Is social capital associated with individual social responsibility? The case of social distancing during the Covid-19 pandemic

John (Jianqiu) Bai · Shuili Du · Wang Jin · Chi Wan

Received: 8 September 2021 / Accepted: 22 August 2022 / Published online: 15 September 2022
© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2022

Abstract
Individual social responsibility is essential to achieving the sustainable development goals of the society, yet there has been very little research on whether and how social and cultural factors influence individual social responsibility. Using the Covid-19 pandemic as our empirical context, this research examines the relationship between social capital and individual social distancing behaviors during the pandemic. Social distancing is a form of socially responsible behavior because it is critical in mitigating the spread of the Covid-19 virus. By exploiting daily mobile GPS location data, we provide strong evidence for the divergent relationships between the two constituents of social capital—civic norms and social networks—and social distancing behaviors. While civic norms are positively associated with social distancing, social networks have a negative association with social distancing. These results are consistent with a nuanced view of social capital: civic norms facilitate cooperation and self-sacrifice for the common good, whereas social networks increase individual embeddedness and hence inertia in maintaining social interactions, resulting in opposite effects on social distancing. Our results contribute to the research at the intersection of social capital and

John (Jianqiu) Bai
j.bai@northeastern.edu

Shuili Du
shuili.du@unh.edu

Chi Wan
chi.wan@umb.edu

1 D’Amore-McKim School of Business, Northeastern University, Boston, MA 02115, USA
2 Peter T. Paul College of Business and Economics, University of New Hampshire, Durham, NH 03824, USA
3 Stanford Digital Economy Lab, Stanford University, Stanford, CA 94305, USA
4 College of Management, University of Massachusetts, Boston, MA 02125, USA
individual social responsibility by highlighting the nuanced effects of social capital on individual responses to the pandemic and provide valuable insights for policymakers and businesses in disaster management.

Keywords Individual social responsibility · Covid-19 · Social distancing · Social capital · Civic norms · Social networks

1 Introduction

Sustainable development is a grand challenge for our society due to concerns about climate change, dwindling natural resources, and public health crises such as a global pandemic (United Nations 2015). Achieving sustainable development goals requires concerted efforts from not only governments and companies, but also individual citizens. Whereas a large body of research examines factors influencing companies’ sustainability and corporate social responsibility (e.g., Basu and Palazzo 2008; Du et al. 2013), there is far less research on what influences individuals’ socially responsible behaviors. Take the Covid-19 pandemic as an example. It is an unprecedented public health crisis that threatens the sustainable development of society due to its large-scale and profound effects on the economy, the social fabric, and our lifestyles. Individuals’ socially responsible behaviors such as social distancing is a key behavioral approach to mitigate the spread of this highly contagious virus. However, while practicing social distancing has the public benefit of slowing the transmission of the Covid-19 virus, it inflicts private costs on individuals, such as inconvenience and emotional and psychological stress associated with decreased social interactions. Thus, whether and to what degree individuals practice social distancing is in the realm of individual social responsibility, subject to the influence of internal norms and social pressure.

Within the broad context of individual social responsibility, this paper investigates whether and to what extent social capital is associated with individuals’ socially responsible behavior using the empirical data on social distancing behaviors during the Covid-19 pandemic. Social capital is defined as the civic norms and social networks that facilitate collective actions and foster cooperation and trust within a community (Fukuyama 1997; Guiso et al. 2004, 2009; Woolcock 2001). There is considerable evidence showing that a region’s social capital affects the social and economic behaviors of its residents, such as crime rates, education, and financial behaviors (e.g., Buonanno et al. 2009; Guiso et al. 2004; Putnam 2001). However, there is little evidence on the association between social capital and individual social responsibility, particularly with regard to individual compliance with social distancing in the context of a global pandemic. Understanding the linkage between social capital and social distancing behavior could contribute to the literature at the interface between social capital and individual social responsibility, and provide valuable insights to public policymakers and businesses in dealing with social and business challenges associated with a pandemic.

In contrast to prior research that regards two aspects of social capital—civic norms and social networks—homogenously in how they restrain opportunistic and
norm-deviant behaviors, we hypothesize differential effects of civic norms and social networks on individual social distancing behavior during the Covid-19 pandemic. In particular, we argue that civic norms are the predominant force facilitating cooperation and self-sacrifice for the common good of the community (Buonanno et al. 2009; Putnam 2001), thus enhancing individual compliance with social distancing, whereas social networks may have an opposite effect. Specifically, high density of social networks increases individuals’ embeddedness in the networks (Woolcock 1998), creating an inertia that makes social distancing more difficult to practice. High density of social networks also increases the likelihood that individuals are exposed to conflicting opinions on whether or not to practice social distancing.

We test our hypotheses by focusing on an essential form of social distancing—the extent to which people in the USA stay at home at the early stage of the Covid-19 pandemic. By employing daily GPS location data from SafeGraph in March and April of 2020, we find that counties with high civic norms are better at social distancing (i.e., stay at home more) compared to counties with low civic norms. In contrast, counties with high-density social networks do worse in social distancing compared to their low-density social network counterparts. Importantly, these results are robust to including a battery of county-level control variables that account for demographic characteristics, economic development, and the severity of the Covid-19 pandemic in the geographic locality.

Our sample period spans a 35-day period, between March 16 and April 20, 2020. These dates are deliberately chosen to provide a clean setting for our tests. Our sample period begins when the US government suspends all travel from European countries (i.e., March 16, 2020) and ends when some US states start to reopen (i.e., the State of Georgia starts to reopen on April 20, 2020). To the extent that the majority of US states instituted some form of stay-at-home order during this period, we re-estimate our baseline regressions to examine whether the effects of civic norms and social networks on social distancing are restricted to the period preceding the stay-at-home orders. We find that our main findings hold both before and after the stay-at-home orders are implemented, albeit slightly stronger for the pre-period in the case of civic norms.

We further examine whether the association between civic norms/social networks and individual social distancing varies by industries. To this end, we use the foot traffic data available from SafeGraph, which tracks daily foot traffic to different points of interest broken down into various industries. Overall, we find that the positive association between civic norms and social distancing only applies to non-essential businesses; civic norms do not affect visits to essential businesses, such as health and personal care stores. In contrast, the negative association between social networks and social distancing manifests in all industries, both essential and non-essential businesses.

This paper contributes to the literature at the intersection of social capital and individual social responsibility. While prior research focuses on the impact of social capital on either corporate behaviors (e.g., Hasan et al. 2017a, 2017b; Hoi et al. 2019) or individual social and economic behaviors (e.g., Buonanno et al. 2009; Guiso et al. 2004; Putnam 2001), we extend this literature by not only examining the relationship between social capital and individual socially responsible behavior (i.e., practicing
social distancing during a pandemic), but also taking a more nuanced view of social capital to reveal the differential effects of its two constituents—civic norms and social networks—on social distancing. To date, there is very limited research linking social capital—a concept that originated in sociology—to individual social responsibility (e.g., social distancing during a global pandemic). Given the unique nature of social distancing behavior, that is, requiring individuals to curtail social interactions that are considered socially desirable at normal times, social capital is an especially pertinent influence factor worthy of investigation.

Second, our study contributes to the recent literature that examines individual social distancing behaviors from the social and cognitive psychology perspectives. For example, Van Bavel et al. (2022) show that national identity significantly predicts public health support (e.g., spatial distancing and stricter hygiene)—respondents who identify more strongly with their nation consistently reported greater engagement in public health behaviors. Gollwitzer et al. (2020) find that partisan differences predict physical distancing behaviors, with US counties that voted for Donald Trump over Hilary Clinton in 2016 exhibited 16% less physical distancing in the early stage of the pandemic. Our study complements this line of emerging literature by shedding light on how the underlying cultural and social characteristics of different counties are associated with people’s social distancing behaviors during the early stage of the Covid-19 pandemic. Our research suggests that policymakers and businesses could use county-level social capital data as input variables when assessing compliance with social distancing and allocating resources for managing the pandemic.

The remainder of the paper proceeds as follows. Section 2 reviews the literature and develops the testable hypotheses. Section 3 discusses the data. We present our empirical findings in Sect. 4 and conclude in Sect. 5.

