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Community Boosts Immunity? Exploring the Relationship Between Social Capital and COVID-19 Social Distancing

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Abstract
The early stages of the COVID-19 pandemic required a dramatic change in social practices, including distancing from social settings, to limit its spread. While social capital has considerable potential in facilitating the adoption of these norms, it also comes with considerable limitations that potentially undermine its effectiveness. We draw upon recently released mobility data from Google, network data from Facebook, and demographic data from the 2018 American Community Survey to determine how both organizational and networked measures of social capital relate to different forms of distancing. In addition, we employ geographically weighted regression to identify how these relationships vary across the nation. Findings indicate that while both forms of social capital can positively relate to distancing, the impacts are spatially inconsistent and, in some locations, social capital can discourage distancing. In sum, more policy efforts are needed to address not only low-social capital, but also unhelpful social capital.

Keywords COVID-19 · Social capital · Social distancing · Big data · Geographically weighted regression

1 Introduction

The social distancing embraced in most US jurisdictions as a means to address the COVID-19 pandemic calls for expanded personal space when interacting in person and avoiding large gatherings, schools, workplaces, and stores. Distancing has been characterized as both important for personal wellbeing and a civic responsibility. Anthony Fauci, the Director of the National Institute of Allergy and Infectious Diseases, has stated, "You have a responsibility not only to protect yourself, but you

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almost have a societal, moral, responsibility to protect other people" (Noah 2020). Social distancing policies are unprecedented in recent history not only for their mass scale, taking place across much of the country, but also for the relative suddenness of their implementation.

The willingness of people to socially distance so suddenly has been mixed. Though most Americans initially supported some form of distancing until the risk has subsided (Politico, 2020), it is not clear how willing they are to distance in practice (Mcminn, 2020). There have also been widely publicized protests against distancing in its early stages (Beckett, 2020). Several factors may explain this resistance. For example, public trust in the government is at historic lows (Pew Research Center, 2019) and trust in the healthcare system is, at best, irregular (Gibbons, 2019). The inconsistent early adoption of distancing policies by state and local governments has exacerbated low confidence (Brennen et al., 2020). By the end of March 2020, only 25 out of 50 states and 132 out of 3108 counties had adopted social distancing policies (The National Association of Counties, 2020). Moreover, misinformation surrounding how to keep oneself safe from COVID-19 has been rampant, especially in the pandemic's early stages (Brennen et al., 2020). Given the possibility the pandemic will continue for years and that similar outbreaks may follow it, knowing what predicts compliance with distancing orders is a critical issue.

One promising tool policymakers and community members can use to encourage distancing is social capital (Kahn & Costa, 2020). While this is a widely defined concept (Bourdieu, 2002; Coleman, 1988; Portes, 1998), it is most commonly associated with the framing from Putnam (2000) as the sum benefit of organizations and social networks for a community. These networks can be leveraged by communities to spread information on the importance of distancing and encourage community members to distance. Social capital has been linked with effective preparations and crisis management during outbreaks of SARS, Ebola, and Zika (Brayne, 2017; Koh & Cadigan, 2008; Kruk et al., 2015; Trapido, 2019; Vinck et al., 2019; Wilkinson & Fairhead, 2017). Some evidence suggests that social capital helped promote effective distancing practices in Taiwan, which avoided a mass COVID-19 outbreak (Shapiro, 2020). However, social capital can have positive or negative impacts (Portes, 2014). For example, social capital can facilitate unhealthy collective behaviors (Blair et al., 2017; Kawachi et al., 1998; Lochner et al., 2003; Reich, 2018; Villalonga-Olives & Kawachi, 2017; Vinck et al., 2019), which could include resistance to social distancing.

To determine how social capital relates to social distancing, we take advantage of county-level mobility data recently made available from Google (Google LLC, 2020). We also draw upon social network data recently made available from the social networking service Facebook (Facebook, 2020). We derive from this network data a measure of social capital and compare its associations with distancing against a measure of social capital based on organizations (Rupasingha et al., 2006). We focus specifically on the early stages of distancing to assess the capacity of a given community to distance with short notice. To unlock the variation in the association of organizational and network measures of social capital to distancing, we employ geographically weighted regression (GWR) along with traditional ordinary least squares (OLS) regression. Commonly viewed as an exploratory tool (O'Sullivan &

Unwin, 2010), GWR allows us to generate empirically determined coefficients for each observation, producing a more nuanced assessment of the association between social capital and distancing from a local perspective (Becker, 2019; Fotheringham et al., 2003). Based on such analysis we build a nationwide picture of the relationships between social distancing to social capital.

2 Background

Putman's (2000) framing of social capital uses a "whole network" approach (Wellman, 1988), measuring the connectivity of an entire group as opposed to the connections between individuals (Bourdieu, 2002; Coleman, 1988). In the influential book *Bowling Alone*, Putnam (2000) emphasizes the importance of organizations, such as bowling leagues and nonprofit organizations, in fostering this capital. Regular meetings with these organizations is a key source of bonding social capital, which is based on similar characteristics and beliefs (Coleman, 1988; Portes, 1998; Putnam, 2000). It gives those involved the chance to discuss local issues and solve problems (Tissot, 2015). Churches, for example, motivate civic activity based upon moral and ethical grounds and have pastors and other figures such as deacons who can direct activities (McRoberts, 2003). While not all groups can have such an explicit service orientation, even more casual organizations, such as bowling leagues, can have a formalized structure which can direct civic behaviors (Putnam, 2000). Indeed, the social capital from organizations has been found to encourage basic healthy behaviors that can be routinized into norms, such as exercising (Adler & Kwon, 2000; Kawachi et al., 1998; Portes, 1998; Putnam, 2000).

Social networks are an essential underlying component of social capital. While networks can be fostered in organizational settings (Putnam, 2000), they are not exclusively derived from these places. Social capital can also emerge from informal encounters in one's day to day life, such as casual encounters on the street (Jacobs, 1961) or local stores (Saegert et al., 2002). Social media in its various forms has become increasingly central to building local connections (Boyd, 2015; Lane, 2018). These networks can serve as conduits to spread information about how to properly prepare and respond to a public crisis (Aldrich & Meyer, 2015; Reininger et al., 2013) like a heat wave (Klinenberg, 2003). In this way, more social networks can increase benefits as it facilitates the spread of resources and benefits. Without a specific organizational presence, these kinds of relationships tend to be less formally moderated and consequentially not as predictable as for how useful they will be for prevention (Benjamins, 2006; Thompson et al., 2013; Wingood et al., 2013).

Social capital's effectiveness toward healthy behavior is in part due to the strong social cohesion that it fosters (Adler & Kwon, 2000). Strong cohesion facilitates community members' mutual care of each other (Klinenberg, 2003) and encouragement of positive norms for the good of the community as a whole (Sampson, 2012). Both organizations and social networks more broadly encourage positive interventions, such as a church pastor or a concerned parent in a neighborhood (Lane, 2018). Such interventions can amount to informal social control exerted through subtle or blatant discouragement of activities harmful to the individual or the community (Kawachi et al., 1998).

Social capital also facilitates the sharing of resources, both tangible and intangible, in times of crisis (Aldrich & Meyer, 2015). These resources include items like food, assistance such as transportation to a health care center (Reininger et al., 2013), access to a home with air conditioning during a heat wave (Klinenberg, 2003), and emotional support (Kawachi et al., 1998). People can draw on social capital to get through a crisis, even if they are alone and resource deprived (Walker & Hiller, 2007). Both organizational strength and the presence of networks enable the sharing of resources through social capital. One difference is that some organizations have more complex organization that allows them to directly provide large volumes of resources themselves. While nonprofit organizations are especially designed for this purpose, many different associations can perform these tasks (Allard, 2009; McQuarrie & Marwell, 2009; Thompson et al., 2013). In this way, the presence of organizations may be a more robust indicator of support than networks alone (Putnam, 2000). To this end, we first hypothesize,

H1 The organizational aspects of social capital will be more likely to have an association with social distancing than the networked aspects.

Social capital research often focuses on the problems stemming from its absence, or forces that weaken it (Coleman, 1988; Putnam, 2000; Saegert et al., 2002). Putman (2000), singled out the decline in organizational membership and its consequences for civic oriented social capital. However, some have questioned the importance of this decline for social cohesion (Fischer, 2005), observing the power of informal connections. These connections can include public characters—well connected individuals who can broker information between community members (Lane, 2018). Nonetheless, the local presence of organizations can vary greatly from place to place. In sum, the positive impact of this social capital on health is likely variable across the country (Adler & Kwon, 2000).

