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Capturing Bonding, Bridging, and Linking Social Capital through Publicly Available Data

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A growing body of research has illuminated the powerful role played by social capital in influencing disaster and resilience outcomes. Popular vulnerability mapping frameworks, while well suited for capturing demographic characteristics such as age, race, and wealth, do not include sufficient proxies for social capital. This article proposes a concrete way to measure bonding, bridging, and linking social capital using widely available information. Our social capital index (SoCI) uses 19 indicators from publicly available U.S. census and Environmental Systems Research Institute (ESRI) data for all counties across the contiguous United States. We demonstrate broad variations in the SoCI Index by mapping counties across the continental North America. Validity tests indicate outcomes similar or superior to other approaches such as the Baseline Resilience Indicators for Communities (BRIC) and the Social Vulnerability Index (SoVI). Our new mapping framework provides a more focused way for disaster managers, scholars, and local residents to understand how communities could cope with future disasters based on levels of social ties and cohesion.

KEY WORDS: bonding social ties, bridging social capital, linking social capital, disaster management

越来越多的研究表明，社会资本在影响灾害结果和弹性/恢复力结果一事上发挥着巨大作用。受欢迎的(社区)脆弱性映射框架尽管十分适合于捕捉例如年龄、种族和财富等人口特征, 但却不具备充分的社会资本指标。本文提出一种具体的方法, 通过使用广泛可获取的信息, 衡量整合型、桥接型、连结型社会资本。我们的社会资本指数(*SoCI*)将公开获取的美国人口统计与环境系统研究所公司(*ESRI*)数据中的*19*个指标应用于*48*个美国本土州的各个县。我们通过映射北美洲的各个县, 证明了*SoCI*指数中存在的广泛差异。验证测试显示的结果相似于或优于其他方法, 例如"社区基准弹性指标"(*BRIC*)和社会脆弱性指数(*SoVI*)。我们的新映射框架为灾害管理者、学者、地方居民提供了一个更为明确的方法， 用于理解社区在基于社会关系程度和凝聚度的情况下能如何应对未来灾害。

关键词: 整合型社会关系, 桥接型社会资本, 连结型社会资本, 灾害管理

Un creciente cuerpo de investigación ha iluminado el poderoso papel desempeñado por el capital social para influir en los resultados de desastres y resiliencia. Los marcos populares de mapeo de vulnerabilidades, si bien son adecuados para capturar características demográficas como la edad, la raza y la riqueza, no incluyen suficientes representantes para el capital social. Este artículo propone una forma

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concreta de medir la vinculación, el enlace y la vinculación del capital social utilizando información ampliamente disponible. Nuestro índice de capital social (SoCI) utiliza 19 indicadores de datos del Instituto de Investigación de Sistemas Ambientales (ESRI, por sus siglas en inglés) disponibles públicamente para todos los condados de los Estados Unidos contiguos. Demostramos amplias variaciones en el Índice SoCI mediante el mapeo de los condados en toda América del Norte continental. Las pruebas de validez indican resultados similares o superiores a otros enfoques, como los Indicadores de resistencia de base para las comunidades (BRIC) y el Índice de vulnerabilidad social (SoVI). Nuestro nuevo marco de mapeo proporciona una forma más enfocada para que los administradores de desastres, los académicos y los residentes locales comprendan cómo las comunidades podrían hacer frente a desastres futuros en función de los niveles de lazos sociales y cohesión.

PALABRAS CLAVES: vinculación de los lazos sociales, vinculación del capital social, enlace del capital social, gestión de desastres

Introduction

While residents around the world have increased their quality of life in areas such as global child mortality, literacy and per capita gross domestic product (GDP) over the past century, they still face serious threats from extreme weather events and natural-technological catastrophes. Since 1900, for example, nations have monotonically experienced more disasters and disaster damage (Guha-Sapir, Below, & Hoyois, 2017). Rising ocean temperatures and melting ice caps will create more hazards especially for coastal populations around the world, bringing stronger typhoons, higher water levels, and more extreme temperatures (United States Global Change Research Program, 2018). In the United States, more than 52 percent of the population (163.8 million) live in coastal watershed counties (NOAA, 2013) which will face a variety of increased hazards in the coming decades. It is evident that more intense and frequent extreme weather and climate-related events have become a part of our daily life. The events are anticipated to damage critical infrastructures, ecosystems and social systems leading toward to disruption of their vital services on which the communities depend. Recent hurricanes Harvey, Irma, Maria, and Nate exemplify this trend, together causing more than $200 billion in damage (Fritz, 2018; FEMA, 2018a).

Generally speaking, there are two approaches to managing disasters: a proactive approach that focuses on mitigation and preparedness and a reactive approach that emphasizes response and recovery (Kyne, 2015; Moe & Pathranarakul, 2006). Most societies rely on reactive approaches with little or no emphasis on the alternative. However, facing climate change, we can no longer afford to continue with past coping mechanisms (The National Academies, 2012; US Global Change Research Program, 2018). A more proactive approach is possible by creating a culture of resilience—"the ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events"—which reduces individual, household, and community vulnerability (The National Academies, 2012, p. 1).

In the recent years, disaster managers and scholars have focused on building disaster resilience around the world (Bakkensen, Fox-Lent, Read, & Linkov, 2016; Cutter, Ash, & Emrich, 2016). In the United States, building community resilience has become a foundational concept for effectively managing disasters (Pfefferbaum, Van Horn, & Pfefferbaum, 2017). Two recent executive orders promote resilience (Executive Order No. 13653, 2013; Executive Order No. 13677, 2014). and have guided government agencies toward new disaster approaches including United States Department of Housing and Urban Development's (DHUD) $1 billion initiative to increase natural disaster resilience (US DHUD, 2014) and the United States Department of Homeland Security's (DHS) commitments to do the same (US DHS, 2019). In addition, the United States Federal Emergency Management Agency (FEMA) established an office of Resilience in order to build a culture of disaster preparedness through various programs under the National Disaster Recovery Framework (FEMA, 2018b).

A growing body of evidence suggests that community resilience can be enhanced through social ties, social capital, and cohesion (Aldrich 2012; Aldrich & Meyer 2015; Cai 2017; Pfefferbaum et al., 2017; Reininger et al., 2013). Social capital captures "how involvement and participation in groups can have positive consequences for the individual and the community" (Aldrich & Meyer, 2015, p. 256). In the context of crisis management, studies show that social capital enhances community resilience in responding to and recovering from disasters (Aldrich, 2019; Dow, 1999; Hurlbert, Haines, & Beggs, 2000; Nakagawa & Shaw, 2004; Reininger et al., 2013; Shoji, Takafuji, & Harada, 2019; Smiley, Howell, & Elliott, 2018).