2 Literature review and hypothesis development

Originated in the field of sociology and later extensively studied in the fields of sociology, political science, economics, and business, the idea of social capital dates back to at least Jacobs (1961), who describes it as “neighborhood networks.” There are different conceptualizations of social capital, but the central idea remains the same. Coleman (1988) states that social capital exists in the relations among persons and identifies three forms of social capital: obligations, expectations, and trustworthiness of structures, information channels, and norms and effective sanctions. Woolcock (1998) conceptualizes social capital broadly as encompassing the norms and networks facilitating collective action for mutual benefit and, importantly, he differentiates between two forms of social capital, embeddedness and autonomy and highlights the importance of having a strategic combination of different but complementary types of social relations. Similarly, Putnam (2001) defines social capital as networks and the associated norms of reciprocity and states that strong indicators of social capital include formal membership in civic organizations, participation in different forms of informal networks (e.g., civic participation like signing a petition), and organized altruism (e.g., blood donation, philanthropy, and volunteering).
There is considerable evidence documenting the desirable consequences of social capital. Social capital is found to be positively associated with educational performance, child welfare, individual health and wellbeing, and negatively associated with crime and individual tax evasion (Buonanno et al. 2009; Coleman 1988; Putnam 2001). Social capital also affects individual economic behavior; for instance, Guiso et al. (2004) find that, in high-social-capital areas, households are more likely to use checks, invest more in stock, have higher access to institutional credit, and make less use of informal credit. In the business literature, research suggests that social capital constrains unethical corporate practices and facilitates value-creating activities and socially responsible corporate policies and behaviors. For example, firms headquartered in high social capital regions are associated with less corporate tax avoidance (Hasan et al. 2017a), lower executive compensation (Hoi et al. 2019), more innovative activities (Gupta et al. 2020), greater emphases on social responsibilities (Fuller and Tian 2006; Jha and Cox 2015).

Although prior research has contributed valuable insights into the impact of social capital, there are several gaps in the literature. First, prior research has focused on the impact of social capital on individual social and economic behaviors and corporate behaviors, but there is little research examining the link between social capital and individual social responsibility, such as prosocial behaviors needed to address complex issues like climate change and public health crisis. Social distancing is a socially responsible behavior with public health benefits. Given that the decision to practice social distancing requires difficult trade-offs and is likely subject to individuals’ internal norms and external social influences, social capital is an especially pertinent factor worthy of investigation.

Second, seminal papers on social capital have emphasized that social capital is multi-dimensional, has different types and forms, and is far from homogeneous, and that social capital can produce both positive and negative externalities (Coleman 1988; Putnam 2001; Woolcock 1998), yet extant empirical research has mostly treated social capital as a monolithic, homogenous concept and has mostly focused on the positive outcomes of social capital. Woolcock (1998) emphasizes that social capital is not an unqualified “good,” i.e., something to be maximized; instead, there are different types of social capital and some could have a downside and therefore should be optimized, not maximized. Woolcock (1998, p. 165) further illustrates, “High levels of social capital can be positive in that it gives group members access to privileged resources and psychological support while lowering the risks of malfeasance and transaction costs, but may be “negative” in that it also places high particularistic demands on group members, thereby restricting individual expression and advancement.” Accordingly, this research seeks to take a more nuanced view of social capital by hypothesizing and empirically testing the separate effects of two constituents—civic norms and social networks—and exploring the potential negative effect of social networks on social distancing.

Prior literature (Hasan et al. 2017a, b; Putnam 2001; Woolcock 1998) identifies two key constituents of social capital, civic norms and social networks. Reflecting the norms component of social capital, Fukuyama (1997) defines social capital as “the existence of a certain set of informal values or norms shared among members of a group that permits cooperation among them.” Coleman (1988, p. 104) considers
norms and effective sanctions as a key component of social capital, and states that “a prescriptive norm within a collectivity that constitutes an especially important form of social capital is the norm that one should forgo self-interest and act in the interests of the collectivity.” Civic norms can be either internalized or supported through external rewards for selfless actions and disapproval for selfish actions. By providing a set of common values and normative expectations as a basis for people to judge conducts, civic norms could facilitate cooperative behaviors and constrain self-serving, opportunistic behaviors (Buonanno et al. 2009).

In our context, the effect of civic norms on social distancing behavior is relatively straightforward. Social distancing is one of the most important steps in slowing the spread of the Covid-19 virus and thus constitutes an essential form of individual social responsibility. For instance, in March 2020, the US government called upon everyone to do the right thing by practicing social distance, such as “work or engage in schooling from home whenever possible,” “avoid eating or drinking at bars, restaurants, and food courts,” “avoid discretionary travel, shopping trips, and social visits,” and “do not visit nursing homes or retirement or long-term care facilities unless to provide critical assistance” (Whitehouse.gov, 2020). Social distancing, however, restricts individual freedom, causes inconvenience, and inflicts emotional and psychological stress associated with reduced social interaction. Thus, it is an action with positive externality (i.e., slowing the spread of the virus) but with significant internal costs to individuals. Civic norms appeal to people’s expectations of civic-minded, socially cooperative behaviors and foster selflessness and individual sacrifice for the advancement of the entire community’s common good (Coleman 1988; Knack and Keefer 1997). Since it is an ethical and socially responsible thing to practice social distancing during the Covid-19 pandemic, people in counties with higher levels of civic norms are more likely to engage in social distancing. Therefore,

H1 Counties with higher civic norms have higher levels of social distancing behavior.

The second key component of social capital is social networks (Putnam 2001; Woolcock 1998). Social capital manifests itself not only in the level of civic norms shared by people in a region but also in the wide array of social networks, both formal and informal, that connect people and foster social interaction and information/resource exchange (Payne et al. 2011; Putnam 2001). Unlike civic norms, the association between social networks and individual social distancing behavior is likely to be mixed. On the one hand, social networks might reinforce civic norms and promote cooperative behavior, thus facilitating social distancing behavior. However, given the unprecedented nature of the Covid-19 pandemic (e.g., the last comparable global pandemic is the 1918 Spanish flu), individuals face the decision on whether or not to practice social distancing for the very first time in their life, with normative expectations related to social distancing only recently and tentatively established. Thus, the positive effect of social networks on reinforcing norms associated with social distancing is likely to be muted.

On the other hand, social networks might negatively affect social distancing behavior in several ways. First, social networks require ongoing social interactions and fulfillment of obligations to maintain social capital. As Portes (1998, p. 4) points out, “social networks are not a natural given and must be constructed through investment
strategies oriented to the institutionalization of group relations.” Both Portes (1998) and Woolcock (1998) point out the potential negative consequences of social capital, including excess claims on group members and restrictions on individual freedom. Second, a high prevalence of social organizations in the community might mean that people are exposed to opinions that they find reputable (e.g., opinions from religious leaders, local leaders, etc.) that contrast with the government’s recommendation of social distancing. In turn, these diverse and conflicting opinions on social distancing will dampen individuals’ willingness and intention to practice social distancing. Thus, due to routine responsibilities and obligations associated with various social organizations as well as conflicting opinions from these organizations on social distancing, people in counties with higher density of social networks are less likely to engage in social distancing. Therefore,

**H2** Counties with higher density of social networks have lower levels of social distancing behavior.

### 3 Data, summary statistics, and empirical specification

In this section, we detail data sources, the construction of key social distancing and social capital variables, and our empirical specification. We also provide summary statistics of our analytical sample. Appendix A provides a detailed description of all the main variables.

#### 3.1 Data sources

**3.1.1 Social distancing data**

We construct our key measures of social distancing using data obtained from SafeGraph Mobile GPS Location Data. The company SafeGraph partners with mobile application services to collect anonymized location activity from approximately 45 million unique devices in the USA. Chen et al. (2019) find that SafeGraph data are generally representative of the US population. SafeGraph aggregates GPS pings from numerous mobile applications to measure the number of devices leaving their assigned home or the median time spent away from home across devices. SafeGraph also provides data on foot traffic patterns to a collection of points-of-interest (POIs), which include retail shops, restaurants, movie theaters, hospitals, and many other public locations individuals may visit when leaving their houses. For each POI, SafeGraph reports its geographic location, industry, and the total number of visitors in their mobile device panel that have visited each day. To preserve anonymity, the data are aggregated to the census block group (CBG) level. We further aggregate the data at the county level to assess the association between county-level social capital and social distancing behavior.

For our empirical tests, we employ three main metrics to measure social distancing based on data from SafeGraph. The first metric, *Stay-at-Home Prevalence*, is the ratio of the number of active devices never observed leaving their (geohash-7) home divided
by the total number of active devices. The second measure, Time Away from Home, is \( \log(1 + 60 \times 24 - \text{time home}) \), where time home is the median observed time at home across all devices observed in a given county on a day.1 In an additional analysis, we also construct Foot Traffic, which is calculated as the logarithm of the number of POI visits in a county during a day.

To facilitate a direct comparison across counties, we benchmark the level of a social distancing proxy against its average value observed during the week of February 6–12, 2020. Specifically, the difference or ratio between the daily value of a proxy and its benchmark in February is used in our empirical analysis. Stay-at-Home Prevalence Difference (Ratio) is the difference (ratio) between the percentage of stay-at-home devices on a day in a county and the mean value of the same county calculated during the week of February 6–12.2

Our primary analysis focuses on the period between March 16, 2020, and April 20, 2020. March 16, 2020, is when the federal government suspends all travel from the European countries to the USA, while April 20, 2020, is when the State of Georgia initiates the reopening of its economy. This period provides a clean setting that allows us to study how the social distancing behavior of people from communities with different degrees of civic norms and social networks varies.