There are also some concerns about the weakening of social networks. Researchers argue that a trend away from living in densely populated areas that prevailed at the end of the twentieth century, which offer reduced opportunities for informal encounters and exchange, and toward commutes of 45 min or more, have also damaged social capital (Putnam, 2000). Also, residential instability is related to reduced social capital (Oishi, 2010). Other research points to individual factors such as intergenerational poverty (Saegert et al., 2002) a lack of education (Helliwell & Putnam, 2007), and, for people of color, living in racially/ethnically heterogeneous communities (Laurence, 2011).

A smaller body of research clarifies that social capital, and robust community more broadly, is not inherently positive (Joseph, 2002; Portes, 2014). For example, places with high social capital may tend to exclude newcomers (Kawachi et al., 1998; Lochner et al., 2003; Villalonga-Olives & Kawachi, 2017), cutting them off from information and resources (Lochner et al., 2003). Alternatively, scholarship shows social capital is not inherently civic-minded, potentially bringing together people uninformed about health (Portes, 1998, 2014), who then share biased or inaccurate information (Reich, 2018). Communities may encourage conformity among members and therefore further discourage questioning of harmful information (Joseph, 2002; Lochner et al., 2003). This kind of active suppression of dissenting voices against bad advice has been found especially strong in community organizations (Joseph, 2002). Given the importance of informal local actors in spreading information in communities that have significant social capital (Jacobs, 1961; Kawachi et al., 1998), social capital can readily undermine the weight of recommendations from knowledgeable authorities (Coleman, 1988; Villalonga-Olives & Kawachi, 2017). This can lead to poor preparedness and response (Blair et al., 2017; Vinck et al., 2019), such as some local communities refusing vaccinations (Reich, 2018).

The internet, and social networking services in particular, have had an increasingly central role in the formation of social capital (Hampton & Wellman, 2018). A recent Pew study found 69 percent of Americans use social networking services like Facebook, with 74 percent of this group using the platform daily (Perrin & Anderson, 2019). Moreover, social media usage is well-represented across demographic groups (Greenwood et al., 2016; Perrin & Anderson, 2019). The structure and composition of the social networks channeled through Facebook are similar to their offline counterparts (Arnaboldi et al., 2013). Indeed, the social networks channeled through Facebook are not simply a proxy of offline social networks; they are an important aspect of users' social lives (Lane, 2018). What is more, formal organizations have increasingly relied upon social media to spread information and encourage discourse between participants and leadership (Afzalan et al., 2014).

Scholars have debated what exactly social capital networks represent on platforms such as Facebook. Earlier scholarship found it to be bridging social capital, connections between people who otherwise share few other links and can be of very different social backgrounds (Ellison et al., 2007), whereas more recent research describes it as bonding social capital (Phua et al., 2017). However, in-person interaction is a pivotal aspect of the cohesion that bonding social capital typically offers (Valenzuela et al., 2009). Recent research on Facebook social networks has shown that sameness matters in these connections, especially between the connections of users in local places (Bailey et al., 2018). Indeed, people may learn about and discuss local community issues with their neighbors on social networking services like Facebook (Hampton & Wellman, 2003; Lane, 2018). Likewise, Facebook is an effective tool to manage preparedness for crisis (Afzalan et al., 2014).

On the other hand, Facebook has attained notoriety as a platform for the spread of misinformation (Vicario et al., 2016). Much of this is due to the kind of 'siloing' of social networks found through bonding social capital. This means that the bad information people encounter with Facebook may be reinforced when discussing it with friends in their social network (Heekeren, 2020). Research has already found that COVID-19 can spread along Facebook social networks (Kuchler et al., 2021). However, the spread of false information pertaining to news events precedes social networking services and these services can facilitate the correction of bad information.

The nature of social capital is also potentially at odds with social distancing. In-person meetings are a cornerstone of the procurement and use of social capital (; Saegert et al., 2002; Jacobs, 1961; Putnam, 2000). Indeed, people who have social capital and are therefore more likely to meet in person may be more likely to practice problematic health behaviors like excessive drinking (Villalonga-Olives & Kawachi, 2017). Arguably the organizational aspects of social capital would have a more robust association, as it has traditionally relied upon in-person meetings (Putnam, 2000). However, more informal connections encourage in-person meetings, such as the desire for casual encounters (Villalonga-Olives & Kawachi, 2017). Nonetheless, this suggests that organizational social capital many have a unique association with weakening social distancing. Based on this, we next hypothesize,

H2 The organizational aspects of social capital are less likely to spatially vary compared to the networked based components.

A final consideration is the location from which one is distancing. The sweeping nature of the shelter at home policies means residents are distancing from very different social settings. This raises questions as for how social capital will relate to distancing from each kind of site. We suspect social capital will most likely have a relationship to recreational distancing. Whether or not one goes to a recreational site has been found more directly influenced by social capital compared to visits to workplaces as people explicitly go to recreational sites to meet friends. People may also go to stores to meet friends, but this is not as often the case as compared to recreational sites (Oldenburg, 1989). Whether social capital has a positive or negative association with distancing from recreational sites depends on the character of the local community. Recall that people may violate the distancing policies to see friends at recreational sites like bars (Villalonga-Olives & Kawachi, 2017). Following the previous reasoning (Jacobs, 1961; Putnam, 2000; Saegert et al., 2002), we believe organizational social capital may have a stronger association with recreational sites. We hypothesize,

H3 Organizational social capital will be less related to workplace distancing than other forms of physical distancing.

In sum, the past literature does not predict whether social capital will promote or impede adherence to social distancing rules. On the one hand, social capital is related to the spread of information about healthy behaviors. What is more, the cohesion social capital brings can exert pressure on people to conform to social distancing. The exact source of the social capita, however, may matter. Organizational social capital has been touted for its role in ensuring healthy behaviors, its key benefit being formalized leadership and mobilization (Cramer et al., 2021; Klinenberg, 2003; Thompson et al., 2013; Wingood et al., 2013). However, social capital is only as effective as the local norms and environment through which these networks exist, and it can aid the spread of misleading information and unhealthy behavior just as it spreads positive outcomes. This raises the question as for the importance of the share of organizations in an area for useful social capital compared to the sheer volume of social networks.

3 Data and Measures

To proxy social distancing, we use measures of mobility from Google (Google LLC, 2020). Google collects mobility trend data on Google Maps users and pairs this data with their extensive database on location classifications. This includes mobility trend data for *grocery*: grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies; *recreation*: restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters; and *workplaces*. For cases where a person works at a grocery or recreation location, Google uses proprietary user data to distinguish workplaces from other similar locations (Google LLC, 2020). The data consists of Google's indications of what percent of regular daily movement to these locations has changed since the advent of COVID-19. Google established a baseline of mobility to and from the above locations from January 3rd to February 6th 2020. Their measure of mobility indicates how much users of Google maps have avoided the above locations from February 16th to March 29th 2020 in comparison to the baseline. The resulting mobility score determines the percentage to which a county's population is distancing from a location. In interpreting these scores, a negative mobility value indicates *more* distancing, as a population is less likely to go to a given place, while a positive mobility score indicates *less* distancing, as a population is more likely to go to a given location. For example, a county with a score of −30 for workplaces means the residents are, on average, 30 percent less likely to go to their workplaces than before the mass outbreak of COVID-19—conversely, a score of 5 means residents of a county are 5 percent *more* likely to go to their workplaces compared to before the outbreak.

This is a useful timeframe as it captures the initial stages of the adoption of COVID-19 distancing policies, demonstrating the initial capacity, and willingness of people in places across the country to distance.

The distinction between the mobility to and from grocery, recreation, and workplace sites is useful to compare as each category plays a different role in social capital. Recreation mobility represents an interesting contradiction: recreational activities/organizations are some of the strongest determinants of traditional social capital (Putnam, 2000). Thus, the draw of such places may undermine the positive impact of social capital, if one exists. However, shelter-at-home policies have dictated the shuttering of such sites in many jurisdictions (The National Association of Counties, 2020). Furthermore, of the locations studied, these are arguably the least essential for wellbeing (Maslow, 1954). The establishments in the grocery store category are typically exempt from distancing policies for exactly this reason (The National Association of Counties, 2020). Like recreation facilities, grocery stores can be a source of social capital (such as a random encounter between neighbors), if to a lesser degree, and thus high social capital could encourage more trips to the grocery store than necessary (Saegert et al., 2002). A failure to enter some places may indicate greater social capital, as it can offer alternative ways to access food without physically visiting a store, whether through connections to people who will shop for others or by providing information on how to get food delivered. Regular interactions between co-workers at workplaces can also be a source of social capital, but social capital is not commonly the primary reason people go to them and whether they are closed varies significantly in different jurisdictions and according to different industries (Putnam, 2000; Valentino-DeVries et al., 2020).

