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ORIGINAL PAPER

The role of social capital, personal networks, and emergency responders in post-disaster recovery and resilience: a study of rural communities in Indiana

Arif Mohaimin Sadri[1] · Satish V. Ukkusuri[2] · Seungyoon Lee[3] · Rosalee Clawson[4] · Daniel Aldrich[5] · Megan Sapp Nelson[6] · Justin Seipel[7] · Daniel Kelly[8]

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Abstract The factors that explain the speed of recovery after disaster remain contested. While many have argued that physical infrastructure, social capital, and disaster damage influence the arc of recovery, empirical studies that test these various factors within a unified modeling framework are few. We conducted a mail survey to collect data on household recovery in four small towns in southern Indiana that were hit by deadly tornadoes in March 2012. The recovery effort is ongoing; while many of the homes,

✉ Arif Mohaimin Sadri
sadri.buet@gmail.com

Satish V. Ukkusuri
sukkusur@purdue.edu

Seungyoon Lee
seungyoon@purdue.edu

Rosalee Clawson
clawsonr@purdue.edu

Daniel Aldrich
daniel.aldrich@gmail.com

Megan Sapp Nelson
mrsapp@purdue.edu

Justin Seipel
jseipel@purdue.edu

Daniel Kelly
drkelly@purdue.edu

[1] Department of Civil and Environmental Engineering, Rose-Hulman Institute of Technology, Terre Haute, IN 47803, USA

[2] Lyles School of Civil Engineering, Purdue University, West Lafayette, IN 47907, USA

[3] Brian Lamb School of Communication, Purdue University, West Lafayette, IN 47907, USA

[4] Department of Political Science, Purdue University, West Lafayette, IN 47907, USA

[5] Department of Political Science, Northeastern University, Boston, MA 02115, USA

businesses, and community facilities were rebuilt in 2013, some are still under construction. We investigate how households in these communities are recovering from damage that they experienced and the role of social capital, personal networks, and assistance from emergency responders on the overall recovery experience. We used an ordered probit modeling framework to test the combined as well as relative effects of (a) damage to physical infrastructures (houses, vehicles, etc.); (b) recovery assistance from emergency responders (FEMA) as well as friends and neighbors; (c) personal network characteristics (size, network density, proximity, length of relationship); (d) social capital (civic engagement, contact with neighbors, trust); and (e) household characteristics. Results show that while households with higher levels of damage experienced slower recovery, those with recovery assistance from neighbors, stronger personal networks, and higher levels of social capital experienced faster recovery. The insights gained in this study will enable emergency managers and disaster response personnel to implement targeted strategies in facilitating post-disaster recovery and community resilience.

Keywords Social capital · Personal networks · Emergency responders · Resilience · Post-disaster recovery · Ordered probit

1 Introduction and motivation

Natural disasters remain among the most likely and devastating events that individuals and communities encounter all over the world. Disaster recovery and resilience have been largely addressed in the domains of physical systems and operations with emphasis on speed, cost, and effectiveness (National Research Council 2012). However, effective response to natural disasters must incorporate dimensions of the social and built environment. Although a large body of the empirical literature addresses emergency preparedness and what happens during a disaster, there is limited focus on post-disaster issues such as how communities contribute to the recovery. In addition, there is limited research that considers both the networks of physical infrastructure and social ties present in a community to address issues related to post-disaster recovery. Most studies have treated resilience more as a technocratic rather than a social problem by examining the scope and speed of rebuilding as functions of the level of damage and the amount of aid (Dacy and Kunreuther 1969; Kamel and Loukaitou-Sideris 2004).

Thus, there is insufficient replicable, empirical evidence investigating the role of social networks, social capital, and other neighborhood-based factors in facilitating or impeding the rebuilding of social infrastructure networks post-disaster. Social systems encompass the relationships among households, neighbors, and community organizations. These relationships influence human interactions such as how information is shared, individual and collective decisions are made, resources are mobilized, and local activities are organized. Organizations such as the American Red Cross, church groups, and local social services organizations can take on the ground role in initial response, information and impact gathering, and needs assessment. These social systems and the social networks that they foster are increasingly recognized as important in disaster response and recovery. Although

[6] Library Sciences, Purdue University, West Lafayette, IN 47907, USA

[7] Purdue Polytechnic Institute, Purdue University, West Lafayette, IN 47907, USA

[8] Department of Philosophy, Purdue University, West Lafayette, IN 47907, USA

there is now a growing body of the literature on the role of social capital in disaster recovery (Aldrich and Crook 2008; Chamlee-Wright 2010; Aldrich 2010, 2011, 2012a, b; Aldrich and Sawada 2015), few of these studies engage the well-developed literature on transportation and distribution networks (Ukkusuri and Yushimito 2008; Ukkusuri et al. 2007, 2014; Hasan et al. 2011; Murray-Tuite and Mahmassani 2004; Ye and Ukkusuri 2015).

Hazard resilience refers to the capacity to forestall the adverse effects of a short-term hazard event preventing it from turning into a long-term community-wide disaster (National Ocean Service website 2016). The ability of communities to successfully recover is linked to the strengths and capacities of individuals, households, schools, businesses, hospitals, and other parts of a community. Community resilience requires a deeper insight into social factors that define a system, as they interplay with physical factors. For example, social and communication networks in the aftermath of a disaster will be influenced by the functioning of transportation networks and the way people make shared trips (Sadri et al. 2015a). Further, these social network ties and the information that people obtain will result in either better or worse decisions that affect the mobilization and functioning of the transportation system. While confronting the immediate threat of climate change, most of the policies provide more consideration toward strengthening physical infrastructure systems to bolster resilience. However, little has been publicly discussed about investing in the social infrastructure of communities to improve overall resiliency to disasters.

This research assesses the combined effects of physical infrastructure damage, characteristics of social capital and personal networks, household characteristics, and recovery assistance from emergency responders on the overall recovery experience at the household level (see Fig. 1 for our conceptual model). This study directs our attention to the importance of elements of social infrastructure systems and networks in facilitating post-disaster recovery. The analysis is based on household surveys conducted in several small

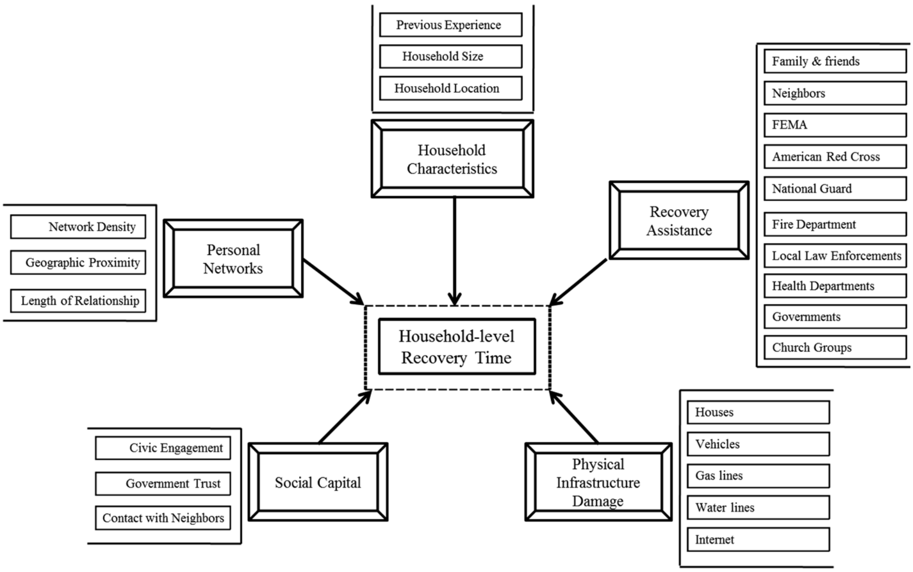


Fig. 1 Conceptual model of household-level recovery time

towns in southern Indiana affected by a tornado in March 2012. Households with stronger personal networks, recovery assistance from neighbors, and higher levels of social capital experienced faster recovery. Overall, communities having strong social ties are likely to better face adverse impacts together and policies should be as such neighborhood attachments are increased.

This study contributes a network design approach that allows one to quantify the social network structure of individuals. The estimation results of the recovery time model could be useful for policymakers to determine the time it would take for households to recover once faced with a tornado and the influence of network structure on the overall recovery experience. Based on the findings of the study, we encourage community leaders and policymakers to consider the importance of social, neighborhood, and community factors as they prepare for disasters. We also recommend engaging senior citizen groups and civic groups in disaster planning scenarios and organizing frequent neighborhood events that build or strengthen social ties as well as help plan for responding to specific scenarios.