3.1.2 Social capital measures

Following prior literature (Hasan et al. 2017a, b; Rupasingha et al. 2006), we obtain social capital data from the Northeast Regional Center for Rural Development (NRCRD) at the Pennsylvania State University. NRCRD social capital dataset provides the most comprehensive information on key social capital variables at the county level within the USA and is widely used in academic research (Li et al. 2018; Putnam 2007; Rupasingha et al. 2006).

The NRCRD social capital data contain information on voter turnouts in presidential elections (Pvote), response rates in US census surveys (Respn), the total numbers of nonprofit organizations (Nccs), and the total numbers of 10 types of social organizations (Assn) for all US counties in the years of 1990, 1997, 2005, 2009, and 2014. The 10 types of social organizations are religious, political, professional, labor organizations, civic and social associations, business associations, bowling centers, fitness and recreational sports centers, sports teams and clubs, golf courses and country clubs. Given our research design, we utilize the most recent (i.e., 2014) wave of NRCRD data.

Rupasingha et al. (2006) describe in detail how to use the NRCRD data to measure social capital across US counties. Specifically, because there are no legal or direct material incentives to vote or to participate in census surveys (Guiso et al. 2004; Knack 1992; Putnam 2001). The Pvote and Respn measures likely reflect individual behaviors

---

1 We closely follow Allcott et al. (2020; Appendix A.1.2) to aggregate the census block group-day level to the county level. Specifically, for the “device count” and “completely home device count” variables, we take the sum. For the “median home dwell time” variable we take the mean weighted by “the device count” in the census block group.

2 This practice is in line with the construction of SafeGraph’s shelter-in-place index. For more details, see https://www.safegraph.com/dashboard/covid19-shelter-in-place.
that are manifestations of civic responsibilities, and consequently, are indicators of civic norms. On the other hand, the Assn and Nccs measures capture a wide range of horizontal social interactions via formal and informal organizations and thus are good indicators of the density of social networks. While high-density social networks might facilitate cooperation, they might also place high demands on individuals to maintain ongoing social interactions, leading to habitual gatherings and inertia during the Covid-19 pandemic.\textsuperscript{3}

Following prior literature (Hasan et al. 2017a), we use the first principal component from a factor analysis based on Pvote and Respn to capture the strength of civic norms in a county, creating the Civic Norms variable. We use the first principal component from a factor analysis based on Assn and Nccs to capture the density of social networks in a county, creating the Social Networks variable.

3.1.3 Control variables

We include an array of control variables to capture factors other than social capital that could also affect people’s social-distancing behavior during the Covid-19 pandemic. These variables focus on differences in demographics and economic development across different counties. Specifically, we include the logarithm of per capita income in a given county (\(\text{Ln(Per Capita Income)}\)), the logarithm of counties’ population (\(\text{Ln(Population)}\)), population growth (\(\text{Population Growth}\)), percentage of religious adherents (Religiosity), percentage of population over 65 years of age (% Population over 65), percentage of population with a college degree (% Population with a College Degree) and population density per square mile (Population Density).

We further collect county-level weather and the labor-force composition data from Kaggle County Business Pattern Databases, respectively.\textsuperscript{4} We construct a dummy variable indicating whether daily temperature is in the range of 60 to 85 °F, which is often considered as being ideal for outdoor activities (Temperature 60–85 °F). We employ the definition of essential industries in Papanikolaou and Schmidt (2022) to calculate the percentage of workers that are employed in the essential industries as a key control (%Essential workers). We reported the pairwise correlations for all key variables in Appendix B.

3.2 Sample selection and summary statistics

Our final sample, as shown in Table 1, contains 108,144 county-day observations corresponding to 3,004 unique counties. Relative to a county’s benchmark level in February, during the sample period (March 16 to April 20, 2020), about 10% (avg. Difference / equal 0.099) more active devices (i.e., cell phones) remain completely at home in March, which corresponds a 44.5% (avg. Ratio / equal 1.4447) increase. Similarly, as

\textsuperscript{3} Some anecdotal examples include gyms and golf clubs that are allowed to be open despite stay-at-home orders that are in place. See, for example, https://komonews.com/news/coronavirus/arlington-gym-re-opens-in-defiance-of-inslee-stay-home-order.

\textsuperscript{4} Please see more details of these databases at: https://www.kaggle.com/code/johnjdavisiv/us-counties-weather-health-hospitals-covid19-data/data and https://www.census.gov/programs-surveys/cbp.html.
Table 1 Summary statistics

| Variable                              | Mean  | SD   | Q1    | Median | Q3    | N     |
|---------------------------------------|-------|------|-------|--------|-------|-------|
| **Proxies of stay-at-home behavior**  |       |      |       |        |       |       |
| Stay-at-Home Prevalence – Difference  | 0.0999| 0.0751| 0.0504| 0.0967 | 0.1456| 108,144|
| Stay-at-Home Prevalence – Ratio      | 1.4447| 0.3421| 1.2117| 1.4166 | 1.6403| 108,144|
| Time away from home – Difference     | −0.1963| 0.2066| −0.3049| −     | −0.0643| 108,144|
| Time away from home – Ratio          | 0.9706| 0.0310| 0.9545| 0.9733 | 0.9904| 108,144|
| **Social capital**                   |       |      |       |        |       |       |
| Civic norms                          | 0.0243| 1.0271| −0.5993| 0.1040 | 0.7220| 108,144|
| Social networks                      | −0.0081| 1.0820| −0.7313| −     | 0.4437| 108,144|
| **County-level controls**            |       |      |       |        |       |       |
| Log Per Capita Income                | 10.66 | 0.22 | 10.51 | 10.64 | 10.79 | 108,144|
| Log Population                       | 10.28 | 1.47 | 9.30  | 10.17 | 11.13 | 108,144|
| Population Growth                    | 0.0020| 0.0111| −0.0050| 0.0014 | 0.0081| 108,144|
| Religiosity                          | 0.6131| 0.2309| 0.4507| 0.5827 | 0.7335| 108,144|
| % Population over 65                 | 0.1940| 0.0448| 0.1644| 0.1906 | 0.2194| 108,144|
| % Population with a College degree   | 21.48 | 9.06 | 15.10 | 19.30 | 25.50 | 108,144|
| Population density (per mile²)       | 149.85| 346.80| 15.96 | 42.14 | 107.19| 108,144|
| Temperature (60–85 °F)               | 0.2584| 0.4378| 0     | 0     | 1     | 108,144|
| % Essential workers                  | 0.2736| 0.1019| 0.2071| 0.2760 | 0.3399| 108,144|
| % Republican                         | 0.6397| 0.1522| 0.5527| 0.6703 | 0.7526| 108,144|
| Cum. Cases/Population                 | 0.0031| 0.0113| 0     | 0.0030 | 0.0025| 108,144|
| Cum. Deaths/Population                | 0.0001| 0.0005| 0     | 0     | 0     | 108,144|

This table reports the summary statistics for the main variables used in the paper. All variable definitions are in Appendix A.
we measure *Time away from home* in logarithm, we observe a 19.6% (avg. Difference $= -0.1963$) reduction in the average time spent outside. Table 1 also shows that, for both stay-at-home measures and social capital measures, there is a large variation in the cross section.

Moreover, Appendix C visualizes geographic variations of our key explanatory variables, social networks and civic norms (Panels 1 and 2), the key-dependent variables, stay-at-home prevalence and time-away-from-home (Panels 3–6), and cumulative confirmed number of cases divided by county population (Panels 7 and 8), at the beginning and end of our sample period (March 16 and April 20, 2020, respectively).

### 3.3 Empirical specification

To study the relationship between social capital and social distancing during the Covid-19 pandemic, we estimate the following multivariate fixed effects regression:

\[
\text{Social Distancing}_{i,t} = \alpha + \beta_1 \text{Civic Norm}_i + \beta_2 \text{Social Network}_i + \gamma X_{i,t} + FE_{st} + \epsilon_{i,t}
\]

where \(i, t, \) and \(st\) index county, day, and state, respectively. \(X_{i,t}\) are county-level control variables discussed in Sect. 3.1.3. For all regressions, we include state × day fixed effects to take into account differences across states on any given day. This is particularly important because different states in the US face varying degrees of the pandemic, employment, and economic conditions, and as a result, introduce stay-at-home as well as reopening directives at different dates. The inclusion of these fixed effects implies that any differences we observe in social distancing are between counties with different degrees of Civic Norms and Social Networks, within the same state on the same day.

We correct estimated standard errors in all regressions by clustering them at the county level. Since our measures of social capital vary at the county level, this clustering method accounts for the concern that residuals are serially correlated within a county (Bertrand et al. 2004).