Google mobility data has a few limitations. Much of the process for how the data is collected, such as how is it determined whether the user is going to a grocery store to shop or is an employee of the store, is proprietary. The lack of readily available alternative mobility data comparable to Google's makes it difficult to validate their measure. As well, the exact number of people who use Google Maps is also proprietary, meaning we could not determine how large of a share of the population uses this service. Google omitted counties that they determined did not have sufficient user data to create estimates (Google LLC, 2020). Despite these limitations, a recent study (Barrios et al., 2021) reports that the Google data yields results comparable with other data sources, which offers a certain level of external validity to the Google data.

We measure bonding social capital two ways: the Social Capital Index (SCI), a measure of organizational social capital (Putnam, 2000), and the Local Social Connectivity Index (LSCI), a measure of networked social capital and derived from the Social Connectivity Index from Facebook. These measures capture different aspects of social capital formation, specific to their medium. The SCI measures organizational aspects of social capital. Meanwhile, the LSCI measures the socially networked components of social capital.

Rupasingha Goetz, and Freshwater (2006) developed the SCI. This measure considers the organizational capacity of a county to build social capital. It is a principal component analysis (PCA) of associations (religious, civic, businesses, political, professional, labor, sports, and miscellaneous recreation) per 1000 (loading 0.634), non-profit organizations per 10,000 (loading 0.676), voter turnout (0.377), and the Census response rate (−0.040). The poor loadings of civic behaviors compared to organizational presence reinforce that this is primarily a measure of the organizational aspects of social capital, its association with civic behaviors is more ambiguous. The resulting PCA score is standardized, with a mean of zero and standard deviation of approximately 1. While this measure was not explicitly designed to measure bonding social capital, validation studies have found it corresponds closely to demographic sameness, like racial/ethnic homogeneity (Rupasingha et al., 2006).

The LSCI is based on Facebook social network data and determines the relative probability a user in one county is connected to another in the US (Bailey et al., 2018). While the SCI is an organizational measure of social capital (Rupasingha et al., 2006), the LSCI is a network measure. Facebook determines a users' place of residence based on their self-reported location, check-ins, and location information determined from use of the Facebook app. Their measure assesses the total connection between the users in two counties, i and j:

$$Social\ Connectedness_{i,j} = \frac{FB\_Connections_{i,j}}{FB\_Users_i * FB\_Users_j} \tag{1}$$

FB_Users_i and FB_Users_j are the number of Facebook users in counties i and j, and $FB\_Connections_{i,j}$ is the number of Facebook friendship connections between the two (Bailey et al., 2019, 6).[1]

To better use Social Connectivity measure to gauge bonding social capital, we emphasize local connections, which demonstrated greater -homogeneity in research on Facebook networks (Bailey et al., 2018, 2019). We compare the probability of connections in one's own county and neighboring counties to the probability of connections in other, more distant, counties:

$$\underset{i}{\begin{matrix} Local\ Social\ Connectedness \\ Index \end{matrix}} = \frac{Social\ Connectedness_{i,i} + \sum_{z=1}^{Z} Social\ Connectedness_{i,z}}{\sum_{l=1}^{L} Social\ Connectedness_{i,l}} \tag{2}$$

The numerator of the local social connectedness index for a focal county i is the sum of social connectedness (see formula 1) within county i and the social connectedness between county i and each neighboring county z. The denominator is the sum of social connectedness between county i and each non-neighboring county l. The final local social connectedness index for the focal county is the ratio between these two numbers. The local social connectedness index aims to gauge the strength of ties/connections within a county and to a county's neighbors. To define neighborhoods, we used first-order queen spatial weights. That is, if two counties shared the same boundary or a vertex, they are defined as neighbors. A county with high bonding social capital has a greater number of local connections than to other counties. A comparison of demographics offers some support that this measure reflects bonding social capital. The median percent White in the 80th percentile for the LSCI is 89.57, comparable to the SCI. Facebook data has similar drawbacks as Google data in that key information is proprietary, such as how residence is established and even the number of users. Also, while this measure allows us to account for both organizational social capital as well as informal social networks, it does not allow us to untangle their separate effects. In our analysis, we standardize this measure (i.e., mean center) to ease its comparability with the SCI.

Our other predictors come from several additional sources. First, we use the 2018 American Community Survey to estimate demographic information about counties. This includes race/ethnicity, including percent non-Hispanic White (reference), non-Hispanic Black, Asian, and Hispanic, given the association of racial/ethnic homogeneity to social capital (Lancee & Dronkers, 2011). We account for socioeconomic status, a critical predictor of social capital, in several ways, including the percent college educated (Helliwell & Putnam, 2007), percent living in poverty, percent with health insurance, and percent unemployed (Saegert et al., 2002). We also

[1] The social connectedness index developed by Facebook only considers whether there is a connection between two users and the fact that the two users may share certain characteristics (e.g., race/ethnicity or interest) is not considered. That is, the strength or similarity of a connection is not included in the social connectedness index, which may cause interdependence within an index. In addition, it is worth noting that the social connectedness index is a feature shared between two counties and it may not be affected by the number of users in other areas.

account for percent female and percent adults over the age of 65 (Walker & Hiller, 2007). Also, in light of evidence that population density supports social capital and long commutes hamper it (Putnam, 2000) we measure percent of workers commuting more than 45 min and population density. Given that unstable communities tend to have low social capital (Oishi, 2010), we assess residential stability with percent homeowners and percent who have lived in their current homes for five years or less.

We include several additional measures using data other than the ACS. The first data source is the County Health Rankings (Robert Woods Johnson Foundation, 2020). We measure the share of violent crimes per 100,000, as originally reported by the Uniform Crime Report (Robert Woods Johnson Foundation, 2020). Crime can have a detrimental impact on the effectiveness of community cohesion (Sampson, 2012). We also draw from the USDA's measures on the economic character of a county to identify counties that primarily conduct agriculture (U.S. Department of Agriculture, 2019). We chose this measure both as a supplemental measure of social-economics as the perceived challenge in maintaining social distancing in a rural setting as well as the essential nature of agriculture (Valentino-DeVries et al., 2020). Also, to determine when a state or county enacted shelter policies, we draw upon the County Explorer (The National Association of Counties, 2020). We establish the number of days since states and counties enacted a shelter policy, starting March 19th 2020 in the case of states and March 16th 2020 in the case of counties. States and counties that did not enact a policy by March 29th were given the maximum value for each. (The National Association of Counties, 2020). Lastly, we measure metropolitan areas using core-based statistical areas (CBSAs). We avoided using COVID-19 mortality data and hospitalization rates due to considerable inconsistencies in these data across the nation (Wu et al., 2020).

For this analysis, we only focus on the 2760 counties in the 48 contiguous states as GWR analysis requires spatial contiguity. Including the omissions from Google, our final data sets, broken down by outcome, included 2297 counties for grocery visits, 2395 counties for recreation visits, and 2531 counties for workplace visits.

4 Analysis

Our main analysis is a two-step process. We conduct OLS models to determine the overall association of our county-level predictors with the three types of mobility measured. OLS is limited in that it presumes local effects are consistent across all observations (Fotheringham et al., 2003). To establish how well social capital predicts social distancing across the US, we supplement these models with GWR (Becker, 2019).

GWR is an extension of the generalized linear modeling by considering the location of each observation and this study focuses on modeling continuous dependent variables as follows. Y_i, $i=1,\ldots, n$, indicates the measure of mobility from a certain location (i.e., grocery, recreation or workplaces) in a county i and other covariates in the same county are denoted as a vector $X_i=(1, X_{i1}, X_{i2},\ldots, X_{ip})^{t}$ of dimensions $(p+1)$, which includes the constant 1 for intercept. A GWR model can be expressed as follows (S. Fotheringham et al., 2003):

$$Y_i = X_i^t \beta(u_i, v_i) + \varepsilon_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} X_{ik}\beta_k(u_i, v_i) + \varepsilon_i$$

where $\beta(u_i, v_i) = \left\{\beta_0(u_i, v_i), \beta_1(u_i, v_i), \ldots, \beta_p(u_i, v_i)\right\}$, (u_i, v_i) represents the coordinates of county i's geographical centroid, and ε_i is the error term with mean zero and common variance σ^2. The parameter estimations, β_k, are specific to each county, which allows us to examine the spatially varying associations. GWR uses the distance between any two counties to yield these estimates. For a given location (u_0, v_0), the $\beta' s$ are locally computed by minimizing the function below:

$$\sum_{i=1}^{n} \left[Y_i - \beta_0(u_i, v_i) - \sum_{k=1}^{p} X_{ik}\beta_k(u_i, v_i) \right]^2 K(\frac{d_{i0}}{h})$$

where K is a kernel function, usually a symmetric probability density function and h is the bandwidth, which controls the smoothness of the estimates. $K(\frac{d_{i0}}{h})$ is the geographical weight specifically assigned to county i and its values depends on the distance between the given location (u_0, v_0) and i (d_{i0}).