2 Background and related work

For policymakers, assessing the structural integrity and readiness of physical infrastructure is a natural first step in times of disaster; however, recent work has shown social infrastructure is equally, if not more, important (Aldrich and Sawada 2015). Studies have long shown that social ties are critical in disaster (e.g., Quarantelli and Dynes 1977), and increasing attention has been paid to the social and community aspects of resilience, beyond the resilience of individuals (Norris et al. 2008). While the definitions of resilience vary, Norris et al. (2008) identify that the key common aspects of the conceptualization involve "an ability or process" as opposed to an "outcome," and "adaptability" as opposed to "stability" (p. 130). For instance, Adger (2000) defined social resilience as the ability of communities to withstand external shocks to their social infrastructure. Social infrastructure, such as physical infrastructure, can be measured, invested in and experience degradation over time. Below, we review related work addressing various aspects of social infrastructure in disaster recovery: social capital, emergency responders and community organizations, personal networks, and neighborhood or household characteristics.

Social capital provides us with a robust set of tools to measure the overall health and strength of a community. Social capital refers to the extent to which an individual involves himself in different informal networks as well as formal civic organizations (Putnam 1995, 2001). This conceptualization of social capital includes many ways in which the members of a community interact, such as participating in recreational activities, talking to neighbors, and joining political parties and environmental organizations. In this sense, social capital reflects the overall pattern of a community's associational life and civic health, the strength of ties between neighbors and friends, and degree of trust and norms of reciprocity among residents. In recent years, social scientists have presented compelling evidence that the strength of social ties is a critical component in disaster response and recovery.

Aldrich (2012a) examined the critical role of social capital in community recovery following a disaster. This study revealed that communities having high level of social capital could reduce the number of migrating victims and valuable resources out of the area. In addition, this helped to quickly disseminate information, financial and physical assistance in the affected communities. To explain variation in the rate of recovery following a disaster, Aldrich (2012b) tested conventional measures of damage, population density (different from network density), human capital, and economic capital, and a popular, yet untested, variable of social capital in about 39 neighborhoods of Tokyo after its 1923 earthquake. The findings of this study suggest that social capital, more than conventional measures, best explains why some areas recovered faster than others. Previously, Nakagawa and Shaw (2004) emphasized the importance of social capital in recovery following a disaster and used post-earthquake cases of Kobe, Japan, and Gujarat, India, to illustrate its critical role. For both cases, the study found that neighborhoods with preexisting community activities and communities with higher levels of social capital experienced faster recovery. Wachtendorf and Kendra (2004) also found that social capital, resources, and expertise are important to the creation of community-based groups after a disaster.

Yamamura (2010) studied the extent to which social capital influences the damage resulting from natural disasters. The study also examined whether the experience of a natural disaster affects individual and collective protection against future disasters. There are three major findings: (1) social capital reduces the damage caused by natural disasters, (2) the risk of a natural disaster makes people more apt to cooperate and, therefore, social capital is more effective to prevent disasters, and (3) income is an important factor for reducing damage, but hardly influences it when the scale of a disaster is small. Dynes (2006) suggested that the key to a successful response to a disaster is the community having access to the social capital necessary to respond to disasters as a unit. The article expressed that the empirical literature on disasters primarily focuses on the destruction of physical capital (infrastructure items) and then on the destruction of human capital (lives), whereas social capital garners less attention because it is less tangible and less affected by disasters out of all forms of capital.

Mathbor (2007) discussed the prospect of effectively using social capital in reducing the adverse impacts caused by natural disasters that hit coastal regions, primarily focusing on three forms of social capital (bonding, bridging and linking) in Bangladesh. The study focused on the role of social work education and practice in building social capital for sustainable disaster relief and management. Murphy (2007) distinguished between two types of emergency response at the local scale: responsibilities of municipal government and initiatives at the community level. These two levels of response are interdependent but separate aspects of emergency management. The study focused more on the social capital resources (networks of strong and weak ties) within communities that may help to increase their resilience to risks and hazards.

Hawkins and Maurer (2010) also examined how different forms of social capital performed in the lives of 40 families following Hurricane Katrina in New Orleans, Louisiana. The study found that residents with low incomes particularly relied on social capital for individual, family, and community survival. In addition, the study revealed that bonding social capital (close ties) was important for immediate support; however, other forms of social capital (bridging and linking) offered pathways to longer-term survival and community revitalization. The paper also discussed how social capital inclusion in social work could affect the way individuals and communities develop following a catastrophic event. Adger (2010) used cases from Southeast Asia and the Caribbean to demonstrate that social capital can help us understand resource management and building resilience in response to climate change. Adger et al. (2005) suggested individuals and communities to consider the mobilization of assets, networks, and social capital to face potential disasters by undertaking adaptive strategies.

Further, studies emphasize assistance from emergency responders as well as other community sources. Bolin and Stanford (1998) explored organized responses to housing and recovery issues and concerns for two ethnically mixed communities in southern California. The study considered the January 1994 Northridge earthquake and qualitatively discussed the performance of community-based organizations (CBOs), non-government organizations (NGOs), and local government agencies being involved in recovery assistance for households having unmet needs through traditional disaster assistance programs. Shaw and Goda (2004) studied the Kobe earthquake in Japan and found civil societies in urban areas to be sustainable when voluntary and non-government activities related to daily services are provided by the resident's associations. Storr and Haeffele-Balch (2012) revealed how CBOs can help heterogeneous, loosely connected communities overcome the post-disaster collective action problem. Based on Hurricane Katrina experience, the study suggested that CBOs can collect and share information about community members' plans and challenges being faced by keeping regular contact with community members through community meetings and other activities.

Network concepts, theories, and methods have been developed to analyze one's personal network structure. More specifically, by considering an individual's personal networks (also known as egocentric networks) it is possible to infer meaningful and relevant information with respect to the local network patterns surrounding the focal individual (also known as ego) and those connected to the ego (also known as alters) (Wasserman and Faust 1994). This allows one to assess the flow of resources through that network based on certain network characteristics such as frequency and duration of contact among network members, network size, and network density (Burt 1984, 2000). Physical or geographic proximity between social network partners affects their interaction and subsequently the formation of network ties (Borgatti and Halgin 2011; Monge and Contractor 2003) by enhancing the mobilization of resources. Network density is an important aspect of egocentric social networks (Borgatti et al. 1998; Wellman 1999). Network density measures the extent to which people in one's social network are involved with others. A dense personal network indicates close interpersonal contacts among alters and helps to promote the sharing of resources.

In contrast, a personal network with many loose connections (also known as structural holes) has been found to facilitate the flow of new or unique information and resources (Park et al. 2012). While most disaster studies examined more aggregate, community-level social capital, social network approaches are still relatively new in disaster and hazards research (Jones et al. 2013). Since ego–alter tie characteristics determine the amount of resource exchange, support, and communication need (Haythornthwaite 2005), they are related to how people exchange assistance in the aftermath of a disaster. For instance, Sadri et al. (2017a, b) examined the influence of personal networks and warning information sources on evacuation decision-making based on egocentric network data obtained from Hurricane Sandy. In contrast, few studies explored social media communication networks such as Twitter more from a complete network perspective to reveal the crisis communication patterns of Hurricane Sandy (Sadri et al. 2017c, d).

Finally, a number of studies looked at the variation in disaster recovery experience across neighborhoods based on demographics. For example, Van Zandt et al. (2012) on Hurricane Ike, Peacock et al. (2011) on Hurricanes Andrew and Ike, and Elliott et al. (2010) on Hurricane Katrina among others. Despite numerous research efforts, the empirical literature does not provide a conclusive evidence on how these multiple aspects of social infrastructure simultaneously affect post-disaster recovery, which is the primary scope of this study.

3 Research design and data summary

This research is based on survey data collected from four small towns in southern Indiana that were hit by deadly tornadoes in March 2-3, 2012. Twelve different states in the Midwest and Southern United States were affected by the tornado outbreak that killed 40 people (NOAA 2013). Following NOAA storm survey and media reports, surveys were mailed out to residents in four cities in southern Indiana that experienced the largest impact (Henryville, Marysville, New Pekin, and Lexington) in the spring of 2015 by specifying 3,666 residential addresses close to the actual tornado path (see Fig. 2). The addresses within the zip codes for these four cities were obtained from a private firm providing address data services, and US postal Service database was used to further filter out addresses close to the tornado path. In this process, we also discarded business addresses, P.O. box, and multifamily housing units and selected addresses with identified names that are likely to produce higher response rates (Link et al. 2008).

The survey included questions about households' post-disaster experiences including evacuation and recovery processes and speed as well as questions about respondents' interaction with neighbors and their communities. We requested that one adult member (at least 18 years old) complete this questionnaire on behalf of the household. Although this method has the weakness of being non-random and non-representative, it is known to yield higher response rates (Gaziano 2005). The mail survey technique adapted in this study followed the standard procedures suggested by Dillman (2007) and Dillman et al. (2014) and used by other scholars (Andrews et al. 2013). An initial letter was sent informing potential respondents about the survey that would come their way followed by the original survey questionnaire (including a pre-stamped envelope enclosed) and finally two post-cards to follow-up. The survey was closed on September 2015, and completed surveys were received from 390 households.