Our paper makes several contributions to the literature. First, while a variety of indices capture demographics such as race, age, and income (e.g., Cutter, Burton, & Emrich, 2010; Cutter et al., 2016), few have focused primarily on social ties despite growing recognition of their importance in resilience. Next, many past studies have used data and information that NGOs, residents, and non-scholars find challenging to download and engage. Our paper uses indicators from publicly available sources such as the United States Census and the Environmental Systems Research Institute (ESRI) that nonexperts and citizen scientists can access. Finally, where past studies of social capital have theoretical frameworks incorporating a variety of ways to organize social capital, ours builds on bonding, bridging, and linking social ties. This paper provides a way to capture social capital and then shows its validity levels as similar to or better than the Baseline Resilience Indicators for Communities (BRIC) and the Social Vulnerability Index (SoVI).

Social Capital in Disasters

Building disaster resilience communities remains among the most desirable outcomes at the federal, state, and local levels. For example, the United States FEMA implemented the National Disaster Recovery Framework in which community disaster resilience was recognized as a critical component of disaster recovery (FEMA, 2018b). Here we define disaster resilience as community members' capacity to utilize local and extra-local resources to deal with shocks and crises (e.g., Chaskin, 2008; Magis, 2010). With this focus, social ties, cohesion, and engagement become critical components in determining the collective action and mobilization of a neighborhood during and after a shock.

The term *social capital* captures the ties which bind people together and serves as the "primary base for a community response" (Dynes, 2005, p. 9). A number of studies have documented that social ties and social cohesion positively impact the disaster outcomes and recovery processes (Dow, 1999; Hurlbert et al., 2000; Nakagawa & Shaw, 2004; Aldrich, 2012; Shoji, Takafuji, & Harada, 2019; Smiley et al., 2018). In this sense, "social capital is central to the lived experience of coping with risk" (Adger 2003, p. 389), with social ties and cohesion assisting survivors in a number of ways (Hawkins & Maurer, 2010). Even before a disaster or crisis occurs, residents in vulnerable areas must decide whether to stay or evacuate, and their decisions are heavily influenced by their social network (Airriess, Li, Leong, Chen, & Keith, 2008; Metaxa-Kakavouli, Maas, & Aldrich, 2018). Then, following a disaster, survivors must decide whether or not to return to a damaged home or business to rebuild. Especially in developed societies with freedom of movement, they can relocate to start fresh in a new community. Doing so would reduce the number of costs associated with rebuilding, including opportunity costs, psychological costs, and financial ones. Strong ties to neighbors and a sense of place—both components of social capital—help pull survivors back to rebuild, whatever the cost (Aldrich, 2012).

Beyond the decision to return or exit a damaged community, many of the challenges facing survivors in the recovery period are collective action problems. For example, food provision, medical aid, crime prevention, and the ability to articulate a shared vision for recovery require residents to coordinate their activities and work collectively (Nakagawa & Shaw, 2004). A final way that social capital accelerates recovery is through mutual aid or informal insurance. Many of the resources we rely on in developed societies—running water, electricity, easy access to food, medical and childcare, and so on—may not be available for days, if not weeks, after a major disaster. Survivors who built connections to neighbors before the event are positioned to offer aid and to receive it, whether a place to stay, tools to remove moldy drywall or information about navigating the bureaucratic maze to receive a rebuilding permit. Bangladesh residents with stronger ties, for example, were better situated to assist each other after the flooding had subsided (Islam & Walkerden, 2014).

Social capital contributes to building disaster resilience by promoting cooperation and collaboration among individual social networks along with engagement to community and regional level various organizations in the disaster management system. Our approach to measuring social capital is outlined in the subsequent sections.

A Framework for Social Capital

This study organizes social capital in three categories: bonding, bridging, and linking. There are a number of other ways to organize measures of social capital, including cognitive and behavioral, communitarian and institutional, and networked versus individual (Lin, 2001; Putnam, 2002; Aldrich, 2012; MarcyCorps, 2017). We have selected our approach as it matches a well-established, highly tested framework that preserves important differences between types of connections and can be mapped onto existing data sources (Szreter and Woolcock, 2004; Woolcock and Narayan, 2000). Further, this approach allows decision makers and scholars to focus in on a single category of social ties—whether bonding, bridging, or linking—in their analyses of their local vulnerability and resilience conditions.

The most common among the types of social ties that we create is a connection to someone quite similar to us. Sociologists label the phenomenon as *homophily*, and it means that our closest friends and contacts likely share our language, ethnicity, culture, and class. Individuals sharing similar characteristics in homogeneous networks build and maintain social capital through cohesion (e.g., Magis, 2010). Vietnamese shrimp farmers in the Gulf Coast of North America, for example, are likely to have closest ties with those who are similarly Catholic and Vietnamese language speaking. Pattinavar caste fishermen in Tamil Nadu, India, typically have friends in the same occupation and caste. Orthodox Jewish diamond dealers in Brooklyn regularly lend expensive merchandise to colleagues from the same background (Coleman, 1988). Social scientists term this kind of connection as *bonding social capital* and some have seen it as "good will, fellowship, mutual sympathy, and social intercourse among a group of individuals and families who make up a social unit" (Hanifan, 1916). During disasters, bonding ties with neighbors, friends, and kin can be lifesaving, as those individuals not only know of your presence (or absence) but also are motivated to come to assist should you be in danger.

The next type of connection comes from weaker or thin ties to people with whom we spend less time and have less in common. The connections, known as *bridging social capital*, may come through a kindergarten in an inner-city (Small, 2009) or through an African American church in a suburban neighborhood (Chamlee-Wright, 2010). These ties are important when we search for jobs (Granovetter, 1983) or need to make peace in an area of India wracked by interethnic strife between Hindus and Muslims (Varshney, 2001). Bridging ties may be especially useful during and after the disaster as these network members may be geographically distant from survivors and therefore better situated to provide aid. Religious communities outside New Orleans in areas such as Baton Rouge and Biloxi immediately opened up shelters for those fleeing from damaged homes Hurricane Katrina in the fall of 2005, for example. Bonding and bridging serve as horizontal frameworks for connections (Aldrich, 2012).