### 4 Empirical results

#### 4.1 Civic norms, social networks, and social distancing

The results of our baseline analyses are in Table 2. The dependent variables are *Stay-at-Home Prevalence* and *Time Away from Home* in the Panel A and Panel B, respectively. For both panels, we start our exploration with simple specifications with either Social Networks or Civic Norms, and then both of them for each dependent variable (i.e., results reported in columns 1–3 and 5–7, respectively). These results show consistently that Social Networks are negatively associated with stay-at-home prevalence while Civic Norms are positively associated with stay-at-home prevalence. The magnitudes of these coefficients are statistically significant (mostly at one percent level) and
### Table 2 Civic Norms, Social Networks, and Social Distancing

#### Panel A

| Dependent Variable: | Stay-at-Home Prevalence |  |
|---------------------|-------------------------|---|
|                     | Difference | Ratio |     |
|                     | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Social Networks     | −0.0176*** | −0.0181*** | −0.0078*** | −0.0855*** | −0.0881*** | −0.0465*** |
|                     | (−13.88) | (−14.97) | (−5.828) | (−14.34) | (−15.50) | (−7.514) |
| Civic Norms         | 0.0247*** | 0.0252*** | 0.0055*** | 0.1255*** | 0.1280*** | 0.0355*** |
|                     | (17.80) | (18.95) | (4.764) | (18.71) | (19.94) | (6.103) |
| Log Per Capita Income | 0.0485*** |       |       |       | 0.2593*** |
|                     | (7.753) |       |       |       | (8.083) |
| Log Population      | 0.0135*** |       |       |       | 0.0453*** |
|                     | (12.590) |       |       |       | (8.684) |
| Population Growth   | 0.2929*** |       |       |       | 1.4023*** |
|                     | (3.230) |       |       |       | (3.459) |
| Religiosity         | −0.0028 |       |       |       | −0.0032 |
|                     | (−0.568) |       |       |       | (−0.143) |
| % Population over 65 | −0.0670*** |       |       |       | −0.5823*** |
|                     | (−3.531) |       |       |       | (−6.264) |
| % Population with College Degree | 0.0011*** |       |       |       | 0.0066*** |
|                     | (8.779) |       |       |       | (10.276) |
| Population Density  | 0.0000 |       |       |       | 0.0000 |
|                     | (0.761) |       |       |       | (0.202) |
| Temperature (60 °F—85 °F) | −0.0024** |       |       |       | −0.0026 |
Table 2 (continued)

Panel A

| Dependent Variable: Stay-at-Home Prevalence | Difference | Ratio |
|-------------------------------------------|-----------|------|
|                                           | (1)       | (2)  |
| % Essential workers                       | (− 2.271) | (− 0.430) |
|                                           | − 0.0250*** | (− 2.952) |
| Constant                                  | 0.0995*** | 1.4447*** |
|                                           | (121.4) | (359.05) |
| State × Day FE                            | Yes      | Yes |
| Adjusted R²                               | 0.558 | 0.5168 |
| No. of Observations                       | 108,144 | 108,144 |

Panel B

| Dependent Variable: Time Away from Home | Difference | Ratio |
|----------------------------------------|-----------|------|
|                                        | (1)       | (2)  |
| Social Networks                        | 0.0341*** | 0.0052*** |
|                                        | (11.52) | (11.86) |
| Civic Norms                            | − 0.0390*** | − 0.0061*** |
|                                        | (− 10.93) | (− 11.30) |
| Log Per Capita Income                  | − 0.1751*** | − 0.0262*** |
|                                        | (− 10.93) | (− 11.98) |
### Table 2 (continued)

#### Panel B

| Dependent Variable: | Time Away from Home |
|---------------------|---------------------|
|                     | Difference          | Ratio |
|                     | (1)     | (2)     | (3)     | (4)     | (5)     | (6)     | (7)     | (8)     |
| Log Population      | (− 9.112) | (− 9.057) | (− 9.057) |
| Population Growth   | (− 10.599) | (− 10.828) | (− 10.828) |
| Religiosity         | (− 0.496) | (− 0.700) | (− 0.700) |
| % Population over 65| (− 1.481) | (− 1.609) | (− 1.609) |
| % Population with College Degree | (− 3.449) | (− 3.400) | (− 3.400) |
| Population Density  | (− 0.0008) | (− 0.0001) | (− 0.0001) |
| Temperature (60–85 °F) | 0.0013 | 0.0002 | 0.0002 |
| Essential workers (%) | 0.1116*** | 0.0168*** | 0.0168*** |

Note: *** denotes statistical significance at the 1% level.
Table 2 (continued)

Panel B

| Dependent Variable: | Time Away from Home |  |  |  |  |  |  |  |
|---------------------|---------------------|---|---|---|---|---|---|---|
|                     | Difference          | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Constant            | −0.1972***          | −0.1965*** | −0.1962*** | 2.0562*** | 0.9705*** | 0.9706*** | 0.9706*** | 1.3088*** |
|                     | (−100.4)            | (−99.70) | (−103.3) | (10.19) | (3270.7) | (3261.4) | (3392.9) | (42.98) |
| State × Day FE      | Yes                 | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R²         | 0.611               | 0.610 | 0.627 | 0.697 | 0.609 | 0.608 | 0.627 | 0.698 |
| No. of Observations | 108,144             | 108,144 | 108,144 | 108,144 | 108,144 | 108,144 | 108,144 | 108,144 |

Panel C

| Dependent Variable: | Stay-at-Home Prevalence |  |  |  |  |  |  |  |
|---------------------|-------------------------|---|---|---|---|---|---|---|
|                     | Difference              | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Association         | −0.0038***              | −0.0241*** | 0.0156*** | 0.0023*** | (−2.590) | (−3.641) | (4.574) | (4.702) |
| Non-profit Association | −0.0093***             | −0.0530*** | 0.0285*** | 0.0044*** | (−4.544) | (−5.600) | (5.621) | (5.830) |
| Political Vote      | 0.0074***               | 0.0460*** | −0.0141*** | −0.0021*** | (5.388) | (6.777) | (−4.141) | (−4.272) |
| Census Response Rate | 0.0020**               | 0.0138*** | −0.0086*  | −0.0011*  | (1.969) | (2.786) | (1.938) | (1.675) |
### Table 2 (continued)

#### Panel C

| Dependent Variable: | Stay-at-Home Prevalence | Time Away from Home |
|---------------------|-------------------------|---------------------|
|                     | Difference | Ratio | Difference | Ratio |
| County-level controls | Yes        | Yes   | Yes        | Yes   |
| Adjusted $R^2$     | 0.736      | 0.717 | 0.699      | 0.700 |
| No. of Observations | 108,144    | 108,144 | 108,144    | 108,144 |

#### Panel D

| Dependent Variable: | Stay-at-Home Prevalence | Time Away from Home |
|---------------------|-------------------------|---------------------|
|                     | Difference | Ratio | Difference | Ratio |
| Social Networks     | $-0.0076^{***}$ | $-0.0439^{***}$ | $0.0253^{***}$ | $0.0038^{***}$ |
|                     | ($-6.402$)   | ($-7.522$) | ($8.408$)   | ($8.639$) |
| Civic Norms         | $0.0057^{***}$ | $0.0326^{***}$ | $-0.0051^*$  | $-0.0009^{**}$ |
|                     | ($5.479$)    | ($6.309$)    | ($-1.901$)  | ($-2.233$) |
| Log Per Capita Income | $0.0525^{***}$ | $0.2598^{***}$ | $-0.1682^{***}$ | $-0.0251^{***}$ |
|                     | ($9.073$)    | ($8.905$)    | ($-9.600$)  | ($-9.590$) |
Table 2 (continued)

Panel D

| Dependent Variable: | Stay-at-Home Prevalence | | Time Away from Home |
|---------------------|--------------------------|--------------------------|
|                     | Difference (1) | Ratio (2) | Difference (3) | Ratio (4) |
| Log Population      | 0.0117***          | 0.0425***          | − 0.0240***          | − 0.0036***          |
|                     | (10.786)          | (7.756)          | (− 8.434)          | (− 8.616)          |
| Population Growth   | 0.3139***          | 1.4000***          | − 0.3380          | − 0.0555*          |
|                     | (3.955)          | (3.544)          | (− 1.622)          | (− 1.791)          |
| Religiosity         | − 0.0060          | − 0.0169          | − 0.0041          | − 0.0007          |
|                     | (− 1.387)          | (− 0.801)          | (− 0.365)          | (− 0.455)          |
| % Population over 65| − 0.0691***       | − 0.6488***       | − 0.2313***       | − 0.0340***       |
|                     | (− 3.735)        | (− 7.036)       | (− 4.645)       | (− 4.565)       |
| % Population with College Degree | 0.0010*** | 0.0065*** | 0.0001 | 0.00001 |
|                     | (7.761)          | (10.057)          | (0.173)          | (0.107)          |
| Population Density  | 0.00001***         | 0.00004***         | − 0.0001***       | − 0.0001***       |
|                     | (3.686)          | (2.624)          | (− 6.768)       | (− 6.775)       |
| Temperature (60 °F—85 °F) | − 0.0023** | − 0.0007 | 0.0005 | 0.0001 |
|                     | (− 2.316)        | (− 0.127)        | (0.124)        | (0.103)        |
| % Essential workers | − 0.0258***       | − 0.1172***       | 0.0990***       | 0.0149***       |
|                     | (− 3.586)        | (− 3.191)        | (5.415)        | (5.487)        |
| % Republican        | − 0.0002          | 0.1089***          | 0.0129          | 0.0013          |
Table 2 (continued)