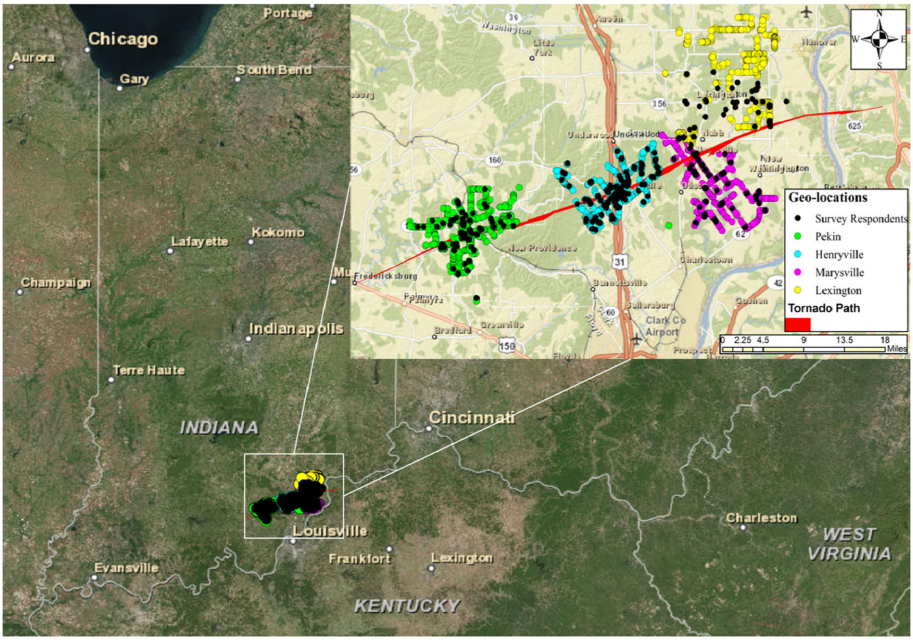


Fig. 2 Geolocations of the survey respondents from the tornado-affected areas of southern Indiana

The overall response rate was 10.64% (Henryville: 14.04%, Marysville: 9.58%, New Pekin: 8.96%, and Lexington: 7.26%). The mean age of the respondents (244 females, 128 males, and 18 unidentified) was 58.3 years with a standard deviation of 14.9. Sixty-seven respondents stated that they were not living in the storm-impacted area at that time, and were excluded. The survey respondents include primarily females (65.59%, $N = 372$), house owners (94.84%, $N = 368$), and white people (98.37%, $N = 367$). The income distribution ($N = 327$): less than $20,000 (6.73%), $20,001-$40,000(32.72%), $40,001-$60,000(22.32%), $60,001-$80,000(15.60%), $80,001-$100,000 (13.46%), and over $100,000 (9.17%). The distribution for educational qualifications ($N = 364$): some high school (3.85%), high school graduate (28.57%), some college or vocational school (32.42%), college graduate (24.18%), and graduate school (10.99%).

To understand the household-level recovery experience of respondents who were affected by the tornado, the following question was used: "Approximately how many days did it take for you to completely recover from the damage (personal properties such as your house, vehicle) due to the tornado?" This question measures household-level recovery time and is our dependent variable. The frequency distribution of the ordered responses to this question is presented in Fig. 3 ($N = 294$). In addition to collecting data on respondents' household-level recovery time, the mail survey also assessed damage to physical infrastructure, social capital, personal networks, recovery assistance from emergency responders, and household-level characteristics. We expect these explanatory variables to predict house-level recovery time, and we discuss each below.

3.1 Damage to physical infrastructure items

Households affected by the tornado experienced significant levels of damage and several physical infrastructure items were destroyed. Two hundred ninety-four respondents reported damage to at least one physical infrastructure item as listed in Table 5 of

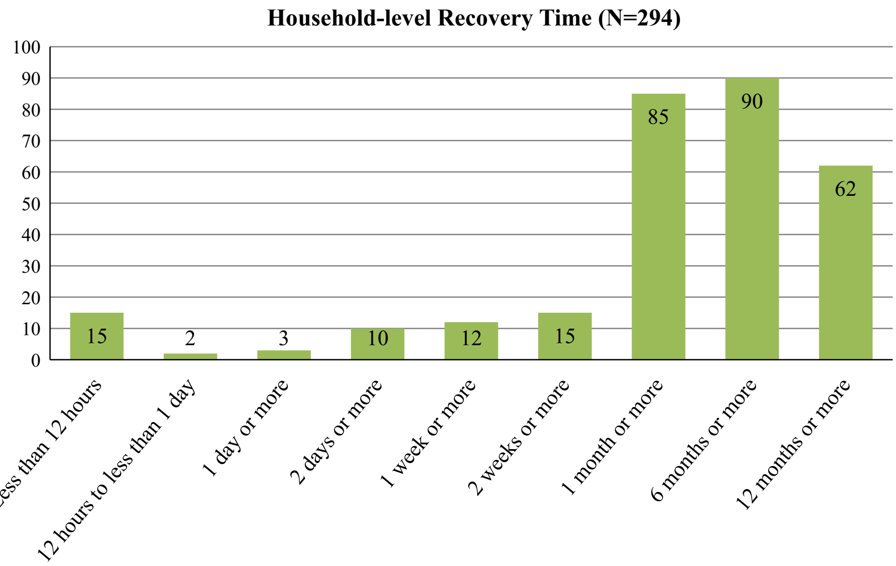


Fig. 3 Frequency distribution of the household-level recovery time

"Appendix." Most of the people (81%) reported damage to or destruction of their homes. Other common items damaged or destroyed include vehicles (52.7%), land telephone lines (51%), electric transmission lines (60.9%), and the Internet (50.3%). Damage to gas lines (7.1%) and water lines (14.6%) was less common. Some people (31.6%) reported additional items such as barns, farmlands, fences, and garages among others. The time required by these households to recover increases at a very high rate for any additional items damaged or destroyed (see Fig. 5 in "Appendix").

3.2 Principal component analysis of social capital

Our measures of social capital are based on 15 items as listed in Table 6 of "Appendix." In general, these items are related to individuals' civic engagement, trust toward community members and organizations, and contact with neighbors. The social capital questions used in this study were adapted from the set of integrated questionnaires proposed by the World Bank Social Capital Thematic Group (Grootaert et al. 2003) to obtain quantitative data on various dimensions of social capital. We used principal component analysis (PCA) and exploratory factor analysis (EFA) to measure different dimensions of social capital for different households in this study, and we found PCA to perform better than EFA. Many researchers have previously used PCA techniques to analyze social capital (Bjørnskov and Svendsen 2003). The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy suggests an overall KMO value of 0.71 (greater than 0.5) which is indicative of strong correlations among the observed variables. In this case, using PCA is justified over EFA. After considering both orthogonal and oblique rotations for PCA with 15 variables listed in Table 6 of "Appendix," some variables (SC_4, SC_6, SC_9, and SC_11) were discarded from the analysis since they failed to explain social capital significantly. The final PCA was based on the remaining 11 variables and PCA with oblique rotation suggests three major components of social capital: (component 1) contact with neighbors, (component 2) government trust, and (component 3) civic engagement. We present these results in Table 7 of "Appendix." The scoring coefficients (component loadings) (both unrotated and oblique rotations) are presented in Table 8 of "Appendix." Scoring coefficients of oblique rotations are used to predict the scores of three components for variable reduction. In Table 9 of "Appendix," the correlation matrix of these variables is presented followed by Figs. 6, 7, and 8 in "Appendix" where we present the association of each component with household-level recovery time. We find that each of the components of social capital is likely to reduce the time of post-disaster recovery. Consistent with past research, the more the individuals of a household are exposed to their communities, the greater their capacity to face sudden shocks.

3.3 Egocentric network analysis of personal networks

We also measure the personal networks of our respondents. We use the personal network research design (PNRD) approach to gather egocentric social network data (Wellman 1979; Burt 1984; Borgatti and Halgin 2012). According to this approach, name generator questions create an exhaustive list of people (alters) with whom the respondent (ego) has some type of relationship. Name interpreter items are then asked to elicit the attributes for each alter identified, as well as the relational (dyadic) attributes between ego and alter. Many classical studies of egocentric networks used this approach previously (Burt 1984; Fischer 1982; Laumann 1966, 1973; Wellman 1979). The specific items from the General Social Survey (GSS) have been widely used by researchers due to their applicability to various contexts and ability to capture ego's core social contacts (Burt 1984; Carrasco et al. 2013; Bailey and Marsden 1999; Kowald et al. 2010; Sadri et al. 2015a). The original questionnaire wording used was: "If you look back over the last six months, who are the four or five people with whom you discussed matters important to you?" (Burt 1984). A researcher can modify this name generator question to best match the specific line of research (Borgatti and Halgin 2012). In this study, we used: "The following questions are about people with whom you have interacted closely during the time of tornado evacuation and/or recovery. Please name up to 5 people who were most helpful to you. Write down their first name or initials." This approach has some limitations such as biases that occur in recall and people's propensity to forget their close contacts among others (Marin 2004; Brewer 2000; Marin and Hampton 2007; Carrasco et al. 2013).

