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Uneven Growth in Social Capital Organizations After Disasters by Pre-Disaster Conditions in the United States 2000–2014

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Abstract

Introduction: Community-level social capital organizations are critical pre-existing resources that can be leveraged in a disaster.

Aim: The study aimed to test the hypothesis that communities with larger pre-disaster stocks of social capital organizations would maintain pre-disaster levels or experience growth.

Methodology: An annual panel dataset of counties in the contiguous United States from 2000 to 2014 totaling 46620 county-years, including longitudinal data on disasters and social capital institutions was used to evaluate the effect of disaster on growth of social capital.

Results: When a county experienced more months of disasters, social capital organizations increased a year later. These findings varied based on the baseline level of social capital organizations. For counties experiencing minor disaster impacts, growth in social capital organizations tends to occur in counties with more social capital organizations in 2000; this effect is a countervailing finding to that of major disasters, and effect sizes are larger.

Conclusion: Given the growing frequency of smaller-scale disasters and the considerable number of communities that experienced these disasters, the findings suggest that small scale events create the most common and potentially broadest impact opportunity for intervention to lessen disparities in organizational growth.

Keywords

disaster planning; capacity building; natural disasters; social capital; disaster resilience

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Authors contribution. YM: conceptualization, data acquisition, interpretation of results, led drafting and revision of manuscript; LC: conceptualization, interpretation of results, drafting and revision of manuscript; KS: conceptualization, data acquisition, data analysis, interpretation of results, drafting and revision of manuscript; JH: conceptualization, coding of social capital organizations, interpretation of results, revision of manuscript; and GL: data acquisition, interpretation of results, revision of manuscript.

Introduction

Climate change is increasing temperatures, leading to more intense storms and weather-related disasters of all types.^{1,2} Simultaneously, the growing investments in assets and property in highly vulnerable areas has put more infrastructure, institutions, and households at risk.^{3,4} Over the past 15 years (2006 - 2020), 15 or more billion-dollar weather-related disaster events have impacted the US each year; with 173 unique events costing greater than \$1 billion, totaling \$1,036 trillion in damages.⁵ While research and media attention focus on the impacts of these large-scale disasters, smaller-scale weather-related emergencies and disasters also affect a growing number of individuals across the US.^{6,7} The impacts of weather-related disasters are not distributed equitably, with increased risk for harm among vulnerable populations, including rural communities, racial minorities, and those with higher levels of poverty.⁸⁻¹⁰

Given the inevitable increased frequency of natural hazards, a primary goal of disaster preparedness is to mitigate the immense public health impact of climate-related natural disasters.^{11,12} Disaster-impacted populations have increased incidence of poor health outcomes and indicators, including mortality,¹³⁻¹⁵ myocardial infarction,¹⁶⁻²¹ and use of medical care.^{22,23} Many disasters require those exposed to relocate temporarily or permanently, impacting health through increased stress, interruptions to usual care, or financial strain.²⁴ Post-disaster, long-term displacement causes increased incidence of depression, anxiety, and post-traumatic stress disorder.²⁵⁻²⁷ Displacement has also been linked with exacerbations of chronic illness and challenges with medication management.^{28,29}

A critical component of disaster recovery and resilience is social capital, defined as ‘the norms and networks that facilitate collective action,’ or the ‘resources embedded in social networks and social structure that can be mobilized by actors.’³⁰ Social capital is viewed as essential for responding to the new and unexpected problems that arise in disasters and is distinct from other types of capital that communities maintain.³⁰⁻³² Social capital is less affected than physical and human capital in a disaster as it is not a physical asset that can be physically damaged in a hazard event. Consequently, social capital is a critical pre-existing resource that can be leveraged in a disaster to respond to the novel problems that arise rather than setting up new systems, structures, and norms solely for emergency response purposes.³⁰ Establishing a mechanism where communities can foster collective responsibility, identify community capacities, and become involved in planning, works to increase social capital.^{30,33,34}