Linking social capital, the third and final type of connection sits between regular people and someone in power or authority. These ties facilitate the flow of services and assistance from well-resourced organizations, whether public or private (Aldrich, 2012; Magis, 2010). Where bonding and bridging ties are horizontal in nature, linking social capital is vertical. Linking social capital is essential for connection between disaster victims and those who control resources, and knowledge about access to various available resources in different levels of governmental organizations (Pfefferbaum et al., 2017). For example, in

Ortley Beach following Hurricane Sandy, residents had struggles convincing local authorities to rapidly remove debris from lots and parks nearby. Once they reached out to a college friend working in the governor's office, garbage collectors moved to clean up the neighborhood (Interview with local resident December 2017). In areas of India following the 2004 Indian Ocean tsunami, few villagers had ties to their local collectors, that is, the government ombudsman who helped organize relief and aid. For the few towns that did have this tie, though, they were placed on the map for disaster relief (Aldrich, 2012).

While bonding social capital is the most common, it may not be sufficient to do more than just "get along." Bridging and linking ties, while harder to create and maintain, can help vulnerable populations get ahead, especially when normal service providers—such as doctors, daycare providers, grocery stores, and other critical needs—are shut down. Any framework that captures the multifaceted relationships we have with others and the myriad of ways that these ties provide assistance during crises and shocks will need to include all three categories of social capital.

Methods

In this study, we created a hierarchical index with three components: bonding, bridging, and linking. For each of the three components, we used arithmetic averages to create the sub-index scores and we then added them (with equal weights) to create our final Social Capital Index (SoCI). Prior to the index construction, we conducted data pre-processing (cf. Cutter, Ash, & Emrich, 2014) to impute missing data, checking for multicollinearity, carrying out a min-max transformation and building a reverse scale for some indicators. We first begin with the creation of proxies for the three most commonly referenced types of social capital: bonding, bridging, and linking. Then we constructed a composite SoCI made up of these three categories and show a spatial distribution of this attribute at the county level within the continental United States. As other indices have done, we seek to show the validity of the index through a variety of quantitative tests. For example, the Baseline Resilience Index for Communities (BRIC) and SoVI have used analytical techniques to validate their proxy decisions and we follow suit. Our indicators are positively related to BRIC and negatively related to SoVI, demonstrating that our approach brings with it a measurably different set of assumptions and outcomes than a past disaster- and vulnerability-related indices.

Despite the broad availability of these indicators for nearly all 3000 North American counties, there are four, namely Ziebach County, SD, Zavala County, Zapata County, and Loving County in TX, that lack data for some of the selected 19 indicators (Appendix Table C1). For such cases, we used the mean value of each indicator to impute missing data. In checking the correlation among selected indicators, all show low correlations except a correlation of 0.76 between language competency and ethnicity similarity. Overall, these indicators are not strongly overlapping and capture discrete aspects of bonding, bridging, and linking ties at the county level.

This study uses the minimum-maximum method to transform the values of selected indicators into a range of 0 and 1; 0 being the lowest rank for a specific indicator and 1 being the best value (Cutter et al., 2010). The adjustment is done by subtracting the minimum value and dividing by the rage of the indicator values (OECD, 2008). All indicators under each of the subcategories, namely bridging, bonding, and linking are summed and weighted equally. For bonding, the normalized 10 indicators are summed together and divided by ten, and so forth. Next, the three subcategories are summed together resulting in social capital scores of between 0 and 3; 0 being minimum the lowest ranking and 3 as the highest ranking.

Social Capital Indicators

The study employs two criteria in selecting data for the social capital composite indicator. They are (i) relevance to the concept measured and (ii) accessibility and availability of the data. First, we based data selection on the relevance to each of the three sub-groups, namely bonding, bridging, and linking social capital. Next, the index data needed to be accessible and available to researchers and citizen scientists from a variety of types of institutions so that updating the index, replication, and testing are is possible. On the basis of the two criteria, we selected 10 indicators for bonding, eight for bridging, and eight for linking social capital (Table 1). Among 19 indicators, 10 of them are from the ESRI GIS data whereas the rest are from the US Census 2010 and County Business Patterns 2010. All of these data are publicly available, anonymized, and aggregated by their dataset creators; as such, no Institutional Review Board (IRB) protocol is necessary for analyzing data at the county level.

Bonding Indicators

To measure bonding social capital, we use ten indicators to measure the thick connections among individuals looking at the similarity in demographic characteristics, attitudes, and resources, that is, homophily. The first indicator under the bonding category is race similarity and is computed using the race fractionalization concept developed as shown in Equation (1) in Appendix A (Alesina et al., 1999). Race similarity is measured between 0 and 1; 0 being complete homogeneity and 1 being complete heterogeneity. We exclude Hispanic from the race similarity calculation because Hispanics serve as a measure of ethnicity, not a race, and are not a mutually exclusive category (Alesina et al., 1999). Second, we compute ethnicity similarity for the Hispanic category using Equation (2) (see Appendix A); it is measured between 0 and 1; 0 being complete homogeneity and 1 being complete heterogeneity. Homophily encourages bonding and thus the ethnic indicator

Table 1. Selected Indicators in the Social Capital Index

No.	Social Capital (SoC) Concept	Study Indicator	Association With SoC	Justification	Source
	Bonding				
1	Race similarity	Race Fractionalization (0 = complete homogeneity to 1 = complete heterogeneity)	Negative	Alesina, Baqir, and Easterly (1999)	US Census (2010b)
2	Ethnicity similarity	Ethnicity Fractionalization (0 = complete homogeneity to 1 = complete heterogeneity)	Negative	Alesina et al. (1999)	US Census (2010b)
3	Educational equality	Negative absolute difference between % of total population with college education and % of total population with less than high school education	Negative	Norris, Stevens, Pfefferbaum, Wyche, and Pfefferbaum (2008); Morrow (2008)	US Census (2010b)
4	Race/income equality	Gini coefficient (0 = perfect equality to 1 = perfect inequality)	Negative	(Cutter et al., 2010)	US Census (2010b)
5	Employment equality	Absolute difference between % of total employed and % of total unemployed labor force	Positive	Tierney, Lindell, and Perry (2001)	US Census (2010b)
6	Gender income similarity	Gender income fractionalization (0 = complete homogeneity to 1 = complete heterogeneity)	Negative	Norris et al. (2008)	US Census (2010b)
7	Language competency	% of total population proficient English speakers	Positive	Morrow (2008)	US Census (2010b)
8	Communication capacity	% of total households with a telephone	Positive	Cutter et al. (2010)	US Census (2010b)
9	Non-elder population	% of total population below 65 years of age	Positive	Morrow (2008)	US Census (2010b)
	Bridging				
10	Religious organizations	Religious organizations per 10,000 persons	Positive	Chamlee-Wright (2010)	US Census (2010a)
11	Civic organizations	Civic organizations per 10,000 persons	Positive	Cutter et al. (2016)	US Census (2010a)
12	Social embeddedness-charitable ties	Member of charitable organization (% of total)	Positive	Norris et al. (2008)	ESRI (2017)
13	Social embeddedness-Fraternal ties	Member of fraternal order (% of total)	Positive	Norris et al. (2008)	ESRI (2017)
14	Social embeddedness-Union ties	Member of union (% of total)	Positive	Norris et al. (2008)	ESRI (2017)
	Linking				
15	Political linkage	% of total voting-age population who are eligible for voting	Positive	Morrow (2008)	US Census (2010b)