The interpretation of GWR coefficients is largely consistent with that of OLS models (Becker, 2019). Explicitly, the regression coefficient of a particular variable—for example, social capital—at a specific location in the model indicates the change in the magnitude in mobility compared to the baseline given a one-unit change. As the GWR model generates results for each county in our data, we use two methods to describe our results. First, we reported summary statistics (minimum, three quartiles, and maximum) of the local coefficient estimates. Second, we mapped out select coefficients for each form of mobility analyzed (Becker, 2019). To address multiple hypothesis testing, we adopted the Fotheringham-Byrne correction to adjust the P-value for visualization (Byrne et al., 2009). Note that using different correction methods does not alter our findings and conclusions. We used the R package *spgwr* to implement the analysis.

5 Results

We report our descriptive values by type of location in Table 1. First, overall, the mobility data suggest effective social distancing in the initial stages (February 16th–March 29th 2020): compared to the baseline (January 3rd–February 6th 2020), there is a 14.15 percent decline in regular visits to grocery stores, a 38.45 percent decline in visits to recreational sites, and a 30.77 percent decline in regular trips to work. As expected, the standard deviation for grocery store mobility and recreation mobility are higher than work mobility. Across each outcome, the average state adopted a shelter at home policy within 8 days and the average county within 13 days. To evaluate the presence of spatial autocorrelation in our data, we report the Moran's I values for each of our predictors (except for state policies, which would have little local variance). These values demonstrate that most of our predictors have

Table 1 Descriptive values by mobility type

Variable	Work					Grocery					Recreation				
	Mean	St. dev	Min	Max	Moran's I	Mean	St. dev	Min	Max	Moran's I	Mean	St. dev	Min	Max	Moran's I
Distancing	−30.772	8.878	−76.00	3.000	0.420	−14.146	15.099	−73.00	128.000	0.427	−38.445	16.956	−100.00	133.000	0.401
COVID cases	7.194	45.907	0.000	1599.000	0.365	7.194	45.907	0.000	1599.000	0.385	7.194	45.907	0.000	1599.000	0.382
Percent black	9.005	14.520	0.000	87.412	0.735	9.005	14.520	0.000	87.412	0.732	9.005	14.520	0.000	87.412	0.710
Percent asian	1.260	2.340	0.000	35.650	0.499	1.260	2.340	0.000	35.650	0.526	1.260	2.340	0.000	35.650	0.522
Percent hispanic	9.300	13.855	0.000	99.069	0.670	9.300	13.855	0.000	99.069	0.747	9.300	13.855	0.000	99.069	0.698
Percent female	49.945	2.354	21.004	58.614	0.176	49.945	2.354	21.004	58.614	0.188	49.945	2.354	21.004	58.614	0.186
Percent college eaducated	21.548	9.436	0.000	78.531	0.408	21.548	9.436	0.000	78.531	0.415	21.548	9.436	0.000	78.531	0.410
Percent 64 and older	18.426	4.542	3.799	55.596	0.381	18.426	4.542	3.799	55.596	0.394	18.426	4.542	3.799	55.596	0.397
Percent living in poverty	12.644	5.188	1.258	45.655	0.561	12.644	5.188	1.258	45.655	0.553	12.644	5.188	1.258	45.655	0.546
Percent unemployed	3.232	1.399	0.000	16.470	0.313	3.232	1.399	0.000	16.470	0.320	3.232	1.399	0.000	16.470	0.322
Percent insured	90.000	4.984	57.623	98.258	0.621	90.000	4.984	57.623	98.258	0.651	90.000	4.984	57.623	98.258	0.631

Table 1 (continued)

Variable	Work					Grocery					Recreation				
	Mean	St. dev	Min	Max	Moran's I	Mean	St. dev	Min	Max	Moran's I	Mean	St. dev	Min	Max	Moran's I
Percent 45 minute commute or longer	84.852	7.876	48.249	99.121	0.383	84.852	7.876	48.249	99.121	0.389	84.852	7.876	48.249	99.121	0.392
Percent homeowner	71.541	8.114	19.607	92.397	0.192	71.541	8.114	19.607	92.397	0.204	71.541	8.114	19.607	92.397	0.210
Percent moved	4.090	1.611	0.000	21.212	0.124	4.090	1.611	0.000	21.212	0.129	4.090	1.611	0.000	21.212	0.136
Violent crime	251.394	191.874	0.000	1819.514	0.318	251.394	191.874	0.000	1819.514	0.309	251.394	191.874	0.000	1819.514	0.313
Local social connectivity index#	1248.716	990.909	0.070	9617.961	0.305	1248.716	990.909	0.070	9617.961	0.347	1248.716	990.909	0.070	9617.961	0.325
Social capital index#	0.007	1.260	−3.183	21.809	0.477	0.007	1.260	−3.183	21.809	0.417	0.007	1.260	−3.183	21.809	0.441
Agricultural	0.163	0.370	0.000	1.000	0.238	0.163	0.370	0.000	1.000	0.152	0.163	0.370	0.000	1.000	0.141
State shelter at home policy date#	8.000	3.294	0.000	11.000	–	8.000	3.334	0.000	11.000	–	8.000	3.327	0.000	11.000	–

Table 1 (continued)

Variable	Work					Grocery					Recreation				
	Mean	St. dev	Min	Max	Moran's I	Mean	St. dev	Min	Max	Moran's I	Mean	St. dev	Min	Max	Moran's I
County shelter at home policy date#	13.000	1.687	0.000	14.000	0.472	13.000	1.750	0.000	14.000	0.508	13.000	1.729	0.000	14.000	0.496
Population density	0.000	0.001	0.000	0.028	0.464	0.000	0.001	0.000	0.028	0.492	0.000	0.001	0.000	0.028	0.488
Metropolitan area	0.374	0.484	0.000	1.000	0.328	0.374	0.484	0.000	1.000	0.319	0.374	0.484	0.000	1.000	0.325
N	2584					2326					2423				

moderate to strong spatial autocorrelations, which may result from spatial heterogeneity and highlights the need for GWR analysis (Fotheringham, 2009).

To better understand how consistent social distancing is across the US, we visualize the distributions of each mobility outcome in Fig. 1. We overlay the 10 most highly populated CBSAs to help orient the reader. When interpreting these results, bear in mind that the more negative a mobility value indicates greater distancing of a population while positive mobility values means no distancing for a population. First, in Fig. 1 we visualize the spatial variation of the three forms of mobility. These maps indicate that the forms of mobility measured are roughly consistent in that the areas with less mobility (blue areas) or greater mobility (red areas) in the same places, notwithstanding small differences such as less recreation and grocery mobility but greater work mobility in the Midwest. The areas with the lowest mobility include parts of the Northeast and northeastern portions of the Midwest. Much of the South and western portions of the Midwest have greater mobility. Some high populated metropolitan areas, like New York, have very low mobility relative to other areas while others, like Atlanta, have only somewhat less mobility compared to other areas.

Next, we visualize our two measures of social capital, the SCI (organizational) and the LSCI (network), in Fig. 2. Like our discussion of Table 1, we report off the working mobility sample. To ease interpretability, we report the standard deviations for each value. Comparing the spatial distribution of organizational and network measures of social capital reveal stark differences. While values for both appear weaker within major urban centers, where they are at their strongest varies considerably. The SCI is strongest in the Midwest and Pacific Northwest and lowest in the Southwest and parts of the South. Meanwhile, the LSCI is strongest in the South, Northeast, and parts of the Southwest. For example, the southwestern section of Texas has very low organizational social capital but very high network social capital. In short, the presence of social capital depends greatly on the type being measured and its location. Compounding matters, comparing Figs. 1–2, we see neither form of social capital corresponds strongly to mobility. To determine whether these forces are related requires subsequent multiple regression analysis.