Social capital has been examined across disaster phases including preparedness,³⁵ response,³⁶ and recovery.^{37,38} It is challenging to administer questionnaires post-disaster; so many studies have relied on proxy indicators. Furthermore, pre-event data is rare in a disaster setting as it is costly and time-intensive to collect data nationally or for areas that are likely to have a disaster within the study period.³⁹ To examine social capital across communities, most disaster research has relied on administrative data for indicators that are widely available across the US, which limit the ability to capture emergent features of communities that may arise in response to a disaster event. In the US disaster research

literature, no national analyses that considered pre-event community features, most notably preexisting stocks of social capital, have been conducted. Pre-existing stocks of social capital shape not only disaster response and recovery but also facilitate organizational emergence in social capital after disasters. These emergent social capital organizations are integral as they can increase community preparedness for future disasters, an important consideration given the rising frequency of disasters.³³ However, no national-level research has considered how social capital before a disaster shapes growth in social capital after disasters, and, more closely, if and how uneven rates of growth may widen disparities in community preparedness for disasters.

This analysis addresses these current gaps in the literature. This study aimed to describe trends in disasters and social capital institutions in the US from 2000 to 2014, and to evaluate the change in social capital institutions in communities resulting from disaster events. The study tested the hypothesis that communities with larger pre-disaster stocks of social capital would maintain pre-disaster levels or experience growth, and that, by extension, communities with smaller pre-disaster stocks of social capital would have lower rates of growth or decreases, which would widen disparities in community preparedness for disasters. Further, the study evaluated whether the association between disaster and social capital was modified by the scope of disaster impact.

Methods

Data

Linked data from 3 primary sources created an annual panel dataset of counties in the contiguous United States from 2000 to 2014 totaling 46620 county-years, including longitudinal data on disasters and social capital institutions. First, the National Establishment Time Series (NETS) data available through the Retail Environment and Cardio-Vascular Disease study was used to measure social capital institutions.⁴⁰ Second, the aggregated version of the Spatial Hazards and Events Losses Database for the United States (SHELDUSTM) version 19 (Center for Emergency Management and Homeland Security, Arizona State University, Arizona, USA) was used to measure disaster impacts.⁴¹ Third, community-level social and demographic characteristics was calculated using data from the Longitudinal Tract Database from Brown University,^{42,43} and from the National Historical Geographic Information Systems.⁴⁴

Measures

Social capital—Social capital organizations were measured using NETS data, which provide an annual national census of business establishments with at least 1 employee, including several types of social capital organizations.⁴⁵ Social institutions provide opportunities for individuals in a community to interact with others to build the trust and relationships necessary for taking collective action.^{46–49} According to the Neighborhood Resources Model,^{50,51} community institutions or organizations are defined as those community resources that stimulate learning and the social environment that ensures the healthy development of children and opportunities for adults. Community social organizations provide a variety of financial, political, human, and social resources to

communities.⁵² Adapting methods from prior social capital research,^{6,53} the following social capital organizations were identified using Standard Industrial Classification (SIC) codes: bowling centers; business associations; civic, social, and fraternal associations; labor unions and similar labor organizations; membership sports and recreation clubs; physical fitness facilities; political organizations; professional membership organizations; public golf courses; religious organizations; and membership organizations not elsewhere classified (See appendix for SIC codes used to identify these social capital resources). The total number of social capital organizations per county per year was calculated.