(*Continued*)

No.	Social Capital (SoC) Concept	Study Indicator	Association With SoC	Justification	Source
16	Local government linkage	% of total local government employees working for local governments	Positive	Murphy (2007)	US Census (2010b)
17	State government linkage	% of total state employees working for the state governments	Positive	Murphy (2007)	US Census (2010b)
18	Federal government linkage	% of total federal employees working for the federal agencies	Positive	Murphy (2007)	US Census (2010b)
19	Political linkage-political activities	Attended political rally/speech/organized protest (% of total)	Positive	Tierney et al. (2001)	ESRI (2017)

negatively correlates with bonding ties (Beaudoin, 2007; Dyson, 2006; Hawkins & Maurer, 2010; Lin, 2001) (see Table 1). Third, we also compute educational equality as the negative absolute difference between the percent of the population with a college education and percent population with less than high school education. Here our logic is that differences in educational levels make individuals less likely to interact and hence mobilize collectively (Morrow, 2008; Norris et al., 2008).

The fourth indicator measures similarity in income and captures economic equality. The Gini coefficient has a value of between zero (perfect equality) and 1 (perfect inequality) and measures race/income equality (Cutter et al., 2010). We expect that a perfect equality value is positively associated with strong bonding among the individuals whereas imperfect equality has a negative association. The fifth indicator captures employment equality which is measured by the absolute difference between the percent employed and the percent unemployed labor force (Tierney et al., 2001). Employment inequality, like education and income inequality, makes higher cohesion and trustless likely. The employment equality is measured as the absolute difference between percent employed and percent unemployed labor force and it is positively associated with the bonding (Table 1).

The sixth indicator is gender income inequality. Gender income inequality could have a polarizing impact. The gender differences are mainly based on culture; scholars have argued that men are more active in public volunteer work after disasters, whereas women tend to undertake in caregiving tasks such as taking care of elders, children, and disabilities (Morrow, 2008). We measure gender income fractionalization between 0 and 1; 0 being complete homogeneity to 1 being complete heterogeneity (see Equation (6) in Appendix A). Gender income fractionalization is negatively associated with bonding social ties (Table 1). The seventh indicator, language competency, is measured by the percentage of the population which is proficient in English (Table 1). Language plays an important role in the resiliency of a community. Many individuals who were foreign-born and who speak English as a second or third language face difficulties in interpreting information and communicating with others. With a growing number of ethnic minorities making up more than one-third of the total U.S. population, language competency has become a serious issue (Elliott & Pais, 2006). We expect that language competency is positively associated with broader bonding outcomes.

The eighth indicator measures communication capacity. Among different means of communication devices, the telephone is the most common and fundamental communication device. The study measures communication capacity as a percent of households with a telephone. Having a telephone could help individuals networking with others while its absence would impede information flow. The last indicator is the nonelderly population. Agility and strength are important dimensions in vulnerable populations because these characteristics can enhance survival during a crisis (Morrow, 2008). Many aging individuals live in institutions such as nursing homes, living assistance homes, and hospitals and may not actively interact with other community members. Thus, the percent of the non-elderly population is positively associated with bonding social capital (Table 1). The indicators (Table 1) that have a negative association with social capital are recoded by subtracting from 1.

Bridging Indicators

To measure bridging social capital, we selected five indicators to measure acquaintances or loosely connected individuals through ties that span social divisions and groups. The connections come from the individuals' involvement in various civic organizations including religious organizations, charitable organizations, churches, fraternal order, and unions. The selected indicators include (i) religious organizations measured in religious organizations per 10,000 persons, (ii) civic organizations, measured in civic organizations per 10,000 persons (Cutter et al., 2016), (iii) social embeddedness-charitable ties, measured in member of charitable organization (%), (iv) social embeddedness-fraternal ties, measured in members of such fraternal orders (%), and (v) social embeddedness-union ties, measured in union membership (%) (Norris et al., 2008).

Linking Indicators

To measure linking social capital, we also captured five indicators that measure connections of regular citizens to those in power. The selected indicators include (i) political linkage, measured as the percent voting-age population who are eligible for voting (Morrow, 2008), (ii) local government linkage, measured in percent of local government employees working for local governments (Murphy, 2007), (iii) state government linkage, measured in percent of state employees working for the state governments (Murphy, 2007), (iv) federal government linkage, measured in percent of federal employees working for the federal agencies (Murphy, 2007), and (v) political linkage-political activities, measured in attended political rally, speech, or organized protest involvement (%) (Tierney et al., 2001).