5.1 OLS

While neither form of social capital relates to grocery mobility, both are related to less recreation mobility. For example, each point increase in the LSCI is related to -1.568 points of recreation mobility. Similarly, each point increase in the SCI is related to -2.041 points of recreation mobility. Meanwhile, there is a divergence in the relationships of social capital and work distancing by the type of capital. While the LSCI has a relation with less mobility, the SCI has a relation with greater mobility. Put differently, each point increase of the SCI is related to a 0.773-point increase in going to work compared to the baseline.

There is some variation as for how the other predictors relate to mobility. In terms of race/ethnicity, the percent Hispanic of a county is related to less grocery and recreation mobility, but not work mobility. Counties with a greater percentage of

Fig. 1 **a** Work mobility. **b** Grocery mobility. **c** Recreation mobility ▸

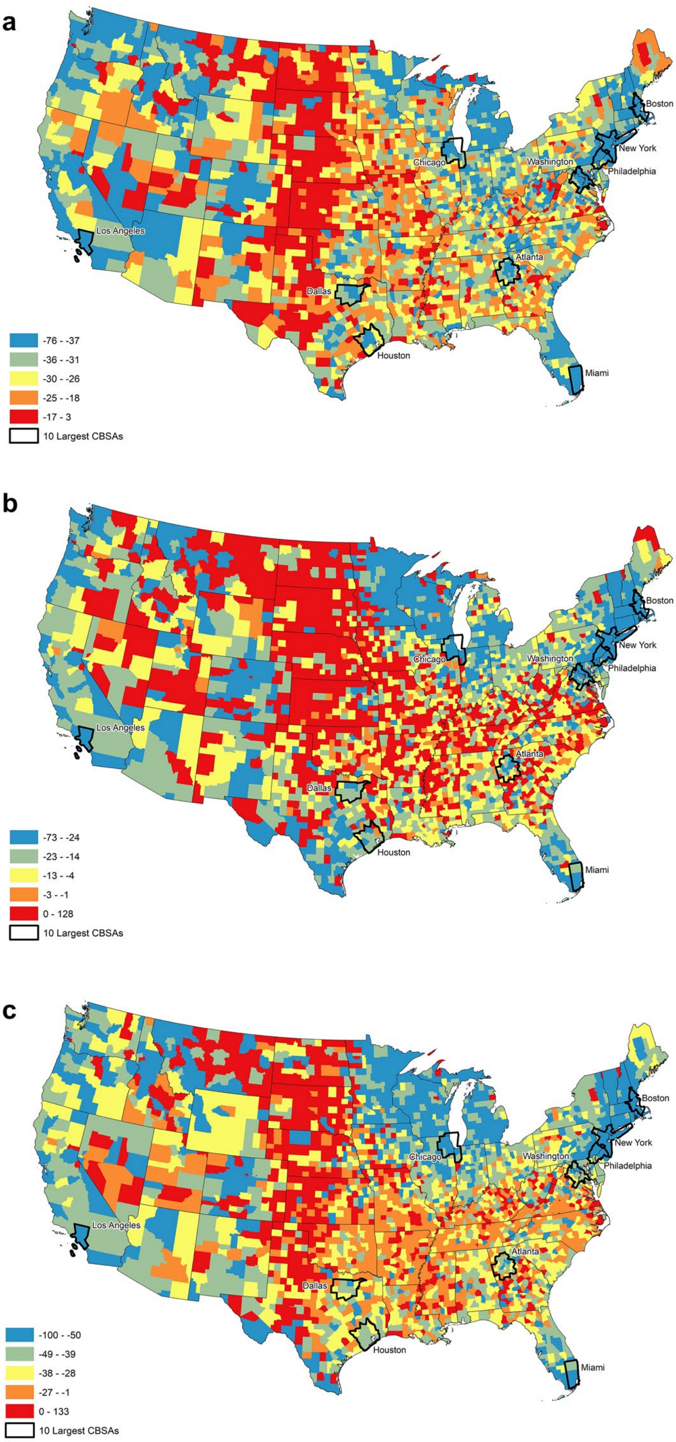
college educated show less mobility from recreation and work. However, poverty is not significantly related to mobility (except for recreation). Agricultural counties are related to more work mobility. Violent crime is related to more grocery mobility but less recreation mobility. Early state shelter policies are related to all forms of distancing measured; the later the state shelter at home policy was enacted, the greater mobility found in a county. Meanwhile, county distancing policies are significantly related to work mobility—the later a county-level policy was enacted the more work mobility can be found in that county. Population density is related to less mobility from recreation and work, but not grocery stores. Last, metropolitan areas are significantly related to less mobility to work and recreation. To ensure no excessive collinearity in our models, we evaluated the variance inflation factor (VIF) scores. In Table 2 we report the scores for work to illustrate their range in value. All VIF scores fell under 4, indicating collinearity is in the acceptable range (Kutner et al., 2005). To determine how consistent these associations are across space, we turn to our GWR results.

5.2 GWR

Table 3 reports the GWR results. Given that the GWR models separate results for all counties for each outcome, a five-value summary is the most efficient means of reporting the range of coefficients. An Akaike Information Criterion (AIC) was used to determine whether the GWR model fit the data better than the OLS model (Fotheringham et al, 2003). We find that all AIC values for the GWR models are much smaller than their OLS equivalents, justifying our GWR models (Burnham & Anderson, 2002). For example, the OLS Grocery AIC was 18,413.57 while the GWR version is 18010.010, indicating it better fits the data set.

The GWR coefficients range dramatically, suggesting that the relationship between social capital and distancing depends on where a county is located. For example, in most counties LSCI is related to less recreation mobility, as evidenced by the coefficients shown for Q1-Q3. However, the maximum coefficient (0.186) suggests that in certain county conditions social capital is related to greater mobility. As such, even though the LSCI has a significant relationship with less recreation mobility in the OLS model, this association does not hold for the entire study area. The SCI displays similar trends. Indeed, many of the other predictors can vary from negative relationships with mobility (more distancing) to positive relationships with mobility (less distancing). The notable exception to this pattern is college education, which retains its relationship with less mobility for both recreation and work across all counties.

These findings raise two critical questions: Which of these coefficients are significant and where, exactly, do they vary? In light of the nature of local estimations, the p values of GWR estimates may be underestimated due to multiple hypothesis testing (Wheeler, 2009). We adopt the Fotheringham-Byrne correction to adjust the P values to reflect the significant local variations more accurately. To better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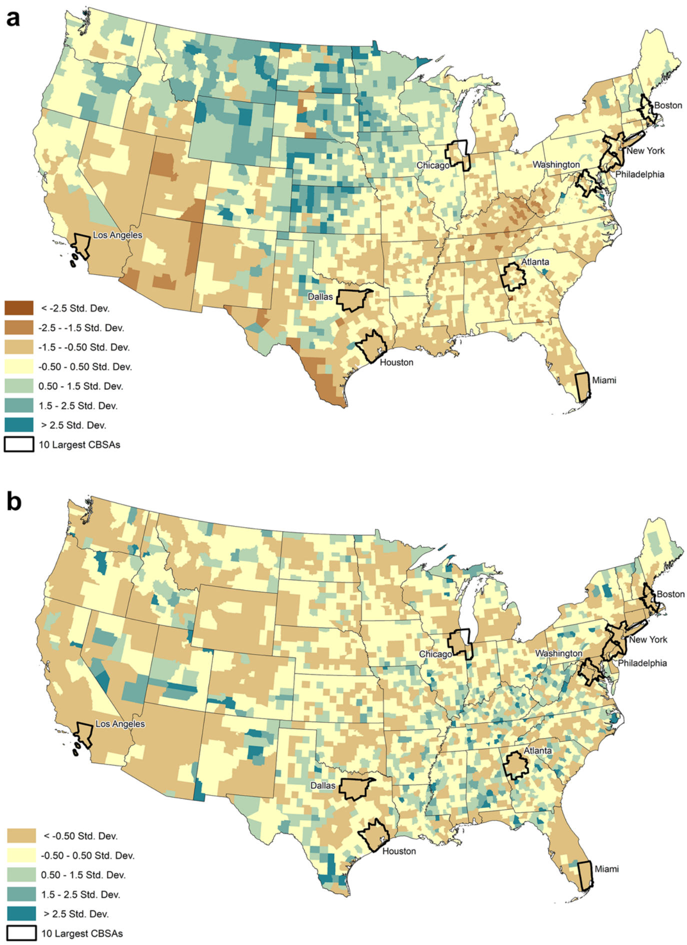

Fig. 2 **a** Social capital index. **b** Local social connectivity index

contextualize our GWR estimates, we make use of a series of maps of the 48 contiguous states, presented in Figs. 3,4, 5, to unpack the local spatial relations of social capital to mobility. Blank areas have statistically insignificant coefficients (adjusted p value > 0.05).