Disaster impact—Disaster impact was measured using 2000 to 2014 data from SHELATUS™ (Center for Emergency Management and Homeland Security, Arizona State University, Arizona, USA), a national database of 18 different hazard types at county level resolution for all 50 states. SHELATUS™ (Center for Emergency Management and Homeland Security, Arizona State University, Arizona, USA) consolidates multiple disaster databases, including data from the National Climatic Data Center, US Geological Survey, and others. For every event with any measured loss, SHELATUS™ provides: location (county), time (begin and end date), inflation-adjusted direct losses (property and crop damage, fatalities, injuries, etc.), and type of hazard (peril).^{54,55} SHELATUS™ (Center for Emergency Management and Homeland Security, Arizona State University, Arizona, USA) is a leading data set relating to disasters and is used across dozens of studies.^{8,56} A typology measured the scale of disaster impacts per month per county using an all-hazards approach to measuring impact. While there is no existing consensus in the disaster literature on a typology/ metric that classifies disaster events by scale of impact, the study created a 3-level typology: major, moderate, and minor impact. While the smaller scale events are less extreme, they occur much more frequently and their impact on health is important to capture.⁸ For each county from 2000 to 2014, a major disaster month was classified as greater than \$50 property damage per capita and/ or 3 or more fatalities, a moderate disaster month as between \$10 and \$50 of property damage per capita and/ or 2 fatalities, and a minor disaster month occurs as fewer than \$10 property damage per capita and/or has 1 fatality from disasters. These levels were contrasted with months in which there were no damages or fatalities from disasters. In cases where multiple hazard types occurred in the same month, all property damages per capita (in 2015 USD) and all fatalities were summed together. The typology variable was created by totaling up the number of months in a year for each category for each county.

Covariates—Covariate data was assessed using data from the Longitudinal Tract Database (Brown University, Providence, Rhode Island, USA), including decennial census data from 2000 and 2010 and 5-year pooled estimates from the 2006 - 2010 American Community Survey, and data from the National Historical Geographic Information Systems, including 2012 - 2016 American Community Survey 5-year pooled estimates. Longitudinal Tract Database (Brown University, Providence, Rhode Island, USA) data are produced at the census tract-level and were aggregated to the county-level. A strength of using the Longitudinal Tract Database (Brown University, Providence, Rhode Island, USA), in conjunction with the NHGIS, was the ability to standardize county boundaries across the time-frame; standardized county boundaries reduced measurement error related to county

boundary changes during the period. To produce annual estimates, the Longitudinal Tract Database (Brown University, Providence, Rhode Island, USA) and National Historical Geographic Information Systems data sets were interpolated; American Community Survey data was assigned to the mid-point year (e.g., 2006 - 2010 to 2008 and 2012 - 2016 to 2014) for the interpolation.

Using these data for each county, the annual community-level social and demographic characteristics were obtained: (1) racial composition, measured as the proportion of white residents, (2) owner-occupied homes, measured as the proportion of owner-occupied housing units (compared to renters), and (3) proportion of college educated, measured as the proportion of residents aged 25 or older who have completed a bachelor's degree. Additionally, the total population of the county was used to adjust the count of social capital organizations, given that counties vary widely in their population.

Analytical strategy—The median, maximum, minimum, and interquartile range of county-months of disaster by level (minor, moderate, major) during the study period 2000 - 2014 were computed to account for the skewed distribution in the analytic sample. Additionally, the counties with the highest county-months of disaster during the study period were identified.

Econometric fixed effects regression models were used to assess growth of social capital organizations across time.⁵⁷ Econometric fixed effects regression was well-suited to this study given the panel structure of the data. As these models measure within-unit change across time, we estimated increases or decreases in the level of social capital organizations in a county from one year to the next, eliminating both unmeasured and measured time-invariant confounders. This sum of social capital organizations for a given county-year was the dependent variable in the study.

To evaluate the effect of disaster on growth of social capital, the model focused on new disaster impacts that occurred each year and lagged the disaster typology variables by 1 year (e.g., assigning 2001 values for the typology to the 2000 case for that county).⁵⁸ The lagged variable accounted for temporal ordering so that social capital organizational growth is predicted 1 year later after disasters. Time-varying covariates were added to control for confounding (racial composition, home ownership, education, and population size). All covariates and the count of social capital organizations were logged prior to inclusion in the model because these variables were skewed to the right. Dummy variables for the year (with 2000 as the reference category) were included to control for overall changes across the time period.⁵⁷ Finally, the core hypothesis of the study was tested by adding an interaction term for the time-invariant social capital organizations in 2000 by each of the 3 time-varying disaster typology variables. The effect estimate for this interaction term assessed the annual change in social capital organizations since 2000 associated with each type of disaster. To illustrate the interaction effect, predicted probabilities based on the 5th, 50th, and 95th percentiles of social capital organizations in 2000 and by the 5th, 50th, and 95th percentile of each disaster impact variable were graphed.