The SoCI

We include 3,134 counties in this study of the contiguous United States. The SoCI for US counties has an average value of 1.166, with a standard deviation of 0.113, a minimum value of 0.708 (lowest social capital), and a maximum value of 1.589 (highest social capital). We grouped SoCI values into five categories for better visualization as shown below in Figure 1. The highest social capital values in the contiguous United States are observed in the West and South Regions and with some spots in Midwest Region: Bristol Bay Borough (1.589) in Alaska, and King County (1.571) in King County in Texas, Kalawao County (1.548) in Hawaii, Blaine County (1.542) in Nebraska, and Kalamazoo County (1.54) in Michigan. Counties (blue) with very high social capital values (>1.39, blue color) are observed in

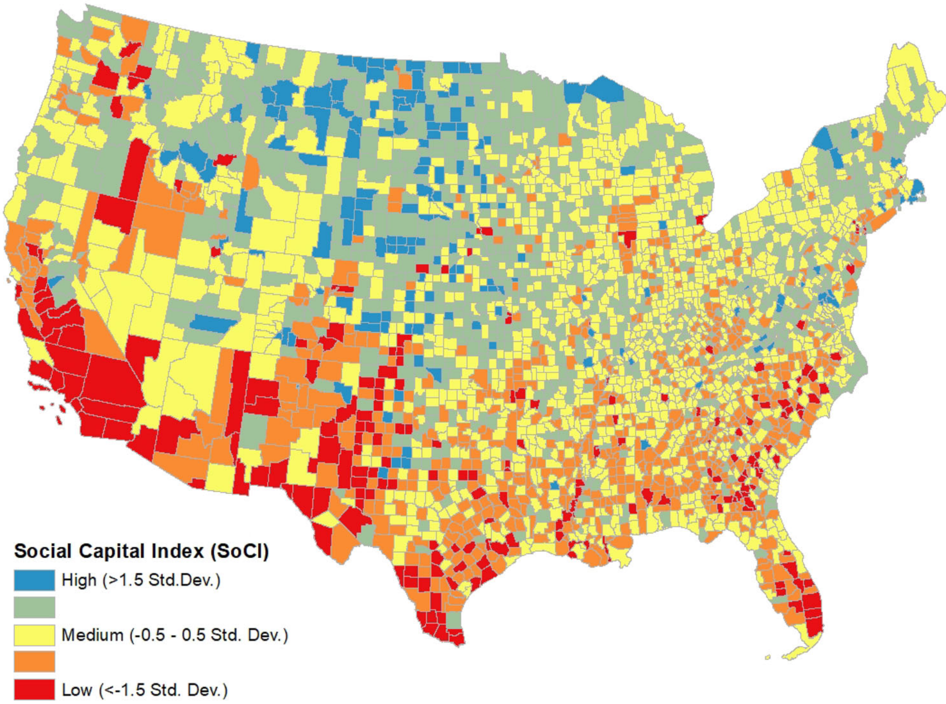

Figure 1. Social Capital Index (SoCI) for contiguous counties in the United States.

Oregon, Montana and Wyoming in West Region whiles other counties are located in North Dakoda, South Dakoda, Nebraska, and Kansas in the Midwest Region. Counties (green) with moderately high social capital (between 1.393 and 1.279) are scattered in the northeast part of Midwest region including Minnesota, Wisconsin, Iowa, Missouri, Illinois, Indiana, Ohio, and Michigan and in the Northeast region in New York, Connecticut, Massachusetts, Maine, Maryland, Pennsylvania (Figure 1). Counties (yellow) with moderate social capital (between 1.279 and 1.166) are scattered in the West region in Nevada, Utah, Colorado, Arizona, New Mexico; in the south region in Texas, Louisiana, Mississippi, Alabama, Georgia, Tennessee, and Kentucky. Counties (orange) with low social capital (between 1.166 and 1.052) are cluttered in the South Region. The counties (red) with very low (between 1.052 and 0.938) are scattered in the southwest of the West Region including California, New Mexico, and Texas.

Past scholarship has also identified the visible north-south divide we found in our SoCI-based geographic analysis of the country (Florida, 2019; SCP, 2018). The exact reasons for the unequal distribution of social ties remain unclear and are not the focus of our paper. Nonetheless, potential interdependent and overlapping explanations include ethnic homogeneity, income inequality, institutional racism, historical migratory patterns, and regional climate (Hendrix, 2018; Rupasingha, Goetz, & Freshwater, 2006; Sunde, 2018). We hope that future research can build on these findings to better identify the causal drivers for these geographic patterns of social capital distribution.

Returning to our findings, we broke the general SoCI into the three sub-categories illuminated above to further explore the geographical trends of the sub-domains (Figure 2A–C). Our index for bonding social capital has an average value of 0.662, with a standard deviation of 0.07, a minimum value of 0.41 (lowest bonding), and a maximum value of 0.84 (highest bonding) Figure 2A.

Our measure of bridging social capital has an average value of 0.25, with a standard deviation of 0.05, a minimum value of 0.05 (lowest bridging), and a maximum value of 0.58 (highest bonding) (see Figure 2B). Our linking SoCI has an average value of 0.26, with a standard deviation of 0.05, a minimum value of 0.09 (lowest linking), and a maximum value of 0.62 (highest linking) (see Figure 2C).

Geographically, there are 1,055, 217, 1,423, and 448 counties in the Midwest, the Northeast, the South, and the West Region, respectively. In the Northeast region, the county with the highest social capital scores within the region is Middlesex County, Connecticut with a social capital score of 1.35. In the Midwest Region, the county with the highest social capital scores was Pope County, Illinois with 1.38. In the South Region, the highest county with social capital scores was Fayette County with a score of 1.65. In the West Region, the county with the highest social capital scores was Bristol Bay Borough, AK with a score of 1.58.

We also check the composition of the overall SoCI by looking into three domains. While no county received the maximum possible score of 3, the county with

