^{***}		-0.178^{***}		-0.178^{***}	
	(0.012)		(0.012)		(0.012)	
Economic dependency	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	No	Yes	No	Yes
Time FE	No	Yes	No	Yes	No	Yes
Observations	34,044	34,044	34,044	34,044	34,044	34,044
R^2	0.434	0.849	0.434	0.850	0.435	0.850
Adjusted R^2	0.434	0.836	0.434	0.837	0.435	0.836
Residual Std. Error	224.682 (df = 34028)	121.008 (df = 31192)	224.670 (df = 34028)	120.620 (df = 31192)	224.460 (df = 34028)	120.969 (df = 31192)

Notes: *p<0 .1; **p<0.05; ***p<0.01. Standard errors in parentheses. All specifications are weighted with population data at the county level. All controls are mean centered and social capital is standardised (mean 0 and SD of 1).

Table 3. *Estimated indirect effect of social capital on retail and recreation mobility through SIPOs, weather conditions and number of COVID-19 cases, February 17 – May 10 2020.*

	Dependent variable:					
	Retail and recreational					
	OLS	FE	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	3.628***		3.556***		3.560***	
	(0.285)		(0.285)		(0.285)	
Weather*Social Capital	-4.111***	-2.863***				
	(0.607)	(0.329)				
SIPO*Social Capital			-0.193	-1.001***		
			(0.242)	(0.130)		
COVID cases*Social Capital					-0.011	-0.156***
					(0.034)	(0.017)
Weather (precipitation)	-11.463***	-4.096***	-8.889***	-2.084***	-8.918***	-2.119***
	(0.577)	(0.292)	(0.440)	(0.195)	(0.439)	(0.194)
SIPO	-34.585***	-3.441***	-34.760***	-4.104***	-34.639***	-3.451***
	(0.202)	(0.193)	(0.249)	(0.211)	(0.203)	(0.193)
COVID cases	-0.343***	-0.609***	-0.330***	-0.621***	-0.338***	-0.780***
	(0.023)	(0.012)	(0.024)	(0.012)	(0.045)	(0.022)
Share of Republican votes in 2016 presidential elections	16.277***		16.913***		17.000***	
	(0.836)		(0.838)		(0.830)	
Population density (1000 people per sqmile)	-0.307***		-0.310***		-0.310***	
	(0.019)		(0.019)		(0.019)	
% people in poverty	0.120***		0.132***		0.137***	
	(0.042)		(0.042)		(0.042)	
% of people above 65	-14.239***		-17.941***		-18.452***	
	(2.635)		(2.652)		(2.564)	
Median income (thousands)	-0.094***		-0.092***		-0.092***	
	(0.011)		(0.011)		(0.011)	
Health risk	-2.951***		-2.922***		-2.917***	
	(0.313)		(0.313)		(0.313)	
Economic dependency	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	No	Yes	No	Yes
Time FE	No	Yes	No	Yes	No	Yes
Observations	20,814	20,814	20,814	20,814	20,814	20,814
R^2	0.658	0.953	0.658	0.953	0.658	0.953
Adjusted R^2	0.658	0.948	0.657	0.948	0.657	0.948
Residual Std. Error	5,765.701 (df = 20798)	2,250.324 (df = 18596)	5,771.964 (df = 20798)	2,251.321 (df = 18596)	5,772.039 (df = 20798)	2,249.842 (df = 18596)