Panel D

| Dependent Variable: | Stay-at-Home Prevalence | | Time Away from Home | | |
|---------------------|-------------------------|-----------------|----------------------|-----------------|
|                     | Difference (1)          | Ratio (2)       | Difference (3)       | Ratio (4)       |
| Cum. Cases/Population | 0.2786*** (4.589)       | 1.9423*** (5.150) | -1.0693*** (-4.949) | -0.1601*** (-4.937) |
| Cum. Deaths/Population | 1.2290 (-1.016)        | 14.180** (-2.107) | -5.2810 (1.102)     | -0.7846 (1.104) |
| Constant             | -0.5804*** (-9.659)    | -1.8201 *** (-6.076) | 1.8693*** (10.308)  | 1.2807*** (47.127) |
| State × Day FE       | Yes                     | Yes             | Yes                  | Yes             |
| Adjusted R²          | 0.751                   | 0.726           | 0.719                | 0.720           |
| No. of Observations  | 108,144                 | 108,144         | 108,144              | 108,144         |

This table reports the results from a fixed effects regression estimating Eq. (1). The sample period is between March 16, 2020 and April 20, 2020. The dependent variables are Stay-at-Home Prevalence (Difference and Ratio) in Panel A; and Time Away from Home (Difference and Ratio) in Panel B, respectively. In Panel C, we break down Social Networks and Civic Norms into their components. Panel D added additional controls to our baseline specifications. All variables are defined in Appendix A. All regressions include State × Day fixed effects. T-statistics are reported in parentheses and are based on standard errors clustered at the county level. ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively.
Is social capital associated with individual social responsibility? The economic large. For example, in column (4) when controlling a full set of county-level controls, the negative coefficient of $-0.0078$ suggests that, ceteris paribus, a one standard deviation decrease in Social Networks is associated with 0.84% ($=0.0078 \times 1.082$) more devices staying completely at home. Consistently, the estimate shown in column 8 suggests that a one standard deviation decrease in Social Networks corresponds to a 5.03% increase ($=0.0465 \times 1.082$) in the stay-at-home prevalence relative to the benchmark level in February 2020. To the extent that people generally carry their mobile devices with them, we interpret this result as suggesting that people in counties with high levels of Social Networks are less likely to stay home.$^{5}$

In contrast, Civic Norms are positively associated with the likelihood of individuals staying home, regardless of whether a difference (column 4) or ratio (column 8) relative to the February benchmark level is used as the dependent variable. Economically, according to column (4), a one standard deviation increase in Civic Norms is associated with 5.65% ($=0.0055 \times 1.0271$) more devices staying completely at home or, as shown in Column (8), a 3.65% ($=0.0355 \times 1.0271$) increase in the stay-at-home prevalence compared to the benchmark level.

Panel B provides confirmatory evidence to the contrasting correlations of Social Networks and Civic Norms with individuals’ stay-at-home choices as assessed by Time Away from Home (i.e., the logarithm of the number of minutes spent outside). For instance, the coefficient estimates reported in column (4) indicate that a one standard deviation increase in Social Networks is associated with an increase of 2.8% ($=0.0276 \times 1.082$) in Time Away from Home relative to the benchmark value, whereas the same magnitude of increase in Civic Norms is associated with a decrease of 0.38% in Time Away from Home.

These results are broadly consistent with our hypothesis that civic norms are positively associated with individual socially responsible behavior to comply with social distancing by voluntarily staying at home more. On the other hand, we observe a negative association between social networks and compliance with social distancing, as counties with a higher level of social networks exhibit a lower level of social distancing behavior.

In Panel C, we break down Social Networks into its two components, Association and Non-profit Association, and find that both are negatively associated with Stay-at-Home Prevalence and positively associated with Time Away from Home. Similarly, breaking down Civic Norms into its components, Political Vote and Census Response Rate, does not change the basic results. Both Political Vote and Census Response Rate are positively associated with Stay-at-Home Prevalence and negatively associated with Time Away from Home.

In Panel D, we present a robustness test by including additional control variables. Since political ideology might correlate with social capital, especially civic norms, as well as capture the different messaging of republican and democrat politicians about the pandemic, we include the county’s political ideology, the percentage of total votes received by President Donald Trump in the 2016 election (% Republican), as an additional control. Further, the local severity of the Covid-19 pandemic might influence

---

5 Note that we use the estimates in specifications with a full set of controls as our preferred specifications to calculate the economic magnitudes.
people’s social distancing decision. Therefore, we also control for the severity of the spread of the virus using the lagged county-level cumulative number of confirmed cases divided by the county’s population ($\text{Cum. Cases/Population}$) and the lagged county cumulative deaths scaled by its population ($\text{Cum. Deaths/Population}$). We find that $\text{Cum. Cases/Population}$ is positively associated with Stay-at-Home Prevalence and negatively associated with Time Away from Home, suggesting that local severity of the pandemic increases social distancing behavior. Including these controls does not change our key results that civic norms are positively associated with social distancing and social networks are negatively associated with social distancing.

4.2 Stay-at-home orders: before and after

The results in Sect. 4.1 focus on the entire sample period between March 16, 2020 and April 20, 2020, yet this period is still characterized by major changes and developments related to the Covid-19 pandemic. In particular, almost all 50 US states instituted some form of stay-at-home order (see Appendix D) during our sample period. For instance, California imposed its state-at-home order on March 19, 2020, making it the first state to order its residents to “stay home or at their place of residence except as needed to maintain continuity of operations of the federal critical infrastructure sectors.”

Although the exact phrase varies from state to state, these stay-at-home orders have the overall goal of discouraging non-essential outings. These stay-at-home orders matter for our analyses to the extent that one might expect that, since people presumably stay home after these directives are implemented, there should be little or no variation in social distancing behavior across different counties within the same state after these orders are put in place. To examine this empirically, we divide our sample period into the subperiod preceding each state’s stay-at-home order and that after the order is implemented by a state. We then re-estimate our baseline regressions for these two subsamples.

The results of this analysis are presented in Table 3. Panel A and Panel B contain the estimated results for the pre-stay-at-home period and the post-stay-at-home period, respectively. We find that, in the pre-stay-at-home period, Civic Norms are positively associated with and Social Networks are negatively associated with social distancing. In the post-stay-at-home period, civic norms are positively correlated with stay-at-home prevalence but not correlated with time-away-from-home; social networks are still negatively associated with social distancing. These results indicate that the positive association between civic norms and social distancing still holds, albeit slightly weakens, during the stay-at-home mandate. This is interesting because it suggests that government mandate does not eliminate the positive association between civic norms and social distancing behavior. In other words, social capital is a social influence mechanism that functions in addition to government mandate.

---

6 Note that to remove county confounding factors, an alternative model could be using other time periods as a control period and potentially implement a difference-in-differences model.

7 See https://www.gov.ca.gov/wp-content/uploads/2020/03/3.19.20-attested-EO-N-33-20-COVID-19-HEALTH-ORDER.pdf.
Is social capital associated with individual social responsibility? The …

Table 3  Civic Norms, Social Networks, and Social Distancing: Before and After the Issuance of the Stay-at-Home Order

| Dependent Variable: | Stay-at-Home Prevalence |  | Time Away from Home |  |
|---------------------|-------------------------|-----------------|-------------------|----------------------|
|                     | Difference              | Ratio           | Difference        | Ratio                |
| (1)                 | (2)                     | (3)             | (4)               |                      |

Panel A: Before Stay-at-Home Order

Social Networks

-0.0060*** (-3.487)

Civic Norms

0.0075*** (5.041)

County-level controls

Yes

Adjusted R2

0.674

No. of Observations

46,076

Panel B: After Stay-at-Home Order

Social Networks

-0.0089*** (-5.593)

Civic Norms

0.0040*** (2.991)

County-level controls

Yes

Adjusted R2

0.717

No. of Observations

57,864

This table reports the results from a fixed effects regression estimating Eq. (1) in two subperiods. The first subperiod (Panel A) is between March 16, 2020 and the effective date of a state’s stay-at-home order. The second subperiod (Panel B) is between the effective date of a state’s stay-at-home order and April 20, 2020. The dependent variables are Stay-at-Home Prevalence (Difference and Ratio) in Columns 1 and 2; and Time Away from Home (Difference and Ratio) in Columns 3 and 4. Control variables are identical to those in Table 2. All variables are defined in Appendix A. All regressions include State × Day fixed effects. T-statistics are reported in parentheses and are based on standard errors clustered at the county level. ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively.