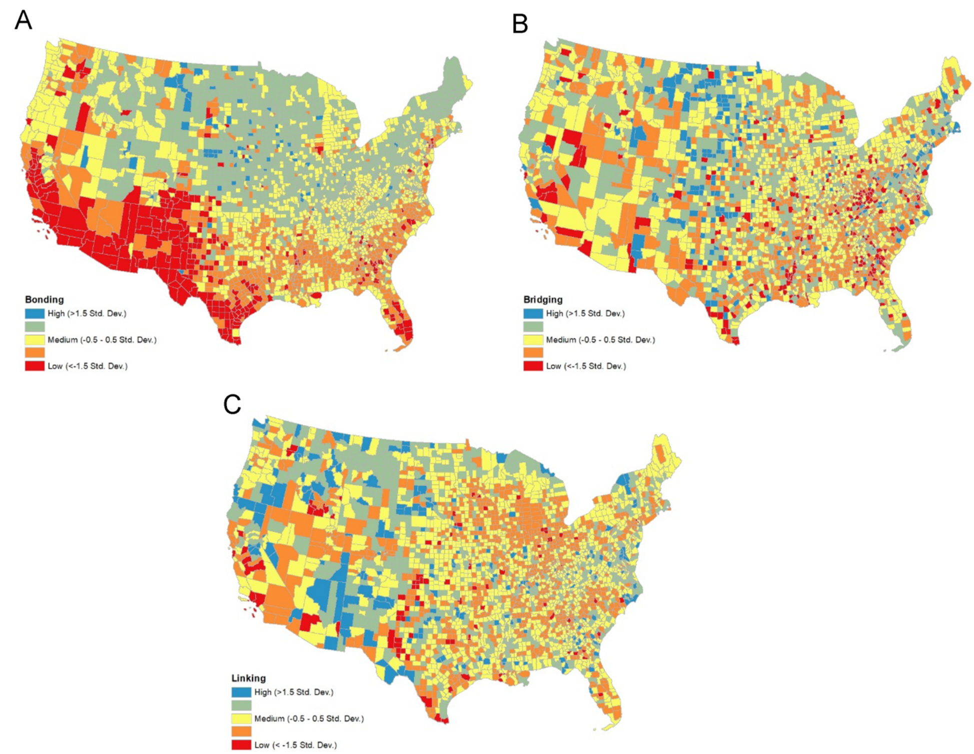

Figure 2. Three components of the Social Capital Index, Bonding, Bridging, and Linking. Note: The scores are classified into low, medium, and high using the standard deviation method used in Figure 1.

the highest social capital score was Bristol Bay Borough in AK with a score of 1.59 (Table 2). That county has a bridging score of 0.45 (maximum 0.57), a bonding score of 0.70 (maximum 0.84), and a linking score of 0.43 (maximum 0.62). Its overall high rank was generated primarily by strong bridging and linking ties but not by bonding social capital, which ranked 798th in the Western Region. The second highest-ranking county was Logan in NE, with high bridging and bonding scores but a low score for linking social capital. Overall, the ten counties with the highest overall social capital scores received them because of higher scores of bonding and bridging ties, not linking social capital.

The lowest ranking county with an overall social capital score of 0.70 was Hardee County in FL and Bronx County in NY. In those locations, their scores were consistently low across all three categories (bonding, bridging, and linking), and this was true as well for the ten countries with the lowest social capital scores across the country.

Validation Analysis

Having constructed the SoCI index and demonstrated geographic variation across the United States, we build on past research which stated that index validation requires empirically testing the sign and significance of the association between any index and relevant empirical outcomes. Past scholarship has tested to see if indices correlate with disaster outcomes such as damage, number of fatalities, and the frequency of disaster declarations (Bakkensen et al., 2016). We build on this approach and empirically validate the SoCI index alongside other two well-known vulnerability and resiliency indices, namely the BRIC and SoVI (Bakkensen et al. 2016) (Table 3).

We generate our hypothesized relationships between SoCI and these disaster outcomes based on existing research which has tied higher levels of social capital to higher levels of disaster resilience (Aldrich, 2012, 2019). We believe that greater levels of social capital would negatively correlate with fatalities and the frequency of disaster declarations. Residents in a community with a higher level of bonding, bridging, and linking ties would be better prepared for shocks, suffer fewer casualties, and be better able to tap into regional and national resources. Vulnerable, elderly residents in Tohoku, Japan, for example, with higher levels of bonding social capital suffered fewer deaths than similar residents in communities with lower levels of such connections (Ye & Aldrich, 2019). However, we are unsure if social capital levels would have any correlation with physical damage from a shock, so we leave that hypothesized relationship as unknown. Based on BRIC's and SoVI's composition, we argue that BRIC should negatively correlate with these three outcomes, while SoVI would correlate positively.

Using data for the years 2000 to 2010 from the Center for Spatial Hazard Events and Losses Database for the United States, Version 17.0 online from the Center for Emergency Management and Homeland Security, Arizona State

Table 2. Ten Highest and Lowest Social Capital Scores in the Contiguous United States

No.	County	State	Population	SoCI	SoCI Rank	SoCI Pct	Bridging	Bridging Rank	Linking	Linking Rank	Bonding	Bonding Rank	Region
High Social Capital													
1	Bristol Bay Borough	AK	997	1.589	3,143	100	0.453	3,140	0.431	3,130	0.705	2,184	West
2	King County	TX	286	1.571	3,142	100	0.475	3,142	0.383	3,088	0.713	2,358	South
3	Kalawao County	HI	90	1.549	3,141	100	0.343	3,008	0.626	3,143	0.581	387	West
4	Blaine County	NE	478	1.542	3,140	100	0.441	3,139	0.318	2,841	0.783	3,125	Midwest
5	Kalamazoo County	MI	250,331	1.542	3,139	100	0.576	3,143	0.297	2,613	0.669	1,490	Midwest
6	Burke County	ND	1,968	1.510	3,138	100	0.428	3,138	0.324	2,898	0.758	3,052	Midwest
7	Hooker County	NE	736	1.489	3,137	100	0.373	3,104	0.322	2,879	0.794	3,133	Midwest
8	Denali Borough	AK	1,826	1.486	3,136	100	0.355	3,061	0.424	3,129	0.707	2,233	West
9	Skagway Municipality	AK	968	1.485	3,135	100	0.410	3,133	0.263	1,909	0.812	3,139	West
10	Fallon County	MT	2,890	1.484	3,134	100	0.364	3,088	0.326	2,910	0.795	3,135	West
Low Social Capital													
1	Hardee County	FL	27,731	0.709	1	0	0.116	24	0.120	4	0.472	36	South
2	Bronx County	NY	1,385,108	0.709	2	0	0.116	25	0.183	75	0.410	2	Northeast
3	Franklin County	WA	78,163	0.724	3	0	0.135	60	0.119	3	0.470	31	West
4	Fresno County	CA	930,450	0.745	4	0	0.108	12	0.166	29	0.470	30	West
5	Hudson County	NJ	634,266	0.746	5	0	0.147	110	0.147	8	0.452	15	Northeast
6	Echols County	GA	4,034	0.756	6	0	0.110	14	0.126	5	0.521	117	South
7	Yuma County	AZ	195,751	0.795	7	0	0.105	8	0.204	255	0.485	51	West
8	Adams County	WA	18,728	0.798	8	0	0.173	313	0.156	13	0.470	29	West
9	Merced County	CA	255,793	0.799	9	0	0.163	236	0.166	26	0.470	32	West
10	Wyandotte County	KS	157,505	0.802	10	0	0.126	41	0.162	20	0.513	99	Midwest

Table 3. Hypothesized Relationships Between Three Indices and Outcomes of Interest