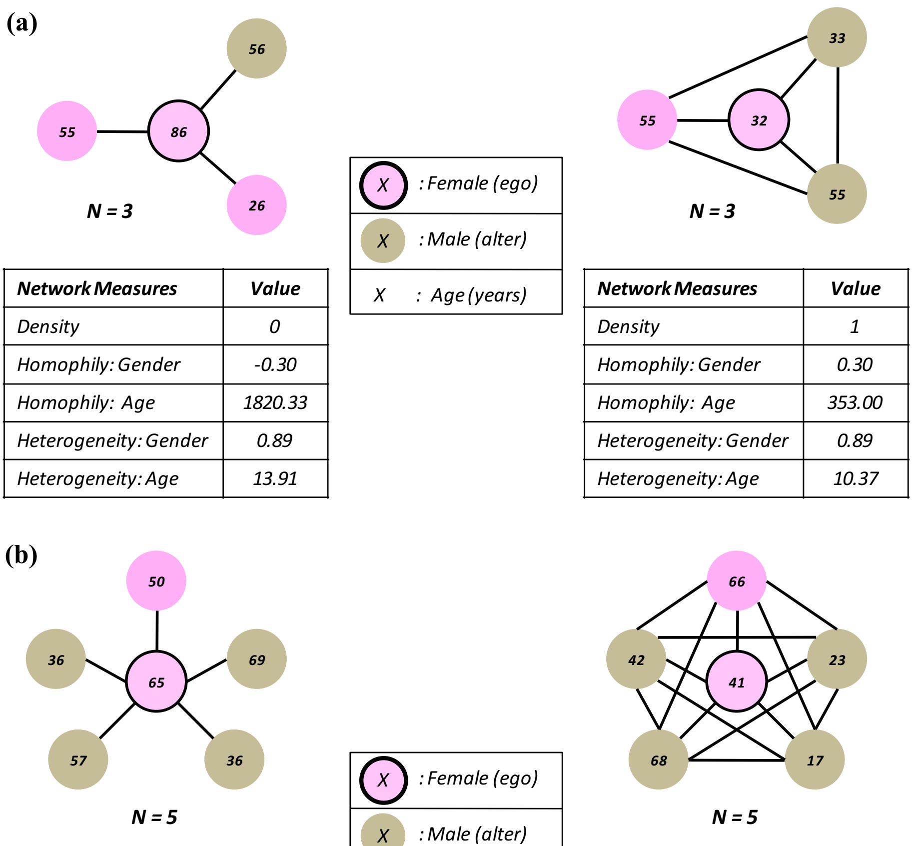
The personal network density was based on the social ties that exist between each pair of alters. This refers to the extent to which ego's alters are connected with each other. In this study, our objective is to explore how personal network density helps to foster the overall recovery experience. Ego network density was measured by considering the proportion of existing ties out of all possible connections among alters. Respondents were asked to answer the following question: "Please think about the relations between the people you just mentioned. Person 1 and Person 2 are: (a) Strangers (b) Acquaintances (c) Especially close." At the dyadic (ego–alter) level, information was gathered about ego–alter ties such as contact duration, frequency of contact, and physical proximity, which refer to the relationships and nature of tie strength between the focal person (ego) and their close contacts (alters). Two measures of dyadic relations were considered. The first one is the duration of ties was measured with the following item: "How long have you known each person (in years)?" In addition, geographic distance between ego and alters was obtained by asking, "How far do you live away from each person (in miles)?" These two measures were averaged across all alters listed by the respondents in order to account for the variations in network size, i.e., the number of alters. These averages were treated as proxy variables to correspond to the above three ego–alter tie attributes in the final model specification.

In this study, the attributes of egos and alters considered included two demographic characteristics: gender and age. By using E-Net, an egocentric network analysis program (Borgatti 2009), the homophily and heterogeneity measures were obtained. Homophily or the similarity between ego and alters was based on Krackhardt and Stern's E-I index measuring ego's inclination toward connecting with alters in the same group or class (Krackhardt and Stern 1988). An E-I score of -1 refers to complete homophily or similarity and + 1 refers to the extreme opposite or complete heterophily (Borgatti and Halgin 2012). The diversity of ego's network can be explained by the heterogeneity measures ranging from 0 to 1, where a higher value indicates more diversity. While the concept of homophily explains how similarity can facilitate the formation of ties among them (Lozares et al. 2013; McPherson et al. 2001; DeJordy and Halgin 2008), heterogeneity of alters in one's personal network can help to enhance ego's social activities and access to resources and information (Monge and Contractor 2003; Bastani 2007; Ibarra 1993). However, homophily and heterogeneity measures were less relevant in the analysis of household-level recovery time since these measures depend on ego (respondent) specific demographics.

Figure 4 explains how ego network characteristics can differ for a given network size, i.e., number of alters. Two example networks from the data are provided for clarification: (a) network size = 3 and (b) network size = 5. However, the data suggest that higher network density is negatively associated with household-level recovery time (Fig. 9 in "Appendix"). It is also observed that the less the average geographic distance with alters is (or higher proximity), as shown in Fig. 10 in "Appendix," the earlier the recovery. In addition, longer-time relationships on average result in faster recovery (Fig. 11 in "Appendix").

3.4 Recovery assistance from emergency responders

Results showed that households received recovery assistance from friends, neighbors, government and emergency agencies, insurance companies, non-profit organizations, and others. Following a disaster, the differences in the amount and quality of assistance



Network Measures	Value
Density	0
Homophily: Gender	-0.30
Homophily: Age	1820.33
Heterogeneity: Gender	0.89
Heterogeneity: Age	13.91

Network Measures	Value
Density	1
Homophily: Gender	0.30
Homophily: Age	353.00
Heterogeneity: Gender	0.89
Heterogeneity: Age	10.37

Network Measures	Value
Density	0
Homophily: Gender	0.60
Homophily: Age	397.40
Heterogeneity: Gender	0.64
Heterogeneity: Age	12.66

Network Measures	Value
Density	1
Homophily: Gender	0.60
Homophily: Age	451.00
Heterogeneity: Gender	0.64
Heterogeneity: Age	21.12

Fig. 4 Personal networks of different characteristics who provided assistance during recovery. **a** Network size = 3, **b** network size = 5

received immediately or in the long run can have significant consequences in the overall recovery experiences of the people. In this study, we provided the survey respondents a list of emergency responders to measure whether they received any form of assistance if they were going through a recovery process ($N = 294$). For those who received assistance, they also rated the usefulness and promptness of the assistance on a scale from 1 to 5, where 1 indicates not being useful or prompt at all and 5 indicates being very useful or prompt. Family and friends (69.4%) and private insurance companies (75.2%) were the most common sources of assistance. Moreover, people who received assistance from these groups rated their assistance to be highly useful and prompt (Table 1).

In addition, nearly one-half of respondents received assistance from neighbors (45.6%) and church group/religious organizations (46.6%), and the assistance was generally prompt and useful. Interestingly, emergency response and assistance from government authorities and agencies were less common. For example, less than one-third of the respondents going through the recovery stage reported that they received assistance from Federal Emergency Management Agency (FEMA) and American Red Cross (ARC). More importantly, assistance from these entities was less useful and prompts as perceived and rated by the tornado-affected households. Similar findings were observed in the case of National Guard, fire department, local law enforcement, and local health department. Some people reported that they received assistance from additional entities such as the Salvation Army, construction companies, and private contractors, grouped as "Others" in Table 1. It is also evident from the data that the total number of emergency responders does not help to

Table 1 Recovery assistance from emergency responders, usefulness, and promptness

Emergency responders	Recovery assistance received?			Usefulness			Promptness		
	(0: No-1: Yes)			(1: Not useful at all-5: Very useful)			(1: Not prompt at all-5: Very prompt)		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Family and friends	294	0.694	0.462	199	4.633	0.965	191	4.654	0.886
Neighbors	294	0.456	0.499	131	4.053	1.361	127	4.244	1.295
People from the city	294	0.143	0.351	40	2.100	1.582	40	2.125	1.522
American Red Cross	294	0.303	0.460	88	2.943	1.711	86	3.093	1.657
Church group or other religious organization	294	0.466	0.500	135	4.244	1.318	131	4.229	1.274
Charitable organization (non-religious)	294	0.235	0.425	68	3.632	1.647	62	3.484	1.677
National Guard	294	0.156	0.364	45	3.089	1.819	42	3.238	1.778
Fire department	294	0.279	0.449	79	3.797	1.453	79	4.139	1.366
Local law enforcement	294	0.252	0.435	74	3.892	1.439	71	4.042	1.478
Local health department	294	0.139	0.347	42	2.595	1.563	40	2.600	1.566
Federal Emergency Management Agency	294	0.265	0.442	78	2.628	1.699	75	2.613	1.668
Private insurance company	294	0.752	0.433	213	4.282	1.168	206	4.112	1.238
Others	294	0.197	0.399	52	4.231	1.198	51	4.020	1.225

reduce the time of recovery (Fig. 12 in "Appendix"). It is more important that they provide quality and relevant assistance as needed to expedite the process.