This study was classified as non-human subjects research by the Institutional Review Board of Drexel University.

Results

A total of 2 findings stand out from the descriptive analysis of disaster impacts typology: (1) disaster impacts are common across counties in the United States, and (2) the range of impacts varies between counties (see Table 1). Only 10 counties (out of 3108 counties, or 0.3%) did not have a single month of disaster impact from 2000 to 2014. The median county experienced 27 months of minor disaster impacts out of the 180 months from 2000 to 2014 (15% of all months), 2 months of moderate impact, and 1 month of major disaster impact. However, these disaster impacts vary widely across counties. A county that experienced a relatively small number of minor disasters at the 25th percentile during the study period had 14 months of minor disasters, while a county at the 75th percentile had 3 times as many impacts (43 months). The variability is greater for major and moderate disasters: while 190 counties (5.7%) had no major or moderate disaster months, 134 counties (4%) had at least 6 months of major impact, and 352 (11%) had at least 6 months of moderate impact. Table 2 shows the counties with the highest number of months across each category in the disaster impact typology. Cook County, Illinois, had by far, the highest number of major months (34). Moderate impacts were highest especially in midwestern counties most notably in rural Iowa. Minor impacts were highest in Erie County, New York, and San Bernardino County, California, where 127 months (70.1% of all months) had minor disaster impacts.

In 2000, a county at the 75th percentile of social capital organizations (34 organizations per 10000 residents) had 54% more organizations than a county at the 25th percentile (22 organizations per 10000 residents), adjusting for population. The growth of social capital organizations over time varied significantly (see Figure 1). Nationally, the number of organizations grew by 81.7% from approximately 600000 organizations in 2000 to 1.1 million in 2014, far exceeding the 12.8% increase in population during the same period. While 225 counties (7.2%) had decreases in organizations or no growth, the median county had 10 more organizations per 10000 residents in 2014 compared to 2000, and 451 counties (14.5%) had 20 or more additional organizations per 10000 residents.

Disaster typology predicted social capital growth, but the results varied by the typology category (Table 3, Model 1). After a year in which a county experienced more months of major disasters or minor disasters, social capital organizations increased the following year. The opposite association for moderate months of disaster was observed. These findings controlled for increases in population, as well as white and college-educated residents, each of which are associated with social capital organizational growth. Results also controlled for dummy variables for years so observed increases were net of a national trend of increased social capital organizations during this period.

The effect of disaster on social capital growth depends on baseline level of social capital organizations (Table 3, Model 2). For major disaster impacts, all counties experienced social capital formation after a year with a major month of disasters. This growth, however, was greatest in counties with low levels of social capital organizations in 2000. For moderate

disaster impacts, the interaction effect with social capital organizations in 2000 was not statistically significant. For minor disaster impacts, a statistically significant and positive interaction effect showed that social capital organizations formation after minor disasters was more likely in counties with more social capital organizations in 2000.

Figure 2 illustrates the differences in social capital formation by baseline level of social capital for each disaster type. The greatest differences in social capital formation were seen for minor disaster impacts. Growth in social capital organizations occurred in counties with more minor disaster months only when the county had a robust baseline level of social capital organizations; in fact, the effect was reversed in counties with less social capital organizations in 2000.