4.3 Foot traffic

Although the most effective way of social distancing is to strictly stay home to avoid any outside contact with non-family members, people still inevitably travel to various locations. We thus employ a unique feature of the SafeGraph data, which provides not only the volume of foot traffic to different points of interest, but also categorizes these locations into different North American Industry Classification System (NAICS) industries.

In Table 4, we examine the relationship between social capital (i.e., Social Networks and Civic Norms) and foot traffic to various points of interests. All these regressions include the full set of county-level controls and state × day fixed effects as in our baseline specifications. We find that Social Networks are consistently and positively associated with people’s foot traffic to various points of interests, including accommodation services, recreational facilities, transportation, religious organizations, health...
Table 4 Civic Norms, Social Networks, and Foot Traffic

| Dependent Variable: Foot Traffic | Accommodation and Food Services | Arts, Entertainment, and Recreation | Transportation | Religious Organizations | Health and Personal Care Stores | Retail Trade |
|----------------------------------|---------------------------------|-------------------------------------|----------------|-------------------------|---------------------------------|--------------|
| (1)                              | (2)                             | (3)                                | (4)           | (5)                     | (6)                             |              |
| Social Networks                  | 0.1230***                       | 0.1164***                          | 0.0837***     | 0.1106***               | 0.1025***                       | 0.0927***    |
| (6.003)                          | (4.937)                         | (4.532)                            | (7.864)       | (5.006)                 | (5.451)                         |              |
| Civic Norms                      | −0.0499***                      | 0.0221                             | −0.0773***    | −0.0657***              | −0.0260                         | −0.0021      |
| (−2.899)                         | (0.952)                         | (−4.910)                           | (5.182)       | (0.838)                 | (1.479)                         |              |
| County-level controls            | Yes                             | Yes                                | Yes           | Yes                     | Yes                             | Yes          |
| State × Day FE                   | Yes                             | Yes                                | Yes           | Yes                     | Yes                             | Yes          |
| Adjusted R²                      | 0.912                           | 0.863                              | 0.789         | 0.952                   | 0.825                           | 0.935        |
| No. of Observations              | 119,692                         | 115,476                            | 99,924        | 118,245                 | 100,527                         | 107,922      |

This table reports the results from a fixed effects regression estimating Eq. (1) across a set of industries. The sample period is between March 16, 2020 and April 20, 2020. The dependent variable is foot traffic, which is the logarithm of the number of daily visits in a county during a day to certain locations (i.e., POI). All controls are the same as those in Table 3. All variables are defined in Appendix A. All regressions include State × Day fixed effects. T-statistics are reported in parentheses and are based on standard errors clustered at the county level. ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively.
and personal care stores, and retail trade. This result suggests that the positive association between social networks and foot traffic manifests in all industries, both essential businesses and non-essential businesses. Interestingly, this positive association is particularly strong in the case of religious organizations, which is consistent with our argument that social networks require regular and routine responsibilities associated with various social organizations, making social distancing more difficult (Woolcock 1998). On the other hand, civic norms are negatively associated with foot traffic in some industries (e.g., accommodation and food services, transportation, religious organizations), but are not associated with foot traffic to essential businesses (e.g., health and personal care stores and retail trade). This result pattern is in line with the idea that civic norms promote socially responsible behaviors whereby individuals voluntarily reduce their non-essential trips and only visit businesses that are absolutely essential to their needs.

5 Conclusion

Grand challenges like a global pandemic and climate change require concerted efforts from governments, businesses, and individuals. Individual social responsibility is essential to achieving the sustainable development goals of our society, yet there has been very little research on whether and how social and cultural factors influence individual social responsibility. Using the Covid-19 pandemic as our empirical context, this research examines the relationship between social capital and individual social distancing behaviors during the pandemic. Individual compliance with social distancing is a crucial factor in mitigating the spread of the Covid-19 virus. In this paper, we provide some of the first large-scale evidence that differences in civic norms and social networks across counties in the USA are correlated with significantly differential social distancing behaviors during the early phase of the Covid-19 pandemic. We find that while counties with high civic norms exhibit higher levels of social distancing behavior relative to their low-civic norms counterparts, counties with high-density social networks exhibit lower levels of social distancing relative to their low-density social network counterparts. Our findings are consistent with the notion that civic norms facilitate socially cooperative behaviors and foster selflessness and individual sacrifice for the advancement of the common good (Coleman 1988), thus enhancing social distancing behavior during the Covid-19 pandemic. In contrast, the negative association between social networks and social distancing suggests that high-density social networks require individuals to maintain ongoing social interaction and fulfill regular obligations, thus making it more difficult for people to practice social distancing.

While our evidence only focuses on a relatively short time horizon during the early stage of the pandemic, it does suggest an important role of the civic norms in facilitating collective actions that might have significant long-term health and economic consequences. Our evidence also underscores the important role that information technology plays in helping policymakers to collect and utilize crucial information for their decision-making on policies that solve societal problems.
This research has important implications for individual social responsibility in the context of the Covid-19 pandemic (Bapuji et al. 2020). It contributes to the social capital literature by documenting that civic norms and social networks are differentially correlated with social distancing behavior, and by providing empirical evidence for both the positive and negative sides of social capital (Portes 1998; Woolcock 1998). It contributes to the literature on individual social responsibility, and social distancing behavior during a global pandemic in particular, by highlighting the relevance of social capital as a theoretical lens to examine individual socially responsible behaviors. Specifically, given the unprecedented nature of the pandemic and the importance of social distancing as a key behavioral intervention to slow the spread of the virus, it is critical for us to understand factors that facilitate or inhibit social distancing behavior. This research contributes an initial understanding of the nuanced relationship between social capital and social distancing behavior in the context of disaster management.

This research provides several practical implications to policy makers and businesses. Our findings suggest that, to promote social distancing, policymakers could implement programs to reinforce civic norms in counties where appropriate and call upon community leaders at various non-profits and associations to encourage social distancing. Policymakers should also work with leaders at nonprofits and social associations to find ways to mitigate the negative effect of social networks on social distancing. Our results also highlight the importance of exploiting information technology in a timely manner to help policymakers gather, observe, and utilize information to more effectively design policies that solve social problems. For businesses, our findings suggest that one way to cope with the unpredictability of demand during times of uncertainty and extreme disruption, such as the Covid-19 pandemic, is to use county- or state-level social capital data to predict individual behavior and plan business operations and staffing accordingly.

There are several promising avenues for future research. First, our findings are based on data from the USA, it would be important and interesting to examine whether our findings on the differential relationships between civic norms and social networks on the one hand and social distancing on the other hand will generalize to other countries. The Covid-19 pandemic is a global crisis, and our research on how individuals, businesses, and governments are reacting to and coping with the pandemic should take into consideration significant differences in economic, cultural, and infrastructure-related factors. Second, it would be interesting to pinpoint the unique features of social distancing as an individual socially responsible behavior, compared with other individual social responsibility such as recycling and volunteering. Social distancing requires individuals to self-isolate and refrain from engaging in behaviors that are considered positive and desirable during normal times (e.g., hanging out with friends at a café). Thus, in addition to social capital, future research should examine other social, cultural, and individual factors that might influence social distancing behavior. It would also be important to examine other aspects of social distancing or other behavioral interventions for a pandemic (e.g., maintaining 6 feet apart from other people, wearing face masks).

Third, future research should unpack the negative association between social networks and social distancing. It would be important to shed light on what aspects of
social networks reduce social distancing behavior. Is it due to the routine responsibilities/obligations associated with various social organizations, the divergent opinions from these organizations on the value of social distancing, or other factors? Future research can also identify social and cultural characteristics that might counteract the negative effects of social networks on social distancing. Last but not least, one critical issue influencing individuals’ compliance with social distancing is related to the public’s trust in government and/or in science (Briscese et al. 2020). Koetke et al. (2021) find that trust in science and trust in the information source of the message on social distancing enhance people’s compliance behavior. It would be worthwhile to examine whether and to what extent trust in government mitigate the negative relationship between social networks and social distancing. Future research could also examine factors that could enhance the public’s trust in government, which would in turn lead to greater compliance behaviors with government recommendations.