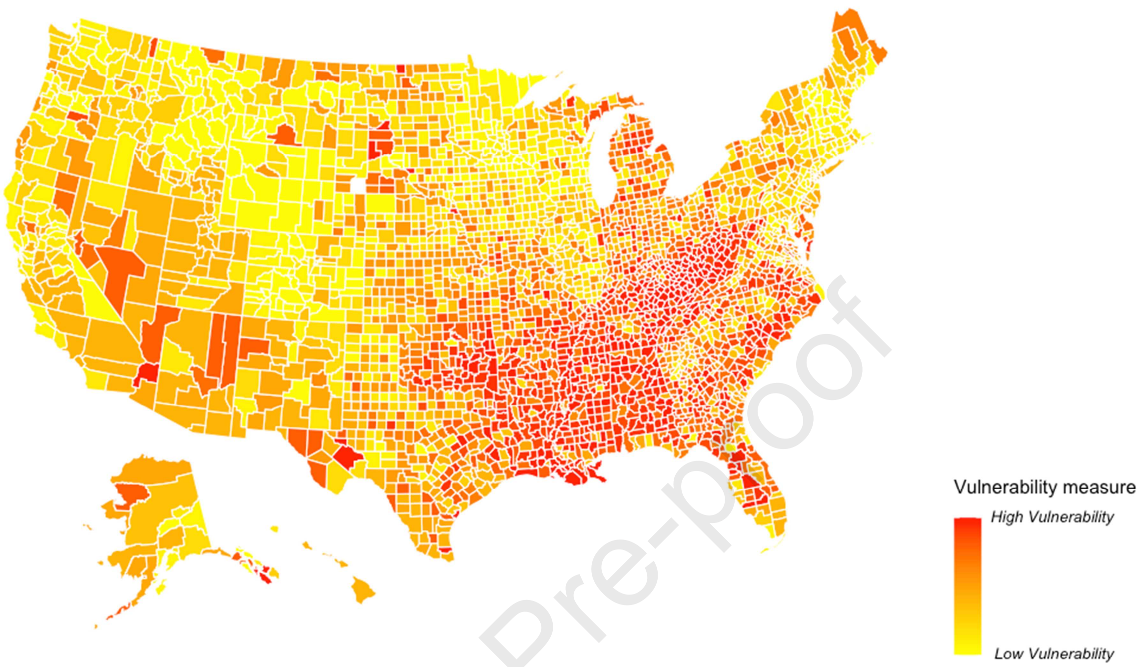
Notes: *p<0 .1; **p<0.05; ***p<0.01. Standard errors in parentheses. All specifications are weighted with population data at the county level. All controls are mean centered and social capital is standardised (mean 0 and SD of 1).

Table 4. *Estimated indirect effect of social capital on shelter-in-place through SIPOs, weather conditions and number of COVID-19 cases, February 17 – May 10 2020.*

	Dependent variable:					
	Shelter-in-place					
	OLS	FE	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	21.464***		21.446***		21.474***	
	(0.115)		(0.115)		(0.115)	
Weather*Social Capital	0.467**	0.624***				
	(0.209)	(0.115)				
SIPO*Social Capital			-0.448***	0.030		
			(0.085)	(0.046)		
COVID cases*Social Capital					0.027*	0.128***
					(0.014)	(0.007)
Weather (precipitation)	6.280***	2.862***	6.077***	2.461***	5.989***	2.401***
	(0.219)	(0.108)	(0.181)	(0.079)	(0.180)	(0.079)
SIPO	16.294***	3.592***	16.052***	3.615***	16.289***	3.587***
	(0.083)	(0.078)	(0.096)	(0.083)	(0.083)	(0.078)
COVID cases	0.091***	0.280***	0.079***	0.280***	0.121***	0.420***
	(0.010)	(0.005)	(0.010)	(0.005)	(0.019)	(0.009)
Share of Republican votes in 2016 presidential elections	-10.482***		-10.815***		-10.562***	
	(0.339)		(0.339)		(0.336)	
Population density (1000 people per sqmile)	0.156***		0.160***		0.155***	
	(0.008)		(0.008)		(0.008)	
% people in poverty	-0.227***		-0.238***		-0.230***	
	(0.017)		(0.017)		(0.017)	
% of people above 65	22.327***		24.274***		22.747***	
	(1.061)		(1.072)		(1.038)	
Median income (thousands)	0.047***		0.046***		0.047***	
	(0.004)		(0.004)		(0.004)	
Health risk	1.136***		1.129***		1.132***	
	(0.126)		(0.126)		(0.126)	
Economic dependency	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	No	Yes	No	Yes
Time FE	No	Yes	No	Yes	No	Yes
Observations	34,044	34,044	34,044	34,044	34,044	34,044
R^2	0.613	0.947	0.613	0.947	0.613	0.947
Adjusted R^2	0.613	0.942	0.613	0.942	0.613	0.943
Residual Std. Error	2,443.749 (df = 34028)	945.564 (df = 31192)	2,442.938 (df = 34028)	946.007 (df = 31192)	2,443.795 (df = 34028)	941.068 (df = 31192)

Notes: *p<0 .1; **p<0.05; ***p<0.01. Standard errors in parentheses. All specifications are weighted with population data at the county level. All controls are mean centered and social capital is standardised (mean 0 and SD of 1).

Figure 3. *County level vulnerability to COVID-19 based on prevalence of chronic health conditions and levels of social capital*



Source: Health risk index and Penn State University-Social Capital (PSU-SC) Index.

Highlights

Between February and May 2020 because of COVID-19 mobility decreased in the US.

Mobility decreased more and faster in counties with high social capital.

Counties with high social capital especially reduced retail and recreation mobility.

Mobility declined in high social capital counties before regulations were introduced.

Poor weather and many COVID-19 cases reduced mobility more with high social capital