Limitations

This study focused on social institutions to assess social capital. While this included identification of membership organizations, neither the strength of individual-level participation in these membership organizations nor organizational size were considered. Despite this limitation, associational memberships have become the preferred indicator for examining social capital as they are believed to create the ‘generalized interpersonal trust’ necessary for building relationships and cooperation necessary for collective action.^{46,59} This may be especially critical in a disaster context as the impacts of the disaster may result in changes to who is active within the group during the response and recovery periods. In addition, different types of associational memberships may uniquely impact social capital.⁵⁹ Future research could consider combining social capital impacts at the community level and individual level as a multilevel concept, as there are co-benefits.⁶⁰ Additionally, the measure of social capital used in this study combined all types of social institutions, which may obscure differences in specific types of social capital formation. Growth of diverse types of social capital resources may provide insights into mechanisms of community resilience. For example, in Puerto Rico following Hurricane Maria, existing faith-based networks, which had developed in response to earlier climate disasters, provided essential support, including sharing their water purification system and providing expertise in food distribution.⁶¹

While this study focused on the benefits of social capital formation for disaster resilience, it is important to acknowledge possible negative effects of social capital. Social capital may be exclusionary, for example, building strong ties and assistance between members of a group based on similarities within the group based on religion or ethnicity/ race.^{6,31} While the model used in this analysis was adjusted for community level factors, including proportion white population, the study did not explore differences in social capital formation by ethnic/ racial composition. Continued research is needed to understand the heterogeneity in terms of racial and ethnic groups’ ability to access and mobilize resources during disasters, and better understand existing community structure (close knit or diverse) for the future preparedness and resilience planning.

The study combined multiple disaster types within a county resulting in heterogeneity that may reduce relevance of findings for specific disaster types and did not account for the impact of disasters in adjacent counties. However, the county-level all-hazards approach is consistent with CDC and FEMA guidance to state- and local-level emergency

preparedness agencies, enhancing the usefulness of the findings to these organizations.⁶² Rather than attempting to understand and plan for every possible direct or indirect impact of specific weather-related disasters, the goal of the current study is to identify capacities and capabilities that broadly mitigate poor outcomes by ensuring that communities and individuals have resources to address a broad range of emergencies. Future research could conduct hazard-specific analyses.

As a result of inconsistent definitions of disaster and data collection processes, different agencies identify different events and provide different estimates of loss (as a marker of severity). Additionally, disaster impact is difficult to measure due to inflation's impact on the comparability of disaster loss estimates across time and changing census boundaries. To reduce misclassification of exposure in this study, this study used SHELDUS™ (Center for Emergency Management and Homeland Security, Arizona State University, Arizona, USA), which incorporates event data from multiple sources and reports inflation-adjusted losses. Additionally, SHELDUS™ (Center for Emergency Management and Homeland Security, Arizona State University, Arizona, USA) updates record linkages across changing census geographic boundaries, reducing geographic misclassification.⁵⁴ However, the use of property damage as an indicator of loss to determine severity may bias the measure of more severe disasters towards wealthier communities (e.g., urban areas, communities in the northeast). The analysis in this study controlled for community-level socioeconomic status to mitigate this issue, but the issue cannot be eliminated completely. Future research could integrate additional measures into the assessment of severity, including supplementing with data from the National Shelter System to incorporate measures of disaster impact on housing in affected communities.

Discussion

Disasters were common in the US during the period observed in this study (2000 - 2014), especially minor disasters. While major disaster impacts were particularly catalytic for low social capital counties, minor-level disasters were more catalytic for high social capital counties, meaning that low social capital counties saw decreases or slower rates of growth in social capital after minor disasters. These moderating findings support the importance of studying pre-existing levels of social capital.

This current research is consistent with prior research that conceptualized disaster recovery as an opportunity for development and recognized that pre-disaster social capital and leadership in the affected community are the most essential elements for effective collective action and recovery. For example, disaster research has found that pre-event planning for recovery and resilience fosters social capital development prior to a disaster and supports intention for collective action after a disaster.^{63,64} Further, social capital in the form of associational membership was found to be associated with engagement in collective action following a disaster.⁶⁵

These findings provide evidence that the growth of social capital in response to a disaster varied by initial levels of social capital as well as scale of disaster. In contrast, prior case studies conducted in Japan, India, and the US suggested that the level of damage

a community experiences was not as important for recovery as the robustness of the social networks present in the community.³¹ This research highlights that *both* the level of damage and previous social organization matter, and that they matter in combination. Thus, the current research conducted with unique nationwide, longitudinal quantitative data provides new evidence that emphasizes the importance of building social capital to support communities facing smaller disasters especially in communities where social capital is low in the first place.