Data availability All data other than SafeGraph Mobile GPS Location Data are publicly available. SafeGraph data is a proprietary data for which we were given special access during the pandemic period. We are happy to direct future researchers who have an interest in using this data to the right point of contact, but it is the researchers’ responsibility to go through the process independently.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Appendix A: variable definition

| Variable names                     | Definition                                                                                                                                 |
|------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------|
| Stay-at-Home Prevalence Ratio      | The ratio of the number of active devices never observed leaving their (geohash-7) home to the total number of active devices in a county on a day. To facilitate a cross-county comparison, this ratio is then scaled by its baseline (average) level observed during February 6–12. The SafeGraph data is at the census block group level. We closely follow Allcott et al. (2020; Appendix A.1.2) to aggregate the census block group-day level to the county level. Specifically, we take the sum over the county for the “device count” related variables. |
| Stay-at-Home Prevalence Difference | The difference between the ratio of the number of active devices never observed leaving their (geohash-7) home to the total number of active devices in a county on a day and its baseline level observed during February 6–12. |
| Time Away from Home Ratio          | Defined as log($1 + 60 \times 24 - \text{time home}$), where \text{time home} is the median observed time at home across all devices observed in a county on a day. To facilitate a cross-county comparison, this number is then scaled by its baseline level observed during February 6–12. As in Allcott, Boxell, Conway, Gentzkow, Thaler, and Yang (2020), for the “home time” variable, we take the mean weighted by “the device count” in the census block group.” |
| Variable names                          | Definition                                                                                                                                 |
|----------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------|
| **Time Away from Home Difference**     | The difference between log(1 + 60 × 24 − time home), where time home is the median observed time at home across all devices observed in a county on a day, and the baseline level observed during February 6–12 |
| **Foot Traffic**                       | The logarithm of the number of visits in a county during a day to certain locations (i.e., POI)                                           |
| **Social Networks**                    | Social Network index based on factor analysis using total numbers of nonprofit organizations (Nccs) and the total numbers of 10 types of social organizations for all US counties (Assn) |
| **Civic Norms**                        | Civic Norm index based on factor analysis using voter turnouts in presidential elections (Pvote) and response rates in US census surveys (Respn) |
| **Association (Assn)**                 | The sum of social organizations (10 types) divided by populations per 100,000                                                                 |
| **Non-profit Association (Nccs)**      | The sum of tax-exempt nonprofit organizations divided by populations per 10,000                                                                 |
| **Political Vote (Pvote)**             | Percentage of voters who voted in presidential elections                                                                                   |
| **Census Response Rate (Respn)**       | The response rate to the Census Bureau’s decennial census                                                                                   |
| **Log Per Capita Income**              | Per capita income at the county level in logarithm                                                                                            |
| **Log Population**                     | Logarithm of population in the county                                                                                                        |
| **Population Growth**                  | Percentage of population growth in a given county                                                                                            |
| **Religiosity**                        | The number of adherents divided by the population in the county                                                                               |
| **% Population over 65**              | Percentage of population that are over 65 years within a county                                                                               |
| **% Population with College Degree**   | Percentage of population with a college degree within a county                                                                               |
| **Population Density**                 | County population divided by county land area                                                                                                 |
| **Temperature (60—85 °F)**            | A dummy variable indicating whether daily temperature is in the range of 60 to 85 °F, which is often considered as being ideal for outdoor activities |
| **% Essential workers**                | Percentage of workers employed in the essential industries in the county                                                                     |
| **% Republican**                      | The proportion of total votes received by President Donald Trump in the 2016 election.” The same as in Allcott et al. (2020)                |
| **Cum. Cases/Population**              | Cumulative number of confirmed Covid-19 cases in a county on a day divided by the county’s total population (lagged)                           |
| **Cum. Deaths/Population**             | Cumulative number of deaths caused by Covid-19 reported in a county divided by the county’s total population (lagged)                         |
### Appendix B Pairwise correlations of Key variables

| Variables                        | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|----------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|------|------|------|------|
| (1) Stay-at-Home Prevalence Difference | 1.000 |     |     |     |     |     |     |     |     |      |      |      |      |      |      |
| (2) Stay-at-Home Prevalence Ratio | 0.970 | 1.000 |     |     |     |     |     |     |     |      |      |      |      |      |      |
| (3) Time Away from Home Difference | -0.604 | -0.585 | 1.000 |     |     |     |     |     |     |      |      |      |      |      |      |
| (4) Time Away from Home Ratio     | -0.607 | -0.589 | 1.000 | 1.000 |     |     |     |     |     |      |      |      |      |      |      |
| (5) Social Networks               | -0.196 | -0.215 | 0.140 | 0.145 | 1.000 |     |     |     |     |      |      |      |      |      |      |
| (6) Civic Norms                   | 0.228 | 0.211 | -0.164 | -0.166 | 0.094 | 1.000 |     |     |     |      |      |      |      |      |      |
| Variables              | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|------|------|------|------|
| (7) Log Per Capita Income | 0.336 | 0.329 | −0.0295 | −0.0296 | 0.304 | 0.404 | 1.000 |     |
| (8) Log Population     | 0.480 | 0.458 | −0.0352 | −0.0358 | −0.0500 | 0.294 | 0.253 | 1.000 |     |
Is social capital associated with individual social responsibility? The...

| Variables                                      | (1) | (2)  | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|------------------------------------------------|-----|------|-----|-----|-----|-----|-----|-----|-----|------|------|------|------|------|------|
| Population Growth                              | 0.183 | 0.184 | -0.117 | -0.121 | -0.265 | 0.167 | 0.127 | 0.300 | 1.000 |       |      |      |      |      |
| Religiosity                                    | -0.116 | -0.087 | 0.084 | 0.085 | 0.530 | 0.062 | 0.175 | -0.296 | -0.218 | 1.000 |      |      |      |      |
| % Population over 65                           | -0.257 | -0.299 | 0.131 | 0.136 | 0.451 | -0.036 | -0.002 | -0.459 | -0.176 | 0.096 | 1.000 |      |      |      |      |
| % Population with College Degree               | 0.408 | 0.407 | -0.311 | -0.313 | 0.046 | 0.339 | 0.705 | 0.488 | 0.277 | -0.058 | -0.186 | 1.000 |      |      |      |
| Population Density                             | 0.180 | 0.159 | -0.160 | -0.162 | -0.070 | -0.002 | 0.216 | 0.286 | 0.031 | -0.047 | -0.134 | 0.242 | 1.000 |      |      |
| Temperature (60°F—85°F)                        | -0.068 | -0.021 | 0.123 | 0.121 | -0.204 | -0.019 | -0.208 | 0.039 | 0.052 | -0.020 | -0.085 | -0.147 | -0.023 | 1.000 |      |
| % Essential workers                            | 0.176 | 0.164 | -0.113 | -0.116 | -0.220 | 0.101 | 0.096 | 0.463 | 0.079 | -0.077 | -0.0235 | 0.099 | 0.101 | 0.024 | 1.000 |
All reported statistics are significant at one percent level.

**Appendix C: Geographic Visualization of Selected Variables**

Panel A. Social Networks and Civic Norms by County

1. Social Networks

![Social Networks Map](image1)

2. Civic Norms

![Civic Norms Map](image2)
Panel B. Stay-at-Home Prevalence Difference by County and Time Period

3. Stay-at-Home Prevalence Difference (Mar. 16)

4. Stay-at-Home Prevalence Difference (Apr. 20)
Panel C. Time Away From Home Difference by County and Time Period

5. Time Away from Home Difference (Mar. 16)

6. Time Away from Home Difference (Apr. 20)
Panel D. Confirm Cases / Total Population by County and Time Period

7. Confirmed Cases/Total Population (Mar. 16)

8. Confirmed Cases/Total Population (Apr. 20)

Appendix D: Date of Stay-at-Home Order

This table reports the dates of stay-at-home order by different states.