These maps reveal some interesting local trends. While both forms of social capital were related to less recreation mobility in the OLS model, neither was significantly related to more distancing on the East Coast. Both appear to have their strongest relationship with less mobility in the western reaches of the US. Interesting trends are also present for work distancing. We find that while the SCI had a significant relation with more work mobility in the OLS model, the places with significant and positive coefficients are largely confined to a section in the Midwest, around Chicago, and in parts of Texas. The LSCI had a significant relationship to more work distancing, through the magnitude of that association varies from the

Table 2 OLS results for mobility by type

Variables	Work	Grocery	Recreation	VIF [a]
COVID cases	−0.005*	−0.005	−0.011*	1.151
	(0.003)	(0.005)	(0.006)	
Percent black	0.022*	−0.020	0.059**	1.929
	(0.014)	(0.027)	(0.030)	
Percent asian	0.221***	0.262*	0.191	2.121
	(0.079)	(0.149)	(0.162)	
Percent hispanic	0.008	−0.235***	−0.095***	1.638
	(0.013)	(0.024)	(0.026)	
Percent female	0.252***	0.290**	0.927***	1.238
	(0.073)	(0.142)	(0.159)	
Percent college educated	−0.564***	−0.606***	−0.766***	2.782
	(0.023)	(0.045)	(0.049)	
Percent 64 and older	−0.223***	−0.092	−0.250***	1.795
	(0.042)	(0.081)	(0.088)	
Percent living in poverty	−0.008	0.052	0.348***	3.087
	(0.049)	(0.097)	(0.107)	
Percent unemployed	−0.955***	0.244	−0.600*	1.677
	(0.148)	(0.302)	(0.332)	
Percent insured	0.138***	−0.154**	0.190**	1.890
	(0.039)	(0.077)	(0.083)	
Percent 45 minute commute or longer	0.115***	0.034	−0.112**	1.536
	(0.021)	(0.042)	(0.045)	
Percent homeowner	−0.072**	0.048	−0.018	3.206
	(0.031)	(0.060)	(0.065)	
Percent moved	−0.395***	−0.225	0.584**	2.013
	(0.129)	(0.244)	(0.275)	
Violent crime	0.001	0.006***	−0.004**	1.618
	(0.001)	(0.002)	(0.002)	
Local social connectivity index#	−0.496***	0.450	−1.568***	2.022
	(0.191)	(0.377)	(0.405)	
Social capital index#	0.773***	−0.562	−2.041***	1.781
	(0.172)	(0.344)	(0.365)	
Agricultural	1.379***	1.547	1.883	1.204
	(0.498)	(1.180)	(1.209)	
State shelter at home policy date#	1.948***	3.269***	4.243***	1.361
	(0.157)	(0.308)	(0.331)	
County shelter at home policy date#	0.398***	−0.261	−0.032	1.294
	(0.153)	(0.298)	(0.321)	
Population density	−0.538***	−0.315	−1.104***	1.332
	(0.155)	(0.304)	(0.327)	
Metropolitan area	−1.004***	−0.148	−1.857**	1.705
	(0.355)	(0.688)	(0.750)	

Table 2 (continued)

Variables	Work	Grocery	Recreation	VIF [a]
Constant	−39.518***	−6.107	−73.057***	
	(6.128)	(12.057)	(13.183)	
Observations	2.584	2.326	2.423	
AIC	17,278.93	18,413.57	19,645.73	
R2	0.416	0.313	0.338	
N	2584	2326	2423	

*$p<0.1$; **$p<0.05$; ***$p<0.01$

#Standardized

[a]VIF scores based on Work model

west (stronger) to the east (weaker). This is notable because it contrasts with the significant coefficients for the SCI and work. Likewise, it contrasts with the significant association between the LSCI and greater recreation mobility found in this area. Last, while neither social capital measure had a significant relation to grocery distancing in the OLS model, the GWR reveals both the SCI and the LSCI have significant local coefficients. For the SCI, there is a strong negative relationship with grocery distancing in the northern Midwest, to the north of Chicago. For the LSCI, there is a strong association with greater mobility where Michigan, Indiana, and Ohio meet.

6 Conclusion

To determine the potential of social capital to facilitate social distancing, we drew upon two measures of social capital, one based on organizations, and the other based on the overall social networks, and established their relationship to social distancing through mobility to three types of locations: grocery, recreation, and workplace. We employed GWR models to unlock the local variation of social capital to mobility. GWR estimation allowed us to discern the underlying spatial structure in the relationship between these variables to identify local unmodeled characteristics.

We found evidence that our measures of bonding social capital have both positive and negative associations with distancing, echoing the literature suggesting both productive and destructive impacts of social capital on community outcomes. Support for our first hypothesis was inconsistent, *H1. The organizational aspects of social capital will be more likely to have an association with social distancing than the networked aspects*. In the OLS model, the SCI measure only had a measurable strong association with recreational distancing. Meanwhile, the SCI score was related to less work distancing. With the GWR results, in some cases the association of social capital (either form) to social distancing was positive while in others it was negative. The direction of the relationship depends not only on the type of social distancing, but where in the US the distancing takes place. For example, while the

Table 3 Summary of GWR coefficients for mobility by type

	Work							Grocery							Recreation						
	Adjusted t-values							Adjusted t-values							Adjusted t-values						
	Min	1st Q	Median	3rd Q	Max	Mean	Std dv	Min	1st Q	Median	3rd Q	Max	Mean	Std dv	Min	1st Q	Median	3rd Q	Max	Mean	Std dv
Intercept	−87.860	−32.723	−13.984	−7.285	20.991	−2.357	2.824	−63.246	−38.368	−10.815	−1.664	8.282	−0.964	1.069	−120.230	−105.650	−93.603	−67.675	−40.096	−4.014	1.011
COVID cases	−8.997	−2.109	−1.240	−0.640	−0.080	−2.178	1.075	−5.399	−1.780	−1.253	−0.364	−0.007	−0.992	0.505	−6.728	−2.501	−1.970	−0.753	−0.179	−1.443	0.430
Percent black	−0.139	−0.045	−0.002	0.042	0.091	0.205	2.010	−0.175	−0.097	−0.046	0.027	0.252	−0.396	2.251	−0.078	−0.026	0.030	0.150	0.376	1.204	2.263
Percent asian	−0.477	−0.201	−0.117	0.031	0.541	−0.069	1.526	−1.215	−0.811	−0.418	0.018	0.543	−0.915	1.316	−1.099	−0.585	−0.252	0.040	0.465	−0.650	0.983
Percent hispanic	−0.181	−0.100	−0.010	0.027	0.216	−0.199	1.915	−0.364	−0.271	−0.177	−0.066	0.232	−3.566	3.818	−0.296	−0.156	−0.095	−0.013	0.279	−1.302	1.919
Percent female	−0.397	−0.099	0.098	0.417	0.880	1.093	2.250	−0.313	−0.007	0.156	0.616	1.352	1.072	1.452	0.142	0.563	0.799	1.284	1.936	3.329	1.306
Percent college educated	−0.767	−0.501	−0.370	−0.343	−0.263	−10.317	4.702	−0.716	−0.508	−0.400	−0.311	−0.120	−5.349	2.381	−0.955	−0.674	−0.618	−0.571	−0.323	−7.323	2.319
Percent 64 and older	−0.422	−0.234	−0.177	−0.088	0.060	−2.036	1.275	−0.465	−0.082	0.195	0.305	0.679	0.658	1.761	−0.425	−0.254	−0.132	−0.027	0.234	−0.797	0.960
Percent living in poverty	−0.357	0.001	0.118	0.170	0.248	1.129	1.390	−0.330	−0.024	0.058	0.218	0.544	0.785	1.342	−0.093	0.227	0.436	0.606	1.036	2.664	1.417
Percent unemployed	−1.982	−1.076	−0.651	−0.518	−0.237	−3.168	1.425	−0.571	−0.179	0.478	0.758	1.103	0.636	1.035	−1.860	−1.108	−0.450	0.109	0.799	−0.769	1.235
Percent insured	−0.130	−0.051	−0.016	0.091	0.413	0.730	2.342	−0.446	−0.174	−0.068	0.034	0.187	−0.684	1.209	0.023	0.152	0.253	0.379	0.732	2.092	1.203
Percent 45 minute commute or longer	−0.029	0.036	0.055	0.127	0.219	2.091	1.588	−0.191	−0.048	−0.012	0.043	0.215	0.010	1.284	−0.256	−0.141	−0.091	−0.045	0.082	−1.291	0.963
Percent homeowner	−0.410	−0.178	−0.095	−0.029	0.033	−2.153	1.826	−0.172	0.059	0.108	0.145	0.174	0.915	0.793	−0.504	−0.075	0.015	0.125	0.292	0.026	1.581