While elucidating the mechanisms through which social capital works to enhance recovery is outside the scope of the current research, case studies provide evidence that social capital acts as a type of insurance that emerged and formalized through individuals sharing food, offering a place to stay or information, bridging between older organizations to make new ones, and mobilizing for collective action through their social relationships.^{35–39} This prior research highlights the importance of focusing resources on building social capital in communities in addition to the traditional focus of policy makers and funders on physical infrastructure so that when a community is faced with the challenge of responding to and recovering from a disaster, they have the networks and connections necessary to collectively act to rebuild. Based on the findings from this research, for communities with low levels of social capital, slower rates of growth of social capital organizations after minor disasters could put many communities at risk of relocations and/ or lack of preparedness.

CDC-sponsored frameworks for disaster preparedness and resilience planning, the Composite of Post-Event Well-Being (COPEWELL) Framework and the National Health Security Preparedness Index (NHSPI), lack nationally available community level metrics of function for self-evaluation, planning, and monitoring. COPEWELL identifies 17 domains of community functioning aligned with NHSPI and supports the well-being of the population: family, religion, politics, economy, health and medicine, education, scientific research, law and the courts, risk management, communications and media, transportation, food, water, energy, leisure, construction and built environment activities, and land use and environmental protection.^{66,67} The current research supports the relevance of NETS data to define and measure county-level social capital for resilience frameworks such as COPEWELL for researchers and communities engaging in disaster preparedness and resilience planning.

For example, disaster preparedness and resilience planning efforts should include multiple networks and informal connections such as specific community groups, religious organizations, and non-profits, and utilize a variety of networks for the mobilization of resources as well as dissemination of knowledge and information about hazards. These efforts should include workshops and other programs to incorporate community experiences, share information, and experiences of prior events to use as reference for planning for the future.

Conclusions

This research is the first to use national data to assess pre-disaster levels of social capital organizations across time within the US, and to evaluate differences in post-disaster growth

in social capital by level of disaster impact. Given the growing frequency of smaller-scale disasters and the substantial number of communities that experienced these disasters, the findings suggest that small scale events create the most common and potentially broadest impact opportunity for intervention.

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Abbreviations.

NETS	National Establishment Time Series
SHELDUS™	Spatial Hazards and Events Losses Database for the United States