| State      | Date Announced | Effective Date | State      | Date Announced | Effective Date |
|------------|----------------|----------------|------------|----------------|----------------|
| Alabama    | 3-Apr          | 4-Apr          | Montana    | 26-Mar         | 28-Mar         |
| Alaska     | 27-Mar         | 28-Mar         | Nebraska   | –              | –              |
| Arizona    | 30-Mar         | 31-Mar         | Nevada     | 1-Apr          | 1-Apr          |
| Arkansas   | –              | –              | New Hampshire | 26-Mar       | 27-Mar         |
| State                    | Announced Date | Effective Date | State            | Announced Date | Effective Date |
|-------------------------|----------------|----------------|------------------|----------------|----------------|
| California              | 19-Mar         | 19-Mar         | New Jersey       | 20-Mar         | 21-Mar         |
| Colorado                | 26-Mar         | 26-Mar         | New Mexico       | 23-Mar         | 24-Mar         |
| Connecticut             | 20-Mar         | 23-Mar         | New York         | 20-Mar         | 22-Mar         |
| Delaware                | 22-Mar         | 24-Mar         | North Carolina   | 27-Mar         | 30-Mar         |
| District of Columbia    | 30-Mar         | 1-Apr          | North Dakota     | –              | –              |
| Florida                 | 1-Apr          | 3-Apr          | Ohio             | 22-Mar         | 23-Mar         |
| Georgia                 | 2-Apr          | 3-Apr          | Oklahoma         | –              | –              |
| Hawaii                  | 23-Mar         | 25-Mar         | Oregon           | 23-Mar         | 23-Mar         |
| Idaho                   | 25-Mar         | 25-Mar         | Pennsylvania     | 23-Mar         | 1-Apr          |
| Illinois                | 20-Mar         | 21-Mar         | Rhode Island     | 28-Mar         | 28-Mar         |
| Indiana                 | 23-Mar         | 24-Mar         | South Carolina   | –              | –              |
| Iowa                    | –              | –              | South Dakota     | –              | –              |
| Kansas                  | 28-Mar         | 30-Mar         | Tennessee        | 30-Mar         | 31-Mar         |
| Kentucky                | 22-Mar         | 26-Mar         | Texas            | 31-Mar         | 2-Apr          |
| Louisiana               | 22-Mar         | 23-Mar         | Utah             | –              | –              |
| Maine                   | 31-Mar         | 2-Apr          | Vermont          | 24-Mar         | 24-Mar         |
| Maryland                | 30-Mar         | 30-Mar         | Virginia         | 30-Mar         | 30-Mar         |
| Massachusetts           | 23-Mar         | 24-Mar         | Washington       | 23-Mar         | 23-Mar         |
| Michigan                | 23-Mar         | 24-Mar         | West Virginia    | 23-Mar         | 24-Mar         |
| Minnesota               | 25-Mar         | 27-Mar         | Wisconsin        | 24-Mar         | 25-Mar         |
| Mississippi             | 31-Mar         | 3-Apr          | Wyoming          | –              | –              |
| Missouri                | 3-Apr          | 6-Apr          | –                | –              | –              |

References

Adler PS, Kwon SW (2002) Social capital: prospects for a new concept. Acad Manag Rev 27(1):17–40
Alesina A, La Ferrara E (2000) Participation in heterogeneous communities. Quart J Econ 115(3):847–904
Allcott H, Boxell L, Conway J, Gentzkow M, Thaler M, Yang DY (2020) Polarization and public health: partisan differences in social distancing during the Coronavirus pandemic NBER Working Paper, (w26946)
Ang JS, Cheng Y, Wu C (2015) Trust, investment, and business contracting. J Financial Quantitative Anal 50:569–595
Bapuji H, de Bakker FG, Brown JA, Higgins C, Rehbein K, Spicer A (2020) Business and society research in times of the corona crisis. Bus Soc 59(6):1067–1078
Basu K, Palazzo G (2008) Corporate social responsibility: a process model of sensemaking. Acad Manag Rev 33(1):122–136
Bertrand M, Duflo E, Mullainathan S (2004) How much should we trust difference-in-differences estimates? Quart J Econ 119(1):249–275
Briscese G, Lacetera N, Macis M, Tonin M (2020) Compliance with covid-19 social-distancing measures in italy: the role of expectations and duration (Vol 27) Cambridge, MA, USA: National Bureau of Economic Research

Springer
Is social capital associated with individual social responsibility? The …

Brockman P, El Ghoul S, Guedhami O, Zheng Y (2019) Does social trust affect international contracting? Evidence from Foreign Bond Covenants Working paper

Buonanno P, Montolio D, Vanin P (2009) Does social capital reduce crime? J Law Econ 52(1):145–170

Chen MK, Haggag K, Pope DG, Rohla R (2019) Racial disparities in voting wait times: evidence from smartphone data (No w26487) National Bureau of Economic Research

Coleman JS (1988) Social capital in the creation of human capital. Am J Sociol 94:95–120

Collins CJ, Clark KD (2003) Strategic human resource practices, top management team social networks, and firm performance: the role of human resource practices in creating organizational competitive advantage. Acad Manag J 46(6):740–751

Du S, Swaen V, Lindgreen A, Sen S (2013) The roles of leadership styles in corporate social responsibility. J Bus Ethics 114(1):155–169

Fukuyama F (1997) Social capital and the modern capitalist economy: creating a high trust workplace. Stern Bus Mag 4:1–16

Fuller T, Tian Y (2006) Social and symbolic capital and responsible entrepreneurship: an empirical investigation of SME narratives. J Bus Ethics 67(3):287–304

Gollwitzer A, Martel C, Brady WJ, Knowles ED, van Bavel, J (2020) Partisan differences in physical distancing predict infections and mortality during the coronavirus pandemic Available at SSRN 3609392

Guiso L, Sapienza P, Zingales L (2004) The role of social capital in financial development. Am Econ Rev 94(3):526–556

Guiso L, Sapienza P, Zingales L (2009) Cultural biases in economic exchange? Quart J Econ 124:1095–1131

Gupta A, Raman K, Shang C (2018) Social capital and the cost of equity. J Bank Finance 87:102–117

Gupta A, Raman K, Shang C (2020) Do informal contracts matter for corporate innovation? evidence from social capital. J Financ Quant Anal 55(5):1657–1684

Hasan I, Hoi CK, Wu Q, Zhang H (2017a) Does social capital matter in corporate decisions? evidence from corporate tax avoidance. J Account Res 55(3):629–668

Hasan I, Hoi CK, Wu Q, Zhang H (2017b) Social capital and debt contracting: evidence from bank loans and public bonds. J Financial Quantitative Anal 52(3):1017–1047

Hoi CK, Wu Q, Zhang H (2019) Does social capital mitigate agency problems? evidence from chief executive officer (CEO) compensation. J Financ Econ 133(2):498–519

Jacobs J (1961) The death and life of great American cities. Random House, New York

Jha A, Cox J (2015) Corporate social responsibility and social capital. J Bank Finance 60:252–270

Knack S (1992) Civic norms, social sanctions, and voter turnout. Ration Soc 4(2):133–156

Knack S, Keefer P (1997) Does social capital have an economic payoff? a cross-country investigation. Quart J Econ 112(4):1251–1288

Koetke J, Schumann K, Porter T (2021) Trust in science increases conservative support for social distancing. Group Process Intergroup Relat 24(4):680–697

Li P, Tang L, Jaggi B (2018) Social capital and the municipal bond market. J Bus Ethics 153(2):479–501

Obstfeld D (2005) Social networks, the tertius iungens orientation, and involvement in innovation. Adm Sci Q 50(1):100–130

Papanikolaou D, Schmidt LD (2022) Working remotely and the supply-side impact of Covid-19. Rev Asset Pricing Stud 12(1):53–111

Payne GT, Moore CB, Griffis SE, Autry CW (2011) Multilevel challenges and opportunities in social capital research. J Manag 37(2):491–520

Portes A (1998) Social capital: its origins and applications in modern sociology. Ann Rev Sociol 24(1):1–24

Putnam RD (2001) Social capital: measurement and consequences. Can J Policy Res 2:41–51

Putnam RD (2007) E pluribus unum: diversity and community in the twenty-first century the 2006 Johan Skytte Prize Lecture. Scand Polit Stud 30(2):137–174

Roberts MR, Whited TM (2013) Endogeneity in empirical corporate finance. In: Constantinides GM, Stulz RM (eds) Handbook of the economics of finance. Elsevier, Amsterdam, pp 493–572

Rupasingha A, Goetz SJ, Freshwater D (2006) The production of social capital in US counties. J Socio-Econ 35(1):83–101

Stock JH, Yogo M (2005) Testing for weak instruments in linear iv regression. In: Andrews DWK, Stock JH (eds) Identification and inference for econometric models: essays in honor of Thomas Rothenberg. Cambridge University Press, Cambridge

Tsai W, Ghoshal S (1998) Social capital and value creation: the role of intrafirm networks. Acad Manag J 41(4):464–476
United Nations (2015) Sustainable development goals. Available at: https://sustainabledevelopment.un.org/?menu=1300, accessed May 19, 2022.

Van Bavel JJ, Cichocka A, Capraro V, Sjåstad H, Nezlek JB, Pavlović T, Jørgensen FJ (2022) National identity predicts public health support during a global pandemic. Nat Commun 13(1):1–14

Whitehouse.gov (2020) The President’s coronavirus guidelines for America: 30 Days to slow the spread, available at https://www.whitehouse.gov/wp-content/uploads/2020/03/03.16.20_coronavirus-guidance_8.5x11_315PM.pdf, accessed June 5, 2020

Woolcock M (1998) Social capital and economic development: toward a theoretical synthesis and policy framework. Theory Soc 27(2):151–208

Woolcock M (2001) The place of social capital in understanding social and economic outcomes. Can J Policy Res 2(1):11–17

**Publisher’s Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.