Table 3 (continued)

	Work						
	Adjusted t-values						
	Min	1st Q	Median	3rd Q	Max	Mean	Std dv
Percent moved	− 1.274	− 0.753	− 0.508	− 0.352	− 0.007	− 2.397	1.281
Violent crime	− 0.007	0.000	0.002	0.003	0.006	0.788	1.782
Local social connectedness index#	− 1.382	− 0.636	− 0.353	− 0.264	− 0.084	− 1.471	0.839
Social Capital Index#	− 0.164	0.247	0.619	1.281	2.458	2.570	1.829
Agricultural	− 4.755	− 2.824	1.235	1.617	2.178	0.037	2.555
State shelter at home policy date#	0.429	0.876	1.095	1.934	3.907	5.543	2.985
County shelter at home policy date#	− 0.113	0.315	0.449	0.589	0.930	1.189	0.593
Population density	− 3.745	− 2.474	− 0.836	− 0.500	6.866	− 1.425	1.580
Metropolitan area	− 2.605	− 1.491	− 0.643	0.017	0.937	− 1.212	1.639
AIC	16,822.250						
R2	0.519						

	Grocery						
	Adjusted t-values						
	Min	1st Q	Median	3rd Q	Max	Mean	Std dv
Percent moved	− 1.407	− 0.490	− 0.048	0.254	0.723	− 0.514	1.474
Violent crime	− 0.006	0.003	0.006	0.010	0.014	2.126	1.732
Local social connectedness index#	− 1.462	− 0.071	1.030	1.439	2.155	1.191	1.628
Social Capital Index#	− 3.533	− 1.769	− 0.494	0.145	0.416	− 1.283	1.772
Agricultural	− 4.586	− 0.532	0.515	2.088	5.760	0.259	1.574
State shelter at home policy date#	1.606	2.810	3.390	3.972	6.802	7.316	2.290
County shelter at home policy date#	− 0.308	1.034	1.275	1.511	1.825	1.763	0.974
Population density	− 1.874	− 0.117	0.154	2.019	10.560	0.310	0.851
Metropolitan area	− 2.231	− 1.813	− 0.505	1.161	3.227	− 0.053	1.603
AIC	18,010.010						
R2	0.432						

	Recreation						
	Adjusted t-values						
	Min	1st Q	Median	3rd Q	Max	Mean	Std dv
Percent moved	− 0.799	− 0.071	0.604	1.108	1.656	1.130	1.514
Violent crime	− 0.020	− 0.007	− 0.003	0.000	0.005	−1.429	2.090
Local social connectedness index#	− 3.048	− 2.471	− 1.278	− 0.290	0.186	−2.058	1.546
Social Capital Index#	− 4.153	− 3.322	− 1.535	− 0.817	− 0.231	−3.170	1.733
Agricultural	− 3.881	− 0.844	2.066	3.213	5.999	0.498	1.322
State shelter at home policy date#	2.477	3.393	3.923	4.492	6.904	7.798	1.844
County shelter at home policy date#	− 0.845	0.133	0.519	0.883	1.460	0.664	0.697
Population density	− 3.924	− 1.692	− 0.714	− 0.331	4.629	−0.720	0.886
Metropolitan area	− 5.094	− 3.171	− 2.485	− 0.724	1.757	−1.645	1.503
AIC	19,194.670						
R2	0.460						

#Standardized

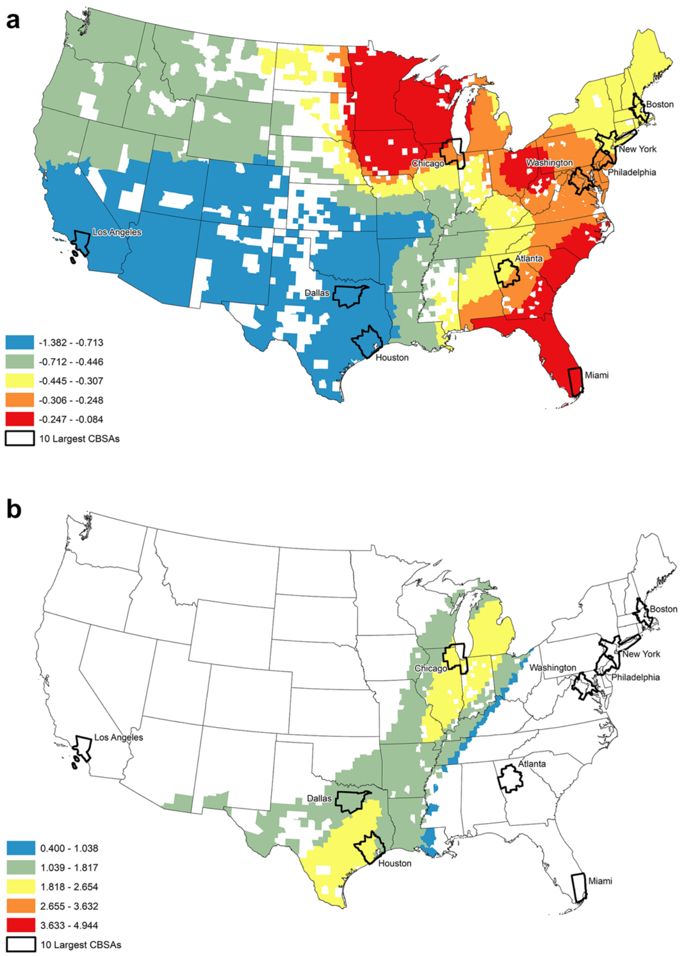

Fig. 3 **a** Work mobility local connectivity index. **b** Work mobility social capital index

OLS models found both the organizational and networked measures of social capital were significantly related recreation distancing, our GWR estimates revealed these relationships were only significant in some places. This means we do not have support for our second hypothesis, *H2. The organizational aspects of social capital are less likely to spatially vary compared to the networked based components.* Moreover, the social capital measures do not always correspond to one another locally, in some places directly conflicting depending on the type of distancing. In particular, the GWR results showed organizational social capital could locally relate to physical distancing from workplaces at rates greater than recreational distancing. This also means we do not have support for our third hypothesis, *H3: Organizational social capital will be less related to workplace distancing than other forms of physical distancing*.

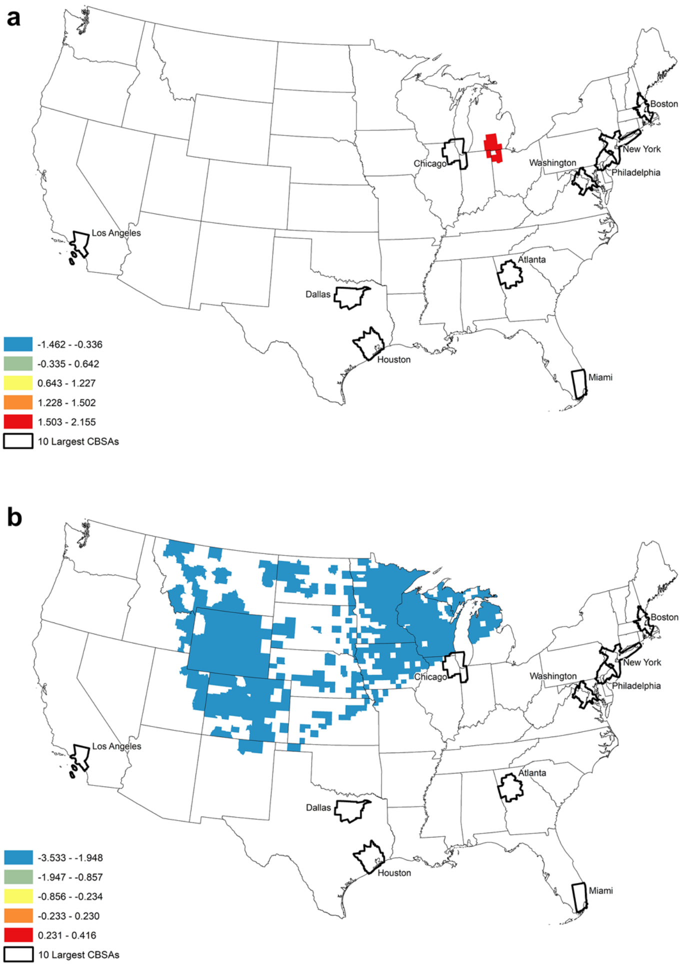

Fig. 4 **a** Grocery mobility local social connectivity index. **b** Grocery mobility social capital index

These results support several insights. First, by directly comparing the association of network and organizational measures social capital to a collective healthy behavior nationwide, we find the relationship between social capital and distancing is not consistent nationwide. The lack of overlap of the network measure to the organizational measure may reflect the digital divide, which would impact the presence of the networked measure. Many people have access to Facebook (Perrin & Anderson, 2019), but 15 percent of Americans, 42 million people, still lack access to fixed internet in their homes, and they disproportionately live in rural areas (Busby & Tanberk, 2020). Thus, it is unsurprising that the inconsistencies we identified between our organizational measure and network measure, based on Facebook, were the most apparent in such areas.