3.5 Household-level characteristics affecting recovery time

In addition to the factors influencing the recovery experience of the tornado-affected households already discussed, specific household characteristics may affect the recovery experience as well. For example, the number of people living in the household is crucial. We found larger-sized households and families take more time recover (Fig. 13 in "Appendix"). On the other hand, more time spent in the current home helps household to recover relatively quicker (Fig. 14, in "Appendix"). This might be because of households' increased exposure and familiarity with community that they belong to. Other household factors such as previous tornado experience are also relevant here which we discuss in model estimation results section.

4 Modeling framework

In this study, we used an ordered probit modeling approach to test the combined effects of all the explanatory variables (see Table 2) and explain the relative degrees to which these variables affect the household-level recovery time. Similar to ordinary least squares regression, this is an effective modeling framework to understand recovery experience of different households since a number of factors could contribute to this timing behavior and the dependent variable (household-level recovery time) can be modeled as ordinal data (i.e., recovery time: less than 12 h, 12 h to less than 1 day, 1 day or more, 2 days or more, 1 week or more, 2 weeks or more, 1 month or more, 6 months or more, 12 months or more) as shown in Fig. 3. However, unlike ordinary least squares regression, ordered probit models account for the unequal differences among the ordinal categories in the dependent variable (McKelvey and Zavoina 1975; Greene 1997; Sadri et al. 2013a, b). For example, it does not require that the difference between two consecutive time intervals is the same as the difference between two other consecutive time intervals, provided one unit change in the independent variable. Here, ordered probit models capture the qualitative differences between different consecutive time intervals. Following the work presented in Washington et al. (2011), consider the following function:

$$y* = \beta X + \varepsilon \tag{1}$$

where y^* is the dependent variable coded as 0, 1, 2,…, 8; β is the vector of estimated parameters and X is the vector of explanatory variables; ε is the error term, which is assumed to be normally distributed (zero mean and unit variance) with cumulative distribution denoted by $\Phi(\cdot)$ and density function denoted by $\phi(\cdot)$. Given a specific recovery time, a household falls in category n if $\mu_{n-1} < y < \mu_n$. The recovery time data, y, are related to the underlying latent variable y^*, through thresholds μ_n, where $n = 1\ldots 8$. We have the following probabilities:

$$\mathrm{P}(y = n) = \Phi(\mu_n - \beta X) - \Phi(\mu_{n-1} - \beta X) \tag{2}$$

where $\mu_0 = 0$ and $\mu_8 = +\infty$ and $\mu_1 < \mu_2 < \mu_3 < \ldots < \mu_8$ are defined as eight thresholds between which categorical responses are estimated. The estimation of this model is relatively easy; the derivation of the likelihood is somewhat straightforward [see McKelvey

Table 2 Descriptive statistics and final model specification of the household-level recovery time

Household-level recovery time	Parameter estimates		Descriptive statistics			
	Coeff.	Std. error	Mean	SD	Min	Max
Constant	0.903***	0.253				
Number of physical items damaged/destroyed	0.226***	0.049	3.408	1.701	0.00	8.00
Social capital						
Component 2: government trust	− 0.107**	0.058	0.018	1.260	− 3.27	3.69
Personal networks						
Network density (1 if density is over 0.40, 0 otherwise)	− 0.382***	0.156	0.474	0.501	0.00	1.00
Average geographic distance (1 if 3 miles or over, 0 otherwise)	0.365***	0.157	0.484	0.501	0.00	1.00
Household characteristics						
Previous tornado experience (1 if no previous experience, 0 otherwise)	0.141	0.149	0.554	0.498	0.00	1.00
Household size (1 if 2 or less people in the household, 0 otherwise)	− 0.256*	0.152	0.601	0.491	0.00	1.00
Number of years lived in the household (3 years or less)	0.970***	0.329	0.070	0.256	0.00	1.00
Recovery assistance						
Neighbors (1 if assistance received from neighbors, 0 if not)	− 0.257*	0.154	0.479	0.501	0.00	1.00
Insurance companies (1 if assistance received from insurance companies, 0 if not)	0.614***	0.177	0.714	0.453	0.00	1.00
Thresholds						
μ_1	0.104	0.072	–	–	–	–
μ_2	0.241***	0.104	–	–	–	–
μ_3	0.588***	0.142	–	–	–	–
μ_4	0.847***	0.156	–	–	–	–
μ_5	1.122***	0.166	–	–	–	–
μ_6	2.016***	0.184	–	–	–	–
μ_7	3.028***	0.202	–	–	–	–
Log-likelihood at zero	− 373.662	–	–	–	–	–
Log-likelihood at convergence	− 336.830	–	–	–	–	–
Pseudo R-squared	0.10	–	–	–	–	–
Number of observations	213	–	–	–	–	–

SD standard deviation

***$P < 0.01$, **$P < 0.05$, *$P < 0.10$

and Zavoina (1975) for details]. By using the statistical software STATA, thresholds μ and parameters β were estimated (see Table 2). The thresholds μ show the range of the normal distribution associated with the specific values of the response variable. The remaining parameters, β, represent the effect of changes in the explanatory variables on the underlying scale. The thresholds μ show the range of the normal distribution associated with the specific values of the response variable. The remaining parameters, β', represent the effect of changes in the explanatory variables on the underlying scale. Marginal effect is an appropriate measure to explain the effects of dummy variables (changing from zero to one) and computed as the difference in the estimated probabilities keeping all other variables equal to their means (see Washington et al. 2011). The marginal effects of factors X on the underlying time of recovery can be evaluated in the following way:

$$\partial \, \mathrm{Prob}(y = n) \, / \, \partial X = -[\phi(\mu_n - \beta X) - \phi(\mu_{n-1} - \beta X)] \, \beta' , \qquad n = 1 , \ldots, 8 \qquad (3)$$

The correlations matrix for the explanatory variables present in the final model specification is reported in Table 3.

5 Model estimation results

To determine the best possible estimation of the ordered probit model, several variables were incorporated and tested, and the best model specification results are presented in Table 2. Most of the variables included in the ordered probit model are statistically significant with plausible signs (direction of effect). However, one variable (previous tornado experience) is not significant at the usual 5 or 10% levels of significance. Based on the discussion on criteria for omitting a variable by Ben-Akiva and Lerman (1985), we include this variable in the final model specification. In addition to the consideration of the combined effects of selected variables, we report marginal effects of the corresponding variables to assess the importance of individual parameters (Table 4). In our results, we only report the average marginal effect across all observations as each observation in the data has its own marginal effect. Reporting marginal effects is important in the case of an ordered probit model because the effect of variables X on the intermediate categories is ambiguous if only the parameter estimates are reported (Duncan et al. 1999).

The constant term in the final model specification suggests that households are more likely to take 12 months or more to recover all else being the same. The variable representing the total number of physical items damaged or destroyed by the tornado was found to be highly statistically significant. However, it is necessary to quantify the level of damage for a given household caused by the tornado in a well-defined manner. We found that the more the items are destroyed, the more it is likely that the households will recover relatively late (12 months or more). This is evident from Table 4 where the average marginal effect suggests that for any additional item destroyed or damaged in the household the probability that it will take 12 months or more to recover increases by 0.05. Now, we determine other important factors that would allow households to recover faster. From the principal components we obtained to measure social capital, we found that the level of trust (component 2) is negatively associated with the recovery time meaning that the more trust the households have for the government officials, the less time they require to recover.