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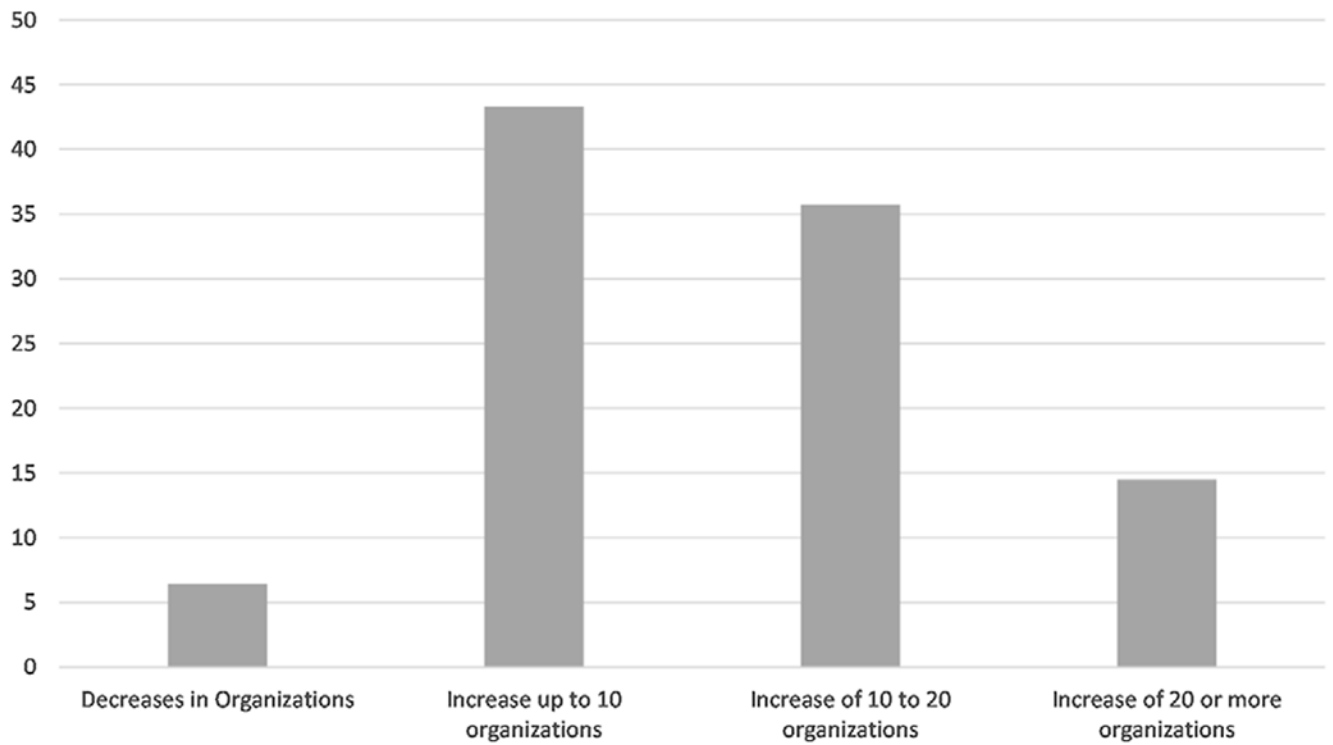


Figure 1.
Percentage of increases in social capital organizations per 10,000 residents from 2000 to 2014 in U.S. counties.