Outcome of Interest/Indices	SoCI	BRIC	SoVI
Ln Damage	Unknown ($\beta1 > = < 0$)	Negative ($\beta1 < 0$)	Positive ($\beta1 > 0$)
Ln Fatalities	Negative ($\beta1 < 0$)	Negative ($\beta1 < 0$)	Positive ($\beta1 > 0$)
Ln Frequency of Disaster Declarations	Negative ($\beta1 < 0$)	Negative ($\beta1 < 0$)	Positive ($\beta1 > 0$)

University (CEMHS, 2018), we tested the significance of the relation and direction between SoCI, BRIC, and SoVI scores and these three outcomes of interest as seen in Equations (7–9) (see Appendix 2 Equations (7–9)). The results in Table 4 show the estimated coefficients match two of the hypothesized directions of the relationships between SoCI and disaster outcomes (i.e., negative for fatalities and declarations) with statistical significance. That is, counties with deeper social ties experience fewer fatalities and seek fewer disaster declarations. The damages coefficient was positive, however, indicating that social ties by themselves cannot reduce damage levels.

We similarly tested the existing frameworks of BRIC and SoVI using these disaster outcomes and were unable to consistently demonstrate the hypothesized correlation with property damage and fatalities (Bakkensen et al., 2016). SoVI had a positive relationship with damage and disaster declarations—logical given its focus on vulnerability—but a negative one with mortality (which is inconsistent with the theory behind it). BRIC had a negative relationship with disaster declarations and fatality—logical given its claims about measuring resilience—but a positive one with damage (which is inconsistent). In short, our SoCI approach has at least the same level of validity as past frameworks while analyzing correlations with disaster outcomes of interest.

Conclusion

This study demonstrates the possibility of quantitatively measuring social capital through three subcategories, namely bonding, bridging, and linking social capital. We constructed an unweighted SoCI using a composite indicator methodology for all counties (3,143) in the contiguous United States using 19 publicly available indicators. Our theoretical approach and indicator selection are based on a growing literature on social capital and resilience. The study then shows how this SoCI approach better captures levels of social connection than existing frameworks and can illuminate social resilience to natural hazards. After constructing the SoCI composite indicator we undertook a validation analysis with empirical data and believe that our current formulation captures variance appropriately.

As with any index, ours has limitations. First, we rely on aggregated proxy data to be able to carry out a large-N analysis across all of the counties in the United States. In doing so we miss many of the nuances and hyperlocal interactions that are

Table 4. Validation analysis of SoVI, BRIC, and SoCI

	Ln Damages	Ln Damages	Ln Damages	LnFatality	LnFatality	LnFatality	Ln Disaster Declaration	Ln Disaster Declaration	Ln Disaster Declaration
SoCI	0.2091***			−0.3205***			−0.2119***		
	(0.0784)			(0.1059)			(0.0319)		
BRIC		0.6245***			−0.3108**			−0.0837***	
		(0.0641)			(0.0857)			(0.0116)	
SoVI			0.0332**			−0.0128**			0.0069**
			(0.0038)			(0.0043)			(0.0019)
Ln Risk Rate	0.6610***	0.6557***	0.6648***	−0.0645***	−0.0629***	−0.0646***	0.5826***	0.5824***	0.5840***
	(0.0105)	(0.0105)	(0.0104)	(0.0140)	(0.0141)	(0.0140)	(0.0050)	(0.0051)	(0.0051)
Ln Population	−0.7274***	−0.7409***	−0.7010***	−0.0303***	−0.0198***	−0.0130	−0.0215***	−0.0108***	−000078*
	(0.0059)	(0.0057)	(0.0067)	(0.0071)	(0.0063)	(0.0068)	(0.0034)	(0.0032)	(0.0036)
Constant	6.9166***	6.9493***	6.8876***	−0.1229***	0.9164***	-0.6777***	1.3322***	1.2287***	0.9245***
	(0.1241)	(0.0642)	(0.0700)	(0.1722)	(0.0836)	(0.0754)	(0.0601)	(0.0454)	(0.0370)
R-Square	0.1934	0.1936	0.1941	0.0114	0.0125	0.0113	0.8532	0.8536	0.8514
Observations	76,310	75,916	76,310	4,421	4,421	4,421	2,619	2,614	2,619

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

so critical for social capital in the local environment. Next, our approach uses data available for the United States, but not necessarily in other countries, whether advanced industrial democracies or developing nations. The reliability and availability of such data in our country already set it off from many countries still struggling to provide critical information to the public. Finally, our framework focuses on a single point in time. Disasters, crises, scandals, and other events no doubt can alter levels of social capital. These results must be viewed in the context of a single snapshot rather than an over-time evaluation.

Nonetheless, our research framework brings important implications for policymakers and practitioners. First, while a variety of local governments, scholars, and decision makers use the widely available BRIC and SoVI indices, we do not believe that either sufficiently incorporates social capital. As a growing body of evidence demonstrates that social capital levels capture a community's resilience to various man-made and natural shocks, our indices need to be better tuned to capture strong variation in social ties across cities, counties, and regions. When experts rely on measures of other available indices that do not capture social capital, they may be misestimating the actual resilience (or, alternatively, the vulnerability) of a community.

Next, social capital serves as a critical resource for governance and a strong predictor of economic and health outcomes. Rather than relying on measures of social vulnerability to predict hot spots and pre-position aid and assistance, we encourage policymakers and practitioners to make use of social capital information in preparing for disasters. In fact, beyond merely measuring social capital, our study underscores research that is possible to deliberately build and enhance social capital in vulnerable areas (Aldrich & Meyer, 2014; Aldrich, Meyer, & Page, 2018). As such, elected officials and local governments in counties with the lowest SoCI should be encouraged to build social capital while those with top rankings show be asked to continue investing (e.g., Tables C1 and C2). Programs could build on the successes found in programs such as BoCo Strong (Boulder Colorado Strong), the Neighborhood Empowerment Network (NEN) in San Francisco, and Boston’s City Resilience Strategy which focuses on social, not just physical infrastructure.

Finally, this approach sets up a clear research agenda. This study is among the first of its kind to measure and map the social capital for disaster mitigation using U.S. Census 2010 data. In the future, the changes of social capital over time and space should be traced by constructing SoCI using historical census data such as 1980, 1990, and 2000. We hope that this research can help advance and guide a field that will be critical to building community resilience to extreme weather shocks and the disastrous consequences of global warming.