Turning to the factors related to personal networks, we found that households having denser personal networks (density over 0.40) are more likely to recover faster (less than 12 h) as compared to recovering later (12 months or more). This is also highly significant and suggests the importance of having denser social networks to seek for assistance following a disastrous experience. In addition, we observed that the recovery experience is better if the average geographic distance of these close contacts from the household is less. To be precise, households having personal networks with an average geographic distance less than 3 miles are more likely recover faster (less than 12 h). The above two personal network characteristics can be related to social cohesion, which influences one's ability to retrieve resources through social ties (Burt 2000; Granovetter 1973; Borgatti and Halgin

Table 3 Correlation matrix of the explanatory variables

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	Component 2: government trust	1.00	–	–	–	–	–	–	–	–
(2)	Network density (1 if density is over 0.40, 0 otherwise)	0.00	1.00	–	–	–	–	–	–	–
(3)	Average geographic distance (1 if 3 miles or over, 0 otherwise)	− 0.02	− 0.29	1.00	–	–	–	–	–	–
(4)	Number of years lived in the household (3 years or less)	− 0.02	− 0.04	0.06	1.00	–	–	–	–	–
(5)	Household size (1 if 2 or less people in the household, 0 otherwise)	0.04	0.09	0.09	− 0.06	1.00	–	–	–	–
(6)	Previous tornado experience (1 if no previous experience, 0 otherwise)	− 0.10	− 0.02	− 0.04	− 0.04	0.00	1.00	–	–	–
(7)	Neighbors (1 if assistance received from neighbors, 0 if not)	0.00	− 0.08	− 0.04	− 0.05	− 0.01	− 0.09	1.00	–	–
(8)	Insurance companies (1 if assistance received from insurance companies, 0 if not)	0.02	0.02	0.04	0.07	− 0.01	− 0.05	− 0.22	1.00	–
(9)	Number of physical items damaged/destroyed	0.00	− 0.10	− 0.10	− 0.12	0.05	0.00	− 0.14	− 0.21	1.00

2011; Borgatti et al. 1998; Wellman 1999; Monge and Contractor 2003; Haythornthwaite 2005; Sadri et al. 2015a).

Households having no previous tornado experience are more likely to recover late (12 months or more) ($\beta = +\,0.141$). This suggests the importance of educating households having no previous experience and making them aware of the possible damages likely to be caused by a tornado. Previous experience is an important contributor in terms of how people perceive risk and behave accordingly (Baker 1991; Hasan et al. 2011; Dixit et al. 2012; Sadri et al. 2013b, 2014, 2015b).

The size of household, as measured by the number of people in the household, is also relevant. The model estimation suggests that households having two or less people are more likely to recover faster (less than 12 h) as opposed to recovering later (12 months or more) which is indicative to more convenience for faster recovery with less people. Household size is an important indicator of how convenient it is for households to react to a situation as a group (Sadri et al. 2014). The number of years lived in the current household also influences the recovery experience. We observed households having spent 3 years or less are more likely to recover late (12 months or more). By spending more time in the

Table 4 Marginal effects of the explanatory variables

Variable description	Marginal effects								
	Less than 12 h	12 h to less than 1 day	1 day or more	2 days or more	1 week or more	2 weeks or more	1 month or more	6 months or more	12 months or more
Number of physical items damaged/destroyed	− 0.020	− 0.003	− 0.004	− 0.012	− 0.010	− 0.010	− 0.016	0.024	0.050
Component 2: government trust	0.009	0.001	0.002	0.006	0.005	0.005	0.007	− 0.011	− 0.024
Network density (1 if density is over 0.40, 0 otherwise)	0.034	0.005	0.007	0.020	0.016	0.017	0.027	− 0.041	− 0.085
Average geographic distance (1 if 3 miles or over, 0 otherwise)	− 0.032	− 0.005	− 0.007	− 0.020	− 0.016	− 0.016	− 0.025	0.039	0.081
Number of years lived in the household (3 years or less)	− 0.085	− 0.013	− 0.018	− 0.052	− 0.041	− 0.042	− 0.067	0.104	0.215
Household size (1 if 2 or less people in the household, 0 otherwise)	0.022	0.003	0.005	0.014	0.011	0.011	0.018	− 0.027	− 0.057
Previous tornado experience (1 if no previous experience, 0 otherwise)	− 0.012	− 0.002	− 0.003	− 0.008	− 0.006	− 0.006	− 0.010	0.015	0.031
Neighbors (1 if assistance received from neighbors, 0 if not)	0.023	0.003	0.005	0.014	0.011	0.011	0.018	− 0.028	− 0.057
Insurance companies (1 if assistance received from insurance companies, 0 if not)	− 0.054	− 0.008	− 0.011	− 0.033	− 0.026	− 0.027	− 0.043	0.066	0.136

local neighborhood, people become more aware and prepared of any uncertainty and cope well in unstable situations. This would also allow them to build stronger connections with their neighbors and more exposure to the community. Number of years spent in the current household is a well-recognized variable in the literature related to emergency preparedness and hurricane evacuation (Sadri et al. 2013a, 2015b).

From the list of emergency responders, we found that households having received assistance from their neighbors are more likely to recover faster (less than 12 h) as compared to those who did not. Average marginal affect suggests that the probability to recover in less than 12 h is increased by 0.023 if assistance is received from neighbors. In contrast, if recovery assistance is received from private insurance companies, the overall recovery experience is slow. The above findings provide some logical inferences related to households' recovery experience after a given disaster. The proposed model would allow one to better understand and predict different fractions of households who are likely to either recover very fast or take a significant amount of time to return to their initial stable condition.

6 Key findings and conclusions

The analytic procedure of this study reveals that the level and types of physical infrastructure damage from tornadoes and various types of assistance households received influence recovery time. Yet, it is also shown that households' background characteristics as well as their social connections and broader community engagement can partly explain their recovery processes. Overall, the study directs our attention to the importance of social infrastructure systems and networks in understanding how households recover from disaster. Household, neighborhood, and community-based factors need to be fully considered in the rebuilding processes and, ultimately, in the steps toward enhancing resilience from disasters. To summarize, this interdisciplinary effort provides with the following key insights:

(a) Delayed recovery experience:

- The more the physical items destroyed, the longer the recovery experience
- Slower recovery experience if assistance received from private insurance companies
- Larger size of households can delay the recovery effort

(b) Faster recovery experience:

- Households recover early if having higher level of trust to the government
- Households with denser personal networks experience quicker recovery
- Households with higher geographic proximity of network partners experience early recovery
- Households with assistance from neighbors experience faster recovery
- Faster recovery experience if having previous disaster experience
- Less time is required if longer time is spent in current home

Based on the empirical evidences as obtained in this study, the following recommendations can be offered. These recommendations emphasize the necessary attention to social infrastructure factors that are largely self-organized by community residents, yet could be improved by policies that provide avenues for the social ties and relationships to be strengthened:

- Community resilience requires an understanding of both physical and social factors. A general policy recommendation is that both social and physical factors need to be considered as communities prepare for disasters.
- It is important to consider physical infrastructure—the power grid or roads—of course, but it is also critically important to understand people and encourage strong neighborhood and community ties that will be instrumental in helping people recover after a disaster.
- The density of people's networks is especially important. Network density measures the extent to which people in one's social network are connected with each other (and is not necessarily associated with density in physical space). A dense personal network indicates close interpersonal contacts among alters and can potentially facilitate information and resource sharing among them. It is not just a matter of knowing lots of different people. It is critical for recovery that the people you know are connected to one another.
- Further, if people you know are in close physical proximity (e.g., next door or within your neighborhood) it is more likely they can help with the recovery process.
- We encourage community leaders and policymakers to consider the importance of social, neighborhood, and community factors as they prepare for disasters.
- We recommend engaging senior citizen groups and civic groups in disaster planning scenarios.
- We recommend neighborhood events that build or strengthen social ties as well as planning for specific disaster scenarios.

Policymakers interested in confronting the immediate threat of climate change are far too prone to prioritize improvements and innovations to physical infrastructure ahead of improving the social infrastructure in communities. Communities with stronger social relationships are likely to overcome sudden shocks and tremendous hardships together. Community planners should seek to strengthen social networks in communities that are most vulnerable to natural or man-made disasters. Researchers have already started to identify areas most vulnerable (Cutter et al. 2003), but more research must be undertaken to pin point which neighborhoods need immediate investments into their social infrastructure, so they can weather future storms. Future studies should collect more comprehensive data to check whether the findings of this study can be generalized to other forms of disaster (hurricanes, floods, earthquakes, among others) and identify possible variations across multiple communities.

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Appendix

See Figs. 5, 6, 7, 8, 9, 10, 11, 12, 13, 14 and Tables 5, 6, 7, 8, 9.