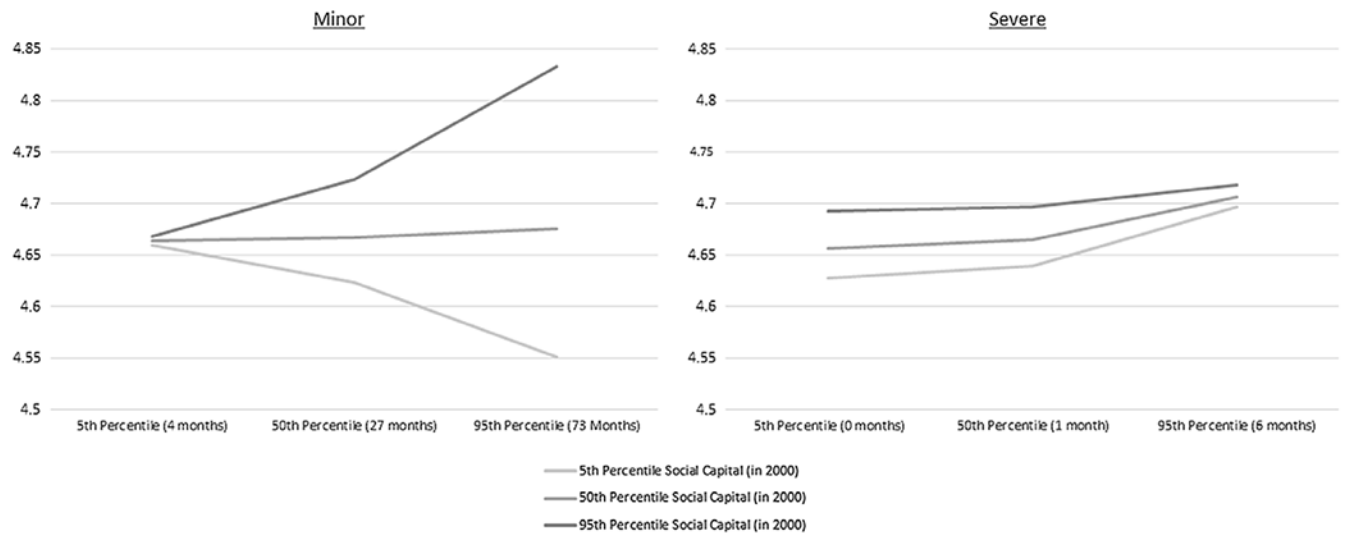


Figure 2.
Predicted probabilities of social capital organization levels by percentiles of disaster impacts and by percentiles of social capital organizations in 2000.

Table 1.

Number of months of minor, moderate, or major disasters in US counties from 2000 to 2014

	Median	Minimum	Maximum	Interquartile Range
Minor Months	27	0	127	14–43
Moderate Months	2	0	26	1–4
Severe Months	1	0	34	0–3

Table 2.

Top 15 counties for disaster impacts by disaster typology

Major Impacts (Months)	Moderate Impacts (Months)	Minor Impacts (Months)
Cook County, Illinois (34)	Wayne County, Iowa (26)	Erie County, New York (127)
Philadelphia County, Pennsylvania (22)	Guthrie County, Iowa (25)	San Bernardino, California (127)
Clark County, Nevada (19)	Emmet County, Iowa (24)	Oswego, New York (125)
Clay County, Nebraska (16)	Taylor County, Iowa (23)	Rutland, Vermont (125)
Issaquena County, Mississippi (15)	Adair County, Iowa (22)	Chautauqua, New York (124)
Jewell County, Kansas (15)	Union County, Iowa (22)	Riverside, California (124)
Shelby County, Tennessee (15)	Adams County, Iowa (21)	Chittenden, Vermont (123)
Adams County, Iowa (14)	Clarke County, Iowa (21)	Erie County, Pennsylvania (121)
Chicot County, Arkansas (13)	Decatur County, Iowa (21)	Addison County, Vermont (119)
Fillmore County, Nebraska (13)	Franklin County, Iowa (21)	Essex County, New York (119)
Gosper County, Nebraska (13)	Franklin County, Louisiana (21)	Kern County, California (119)
Greeley County, Nebraska (13)	Lucas County, Louisiana (21)	Cuyahoga, Ohio (118)
Tensas County, Louisiana (13)	Worth County, Iowa (21)	Crawford, Pennsylvania (117)
Valley County, Nebraska (13)	3 Others ² (20)	Cattaraugus, New York (112)
3 Others ¹ (12)		St. Lawrence, New York (112)

Table 3.

Fixed effects regression of social capital growth by disaster typology

	Model 1	Model 2
Population	1.100 *** (0.013)	1.093 *** (0.013)
Proportion White	−0.149 *** (0.022)	−0.038 (0.022)
Proportion Owner-Occupied Homes	0.008 (0.035)	−0.053 (0.035)
Proportion College-Educated	0.046 *** (0.010)	0.052 *** (0.010)
Hazard Typology: Minor (Months)	0.002 *** (0.000)	−0.004 *** (0.000)
Hazard Typology: Moderate (Months)	−0.007 *** (0.001)	−0.006 ** (0.002)
Hazard Typology: Major (Months)	0.009 *** (0.001)	0.016 *** (0.002)
Social Capital Organizations in 2000 *Hazard Typology: Minor (Months)		0.001 *** (0.000)
Social Capital Organizations in 2000 *Hazard Typology: Moderate (Months)		0.000 (0.000)
Social Capital Organizations in 2000 *Hazard Typology: Major (Months)		−0.002 *** (0.000)
Constant	−6.863 *** (0.135)	−6.774 *** (0.136)
Observations	46620	46620

Standard errors in parentheses

All variables (except hazard typology) are logged. Fixed effects for year dummy variables not shown.

*
 $P < 0.05$,**
 $P < 0.01$,***
 $P < 0.001$