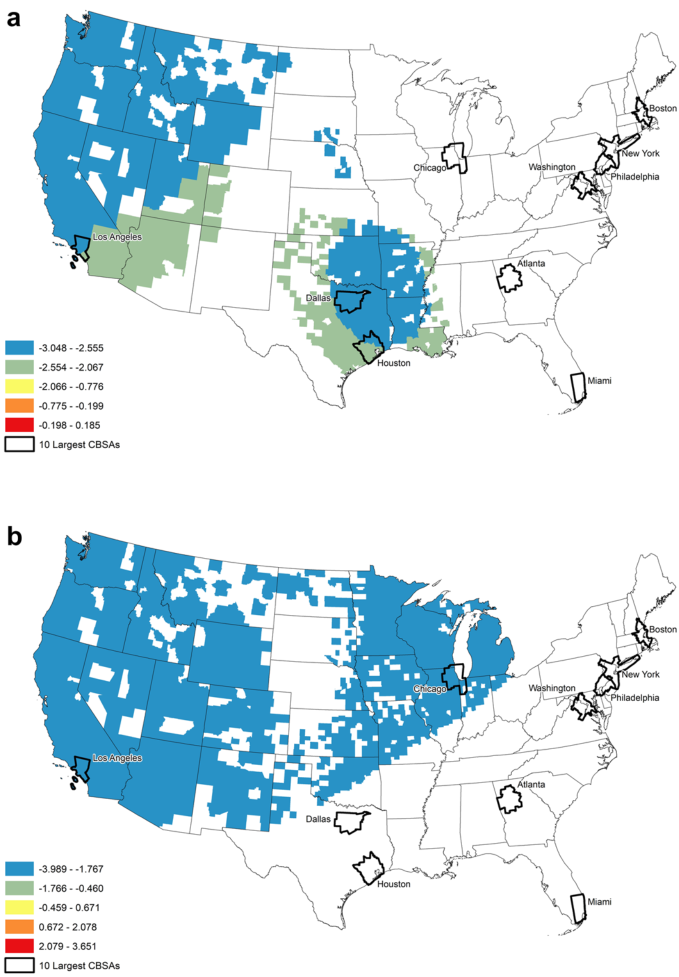

Fig. 5 **a** Recreation mobility local social connectivity Index. **b** Recreation mobility social connectivity index

The second insight was that organizational social capital did not have a consistent local relation to distancing. We find numerous places across the US that have a high degree of organization social capital are not effectively distancing. In this way, the local failure of social capital to aid in distancing is not simply an absence of this capital, as Putnam's (2000) research would suggest. We do not have the data to determine why this is the case. If the anti-vaccine movement (Reich, 2018) and more recent anti-distancing protests are any indication (Beckett, 2020), Portes' (1998, 2014), many organizations may have become conduits of misinformation. More research should be conducted to establish the local reasons why social capital is failing to facilitate social distancing. Our GWR findings suggest locations in which to focus efforts.

A third insight is exploring the potential usefulness of networked social capital overall in encouraging a healthy behavior. We found several cases where the network measure of social capital could promote social distancing when the organizational measure did not. In short, social networks both in and out of organizations have the potential to direct social capital toward useful ends. However, we were not able to directly untangle the digital aspect of this measure from its physical components. We know from past research that the physical and digital networks are deeply intertwined (Boyd, 2015; Lane, 2018), but they are not completely identical, meaning we can only see some of their impact in this study. Likewise, we were not able to study the online presence of organizations as it compares to their in-person presence (Afzalan et al., 2014). Nevertheless, these results make clear that areas with a high density of organizations do not have an inherent advantage for COVID-19 prevention compared to areas that have a high density of networks—organizationally based or otherwise. Future research should compare the associations of digital and in-person social capital as well as organizational and network-based aspects of both to better understand why they diverge for health.

A fourth insight is that distancing is influenced by various local factors. While the data from Google suggest all forms of distancing unfold similarly across the 48 states, the variables that predicted the presence and magnitude of this distancing varied. Social capital was related to recreational distancing in some places, despite the draw social capital could have to these places (Putnam, 2000). The relatively strong associations identified with social capital and recreation distancing could indicate that, of the three forms of distancing measured, recreation is the least essential. However, the relation between of social capital and poor distancing from grocery stores in some areas may have to do with these stores having more of an association with community (Saegert et al., 2002). At minimum, these results demonstrate social capital can only go so far to explain how communities make decisions about distancing. The strong association of organizational social capital to not distancing from workplaces in some locations makes this clear. Future research should do more to explore these different forms of distancing and the push and pull factors to each type of location.

While this study offers insight into how organizational and networked aspects of social capital predicts healthy behaviors, their inconsistency at a national level calls into question their usefulness in facilitating social distancing. Instead, the most consistent force in ensuring adherence to social distancing, as suggested by our GWR models, is the share of college educated residents. This corresponds to previous research (Portes, 1998), in that social capital is more likely to support social good among educated populaces. However, college education is tied into several inequalities in terms of who is educated, also limiting its effectiveness (Helliwell & Putnam, 2007). Moreover, the usefulness of social capital has to contend with an inconsistent government response. While our models make clear social capital's issues exist even when accounting for sheltering policies, it is not unreasonable to argue that a more consistent and early response from authorities could have bolstered social capital's usefulness. For example, one reason why social capital has been more effective in Taiwan is the consistent and early government response (Shapiro, 2020).

Future research should directly compare bonding social capital to bridging social capital. The social capital in this study is mostly comparable to bonding social capital. While bonding social capital is a critical ingredient to ensuring healthy behaviors (Coleman, 1988; Portes, 1998; Putnam, 2000) such as social distancing, bridging social capital is a way to circumvent some of bonding social capital's flaws, such as the spread of bad information (Kim, 2006). The Facebook data used in this study could be modified to allow the direct comparison of its bonding characteristics to its bridging characteristics. Also, more fully longitudinal data should be used in future studies to determine potential causal associations. Longitudinal data could also be used to unpack the countervailing nature of social capital.

Future research might also improve on the use of GWR, which is commonly viewed as an exploratory tool (O'Sullivan & Unwin, 2010). While GWR showed us the local variation of values, it does not directly explain why these variations exist (Fotheringham et al, 2003; Wheeler, 2007). Further, using GWR we cannot directly account for why the positive and negative social capital trends exist. We suggest that the spatial varying associations found in this study may be a consequence of regional differences in unobserved factors, such as culture and attitude. Including an interaction term between the key independent variable and regional variable in an OLS model may provide cursory findings to this possibility. Another approach is to use the spatial regime analysis approach to test whether the coefficients are stable across regions (Curtis et al., 2012), but it should be noted that GWR provides a more local perspective in contrast to the spatial regime analysis. Second, several unobserved factors that may contribute to the spatially varying associations include structural racism (e.g., residential segregation) and trust toward public institutions and governments (O'Sullivan & Unwin, 2010). For the former, areas with high levels of residential segregation may lead to rapid transmission of virus among minorities, who are more likely to be infected than racial/ethnic majority. When residents in a county have low trust toward government, the effectiveness of a policy to slow the spread of virus may be severely undermined. Ascertaining what these local forces are, and how they matter for distancing, would require closer evaluation of these locales.

The COVID-19 pandemic is a test of our ability to manage a significant public health crisis. While our performance on this test has been at best mixed, it offers an unprecedented opportunity to learn from our failings in preparation for future events. Social capital is a tool, and like most tools, it can be used to assemble and take things apart. Our results reaffirm the *potential* of social capital to mobilize to manage a health crisis (Brayne, 2017; Koh & Cadigan, 2008; Kruk et al., 2015; Trapido, 2019; Vinck et al., 2019; Wilkinson & Fairhead, 2017), however, this tool can only work when wielded effectively.

Declarations

Conflict of interest The authors report no conflict of interest.

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