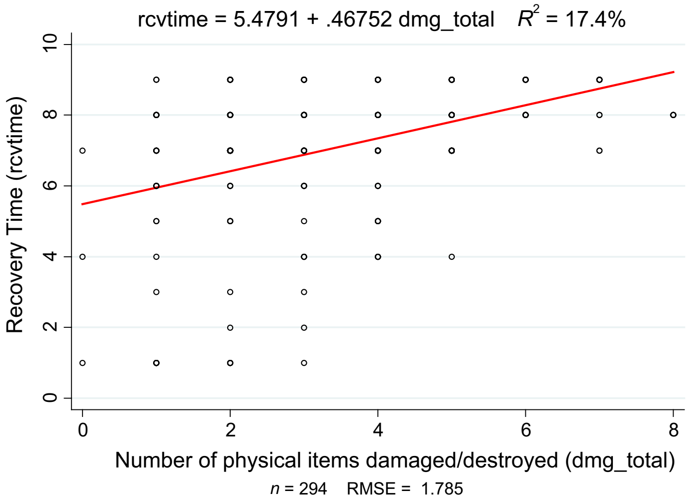

Fig. 5 Recovery time as a function of total number of physical items damaged or destroyed

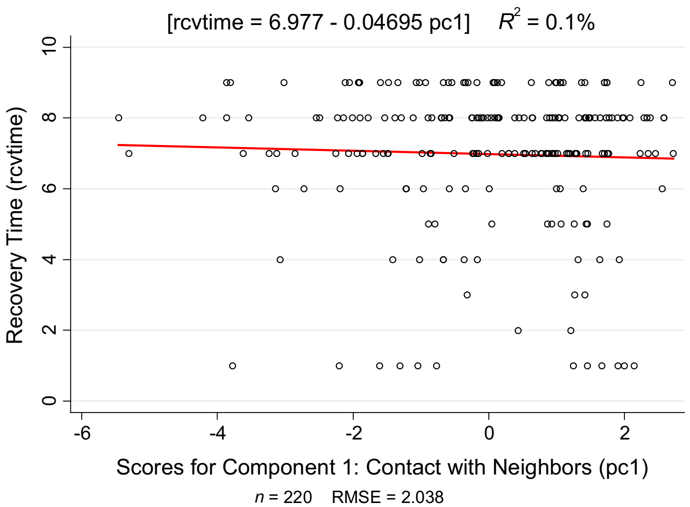

Fig. 6 Recovery time as a function of component 1 (contact with neighbors)

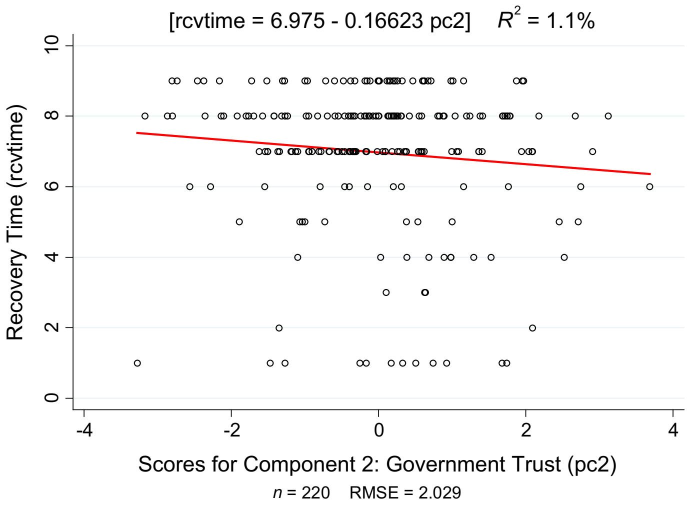

Fig. 7 Recovery time as a function of component 2 (government trust)

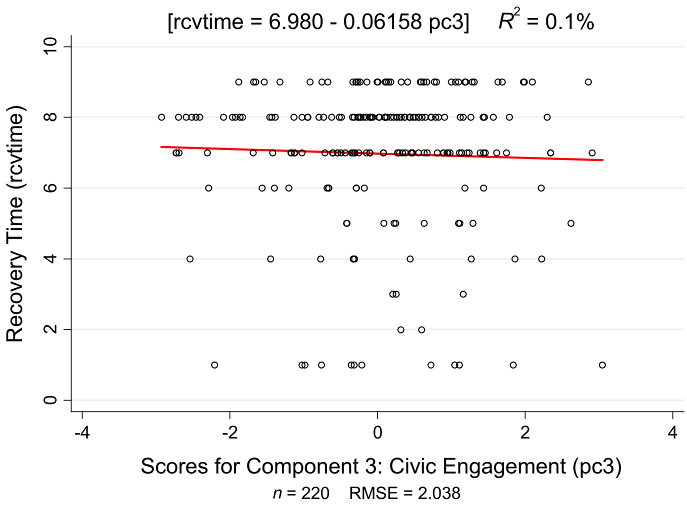

Fig. 8 Recovery time as a function of component 3 (civic engagement)