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Appendix A: Calculations for social capital measurements

1. Race similarity: Race similarity is computed using race fractionalization (Alesina et al., 1999) as follows.

$$\text{Race similarity} = 1 - \sum_{i=n} (\text{Race}_i)^2 \tag{1}$$

Where;

Race similarity = Race fractionalization.

Race_i denotes the share of population self-identified as of race i, and

i = [White, Black, Asian and Pacific Islander, American Indian, two more and some other].

2. Ethnicity similarity: We compute ethnicity similarity for the Hispanic population using the Equation (2).

$$\text{Ethnic similarity} = 1 - \sum_{i=n} (\text{Ethnicity}_i)^2 \tag{2}$$

Where;

Ethnic similarity = Ethnicity fractionalization

Ethnicity_i denotes the share of population self-identified as of Hispanic/Non-Hispanic i, and i = [Hispanic, non-Hispanic].

3. Education equality: The equational equality was computed using the following equations.

$$\text{EE} = (\text{PCE}-\text{LHE}) \tag{3A}$$

Where;

EE = Absolute negative value of education equality.

PCE = Percent total population with college education.

LHE = Percent total population with less high school education.

Next, EE absolute negative value is transformed into a positive value by

$$EER = 1 - EE \tag{3B}$$

Where;

EER = Transformed absolute positive value of EE.

Then EER was normalized with the following Equation (3C).

$$EERN = [(EER - Min.\ EER)/(Max.\ EER - Min.\ EER)] \tag{3C}$$

4. Income inequality: The income equality if is computed as follows. Income inequality was measured with Gini Index, which is a summary measure of income inequality. The Gini coefficient ranges from 0 to 1; 0 indicates a perfect equality (everyone receives an equal share), whereas 1 means a perfect inequality (one or a group of recipients receives all or bigger portion of the income).

$$II = Gini \tag{4A}$$

Where;

II = Income inequality.

Next, income inequality was transformed its negative association by

$$IIR = 1 - II \tag{4B}$$

Where;

IIR = Income equality.

Next IIR was normalized with the following Equation (4C).

$$IIR = [(IIR - Min.\ IIR)/(Max.\ IIR - Min.\ IIR)] \tag{4C}$$

5. Employment equality: The employment equality is computed as follows (Equation (5A) & (5B)).

$$EE = (PEMP - PUEMP) \tag{5A}$$

Where;

PEMP = Percent employed population.

PUEMP = Percent unemployed population.

EE = Employment equality.

Next, EE was normalized with the following Equation (5B).

$$EEN = [(EE - \text{Min. } EE)/(\text{Max. } EE - \text{Min. } EE)] \quad (5B)$$

Where;

EEN = Normalized employment equality.

6. Gender income similarity: The gender income fractionalization is measured as follows (Equation (6)):

$$GIS = 1 - [(MI/TI)^2 + (FI/TI)^2] \quad (6)$$

Where;

GIS = Gender income similarity or gender income fractionalization.

MI = Medium income of non-family household for male householders.

FI = Medium income of non-family household for female householders.

TI = Medium income of non-family household for both male and female householders.

Appendix B: Validation of SoCI for hypothesized outcomes

We run a regression analysis to study correlations between the frequency of Presidential disaster declarations and SoCI with the following Equation (7).

$$\ln PDD = b0 + b1\ SoCI + b2\ \ln R + b3\ \ln POP + e \quad (7)$$

Whereas:

lnPDD = natural log of frequency of Presidential Disaster Declaration.

SoCI = Social Capital Index.

LnR = natural log of risk rate.

lnPOP = natural log of the county's Population.

b0, b1, b2, b3 = coefficients.

We conduct a regression analysis to examine any association between fatalities and SoCI with the following Equation (8).

$$\ln Fatality = b0 + b1\ SoCI + b2\ \ln R + b3\ \ln POP + e \quad (8)$$

Whereas:

lnFatality = natural log of number of fatalities caused by a disaster in the county.

SoCI = Social Capital Index.

LnR = natural log of risk rate.

lnPOP = natural log of the county's Population.

b0, b1, b2, b3 = coefficients.

We utilize a regression analysis to investigate any association between fatalities and SoCI with the following Equation (9).

$$\ln DMG = b0 + b1\ SoVI + b2\ \ln R + b3\ \ln POP + e \quad (9)$$

Whereas:

lnDMG = natural log of damage measured in dollars (2017 CPI adjusted).

SoCI = Social Capital Index.

LnR = natural log of risk rate.

lnPOP = natural log of the county's Population.

b0, b1, b2, b3 = coefficients.

Appendix C

Table C1. Raw Data for the Selected Indicators

	Indicators	Observations	Mean	Std. Dev.	Min	Max
	Bonding					
1	Race similarity	3,143	0.697	0.225	0	1.00
2	Ethnicity similarity	3,143	0.778	0.250	0	1.00
3	Educational equality	3,143	0.601	0.111	0	1.00
4	Race/income equality	3,143	0.488	0.084	0	1.00
5	Employment equality	3,143	0.498	0.119	0	1.00
6	Gender income similarity	3,143	0.110	0.104	0	1.00
7	Language competency	3,143	0.906	0.120	0	1.00
8	Communication capacity	3,143	0.883	0.078	0	1.00
9	Non-elder population	3,143	0.997	0.019	0	1.00
	Bridging					
10	Religious organizations	3,143	0.148	0.103	0	1.00
11	Civic organizations	3,143	0.059	0.030	0	0.11
12	Social embeddedness-charitable ties	3,143	0.357	0.138	0	1.00
13	Social embeddedness- Fraternal ties	3,143	0.266	0.080	0	1.00
14	Social embeddedness-Union ties	3,143	0.402	0.124	0	1.00
	Linking					
15	Political linkage	3,143	0.565	0.088	0	1.00
16	Local government linkage	3,143	0.191	0.078	0	1.00
17	State government linkage	3,143	0.120	0.079	0	1.00
18	Federal government linkage	3,143	0.104	0.105	0	1.00
19	Political linkage-political activities	3,143	0.309	0.128	0	1.00

Table C2. Indicators Imputed for Counties

FIPS	County name	State	Sub-group	Imputed Data Indicator
46137	Ziebach County	SD	Bridging Linking	Charitable, church, fraternal, union, and politicalacts
48507	Zavala County	TX	Bridging Linking	Charitable, church, fraternal, union, and politicalacts
48505	Zapata County	TX	Bridging Linking	Charitable, church, fraternal, union, and politicalacts
48301	Loving County	TX	Bonding	Genderincome