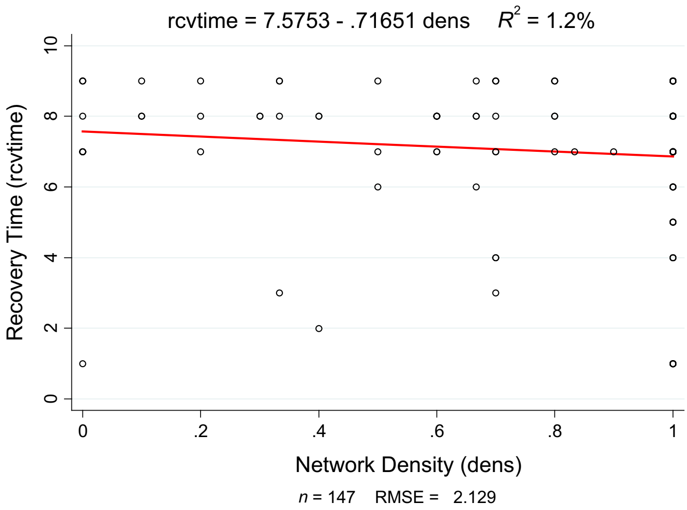

Fig. 9 Recovery time as a function of network density

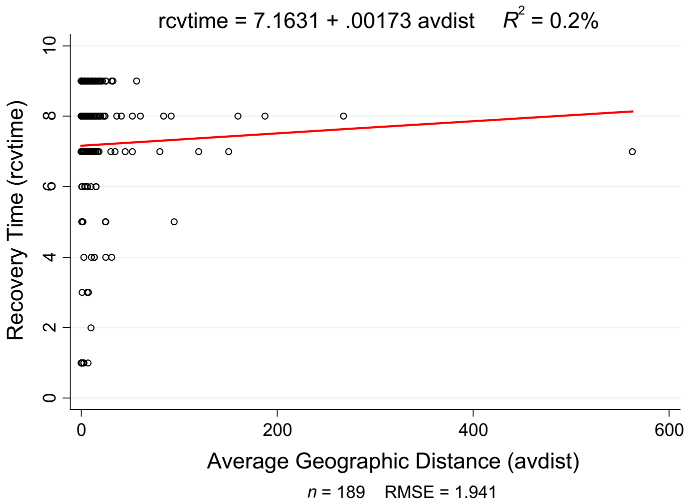

Fig. 10 Recovery time as a function of geographic distance in miles

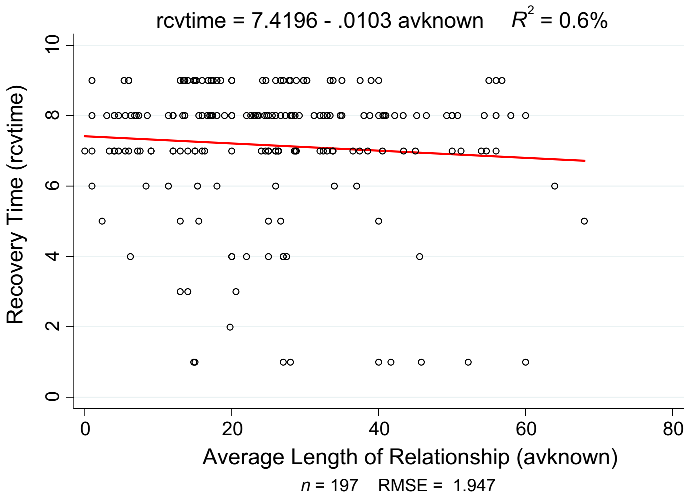

Fig. 11 Recovery time as a function of length of relationship in years

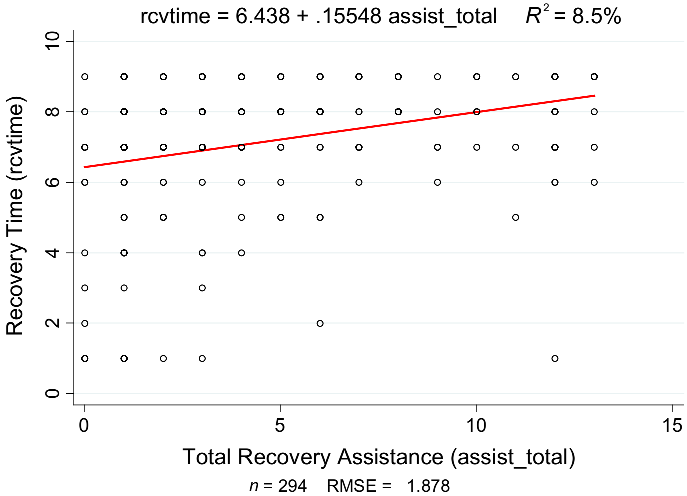

Fig. 12 Recovery time as a function of total assistance received

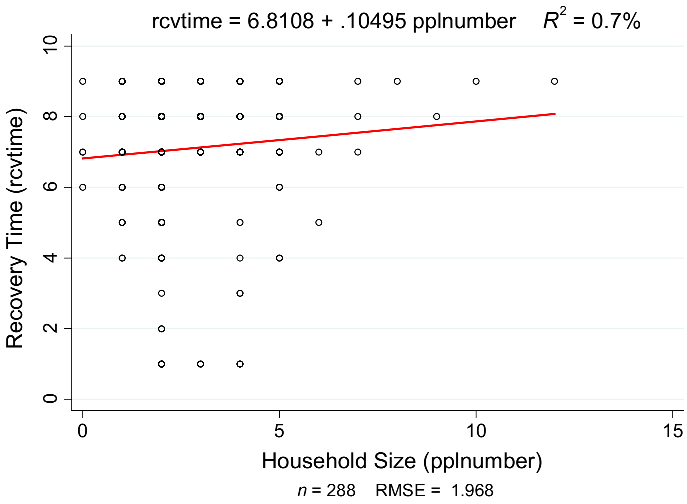

Fig. 13 Recovery time as a function of household size

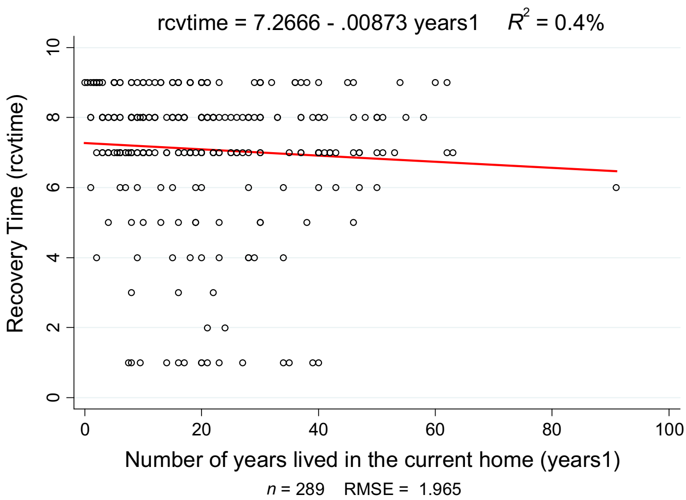

Fig. 14 Recovery time as a function of time spent in the current home

Table 5 Physical infrastructure items damaged or destroyed by tornado as experienced by different households

	Physical item damaged? (0: No-1: Yes)				
	N	Mean	Std. Dev.	Min	Max
House	294	0.810	0.393	0	1
Vehicle	294	0.527	0.500	0	1
Land telephone lines	294	0.510	0.501	0	1
Electric transmission lines	294	0.609	0.489	0	1
Gas lines	294	0.071	0.258	0	1
Water lines	294	0.146	0.354	0	1
Internet	294	0.503	0.501	0	1
Others	294	0.316	0.466	0	1

Table 6 Items used to measure social capital

Label	List of variables	N	Mean	Std. Dev.	Min	Max
SC_1	My neighbors will not take advantage of me	360	4.219	1.081	1	5
SC_2	I trust my neighbors	364	3.986	1.132	1	5
SC_3	I trust my local government officials	364	2.810	0.990	1	5
SC_4	I have influence over making my place a better place to live	359	3.719	1.114	1	5
SC_5	If something came up and I needed to go out, I could ask a neighbor for help in watching kids, etc.	343	3.720	1.341	1	5
SC_6	Most people can be trusted	366	3.443	0.960	1	5
SC_7	My community feels like home	366	3.929	1.098	1	5
SC_8	These days people need to worry about others and not overly look after themselves	364	3.500	1.230	1	5
SC_9	Personally assisting people in trouble is very important to me	367	4.128	0.904	1	5
SC_10	How often do you go to your neighbors' homes or have them to yours? None (37.23%), 1–2 times a month (41.03%), 3–4 times a month (10.05%), 5 + times a month (11.68%)	368	1.962	0.970	1	4
SC_11	How often do you donate blood? None (79.29%), 1–2 times a month (17.17%), 3–6 times a month (2.72%), 7 + times a month (0.82%)	367	1.251	0.541	1	4
SC_12	How often have members of your community come together to solve local problems? None (60.06%), 1–2 times a month (35.85%), 3–4 times a month (2.83%), 5 + times a month (1.26%)	318	1.453	0.617	1	4
SC_13	Did you vote in the most recent election? Yes (85.29%), No (14.71%)	374	1.147	0.355	1	2
SC_14	How often have you contacted elected representatives about issues of concern to you? None (60.43%), 1–2 times a month (31.82%), 3-4 times a month (5.08%), 5 + times a month (2.67%)	374	1.500	0.717	1	4
SC_15	How much of the time do you think you can trust the government in Washington to do what is right? Just above always (0.54%), Most of the time (14.13%), Only some of the time (57.88%), Never (27.45%)	368	3.122	0.651	1	4

SC_1-SC_9 scale: (1) strongly disagree, (2) disagree, (3) neutral, (4) agree, (5) strongly agree

Table 7 Principal components (oblique rotation) ($N = 279$)

Label	List of variables	Component 1	Component 2	Component 3	% Unexplained
SC_1	My neighbors will not take advantage of me	**0.406**	− 0.039	− 0.021	60.02
SC_2	I trust my neighbors	**0.511**	− 0.099	− 0.103	39.71
SC_3	I trust my local government officials	− 0.005	**0.625**	− 0.071	41.53
SC_5	If something came up and I needed to go out, I could ask a neighbor for help in watching kids, etc.	**0.506**	0.033	− 0.073	35.56
SC_7	My community feels like home	**0.407**	0.211	− 0.015	43.27
SC_8	These days people need to worry about others and not overly look after themselves	0.104	0.104	**0.391**	68.50
SC_10	How often do you go to your neighbors' homes or have them to yours?	**0.367**	− 0.190	0.158	60.27
SC_12	How often have members of your community come together to solve local problems?	0.028	0.236	**0.335**	71.06
SC_13	Did you vote in the most recent election?	− 0.043	0.015	**0.543**	60.59
SC_14	How often have you contacted elected representatives about issues of concern to you?	− 0.100	− 0.174	**0.637**	45.06
SC_15	How much of the time do you think you can trust the government in Washington to do what is right?	− 0.040	**0.655**	− 0.055	37.24

Table 8 Scoring coefficients (oblique rotation) ($N = 279$)

	Component 1		Component 2		Component 3		KMO
Label	Unrotated	Rotated (oblique)	Unrotated	Rotated (oblique)	Unrotated	Rotated (oblique)	
SC_1	0.363	0.403	− 0.133	− 0.026	− 0.123	0.009	0.85
SC_2	0.421	0.499	− 0.188	− 0.090	− 0.241	− 0.070	0.76
SC_3	0.201	0.012	0.575	0.618	0.126	− 0.015	0.62
SC_5	0.471	0.501	− 0.080	0.044	− 0.171	− 0.028	0.73
SC_7	0.454	0.413	0.086	0.224	− 0.042	0.037	0.75
SC_8	0.222	0.140	− 0.056	0.142	0.370	0.409	0.77
SC_10	0.313	0.373	− 0.311	− 0.162	0.006	0.172	0.68
SC_12	0.186	0.064	0.098	0.267	0.376	0.359	0.62
SC_13	0.087	0.002	− 0.143	0.062	0.516	0.540	0.47
SC_14	− 0.013	− 0.054	− 0.324	− 0.121	0.558	0.613	0.45
SC_15	0.182	− 0.021	0.606	0.649	0.158	0.000	0.61

Table 9 Correlation matrix ($N = 279$)

	SC_1	SC_2	SC_3	SC_5	SC_7	SC_8	SC_10	SC_12	SC_13	SC_14	SC_15
SC_1	1.00	–	–	–	–	–	–	–	–	–	–
SC_2	0.37	1.00	–	–	–	–	–	–	–	–	–
SC_3	0.07	0.08	1.00	–	–	–	–	–	–	–	–
SC_5	0.33	0.48	0.17	1.00	–	–	–	–	–	–	–
SC_7	0.33	0.47	0.24	0.51	1.00	–	–	–	–	–	–
SC_8	0.17	0.14	0.06	0.13	0.17	1.00	–	–	–	–	–
SC_10	0.22	0.27	0.00	0.42	0.17	0.14	1.00	–	–	–	–
SC_12	0.10	0.03	0.05	0.10	0.20	0.18	0.14	1.00	–	–	–
SC_13	0.03	− 0.01	0.10	0.09	0.07	0.13	0.07	0.01	1.00	–	–
SC_14	− 0.03	0.00	− 0.09	− 0.09	− 0.02	0.07	0.05	0.10	0.21	1.00	
SC_15	0.07	0.03	0.36	0.12	0.19	0.09	0.01	0.17	− 0.02	− 0.07	1.00

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