

Disasters, Local Organizations, and Poverty in the United States, 1998 to 2015

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Abstract

Disaster research has drawn attention to how natural hazards transform local organizational dynamics and social inequalities. It has yet to examine how these processes unfold together over time. We begin to fill this gap with a county-level, longitudinal analysis that examines how property damages from natural hazards correlate not only with local shifts in poverty a year later but also counts of for-profit as well as bonding and bridging social capital organizations. Results show that poverty and all organizational types tend to increase with local hazard damages. They also show that poverty tends to increase most where the number of bonding social capital organizations is also increasing. This pattern suggests a Janus-faced dynamic in which bonding, or more inwardly focused, organizations that arise after disaster may end up inadvertently marginalizing those in more dire need.

Key Words: Disasters; Natural Hazards; Social Capital; Poverty; Bonding Social Capital; Bridging Social Capital

Introduction

The severity, frequency, and pervasiveness of natural hazards are drawing increased attention from scholars, policymakers, and the public for good reason: recent human and material costs have been high, and future impacts are forecast to be even higher (Preston 2013). Yet, such events are not new, nor are their sociological investigation. From its earliest days, disaster research has aimed not only to improve emergency response but also to engage fundamental questions about social life, including most prominently how organizations act, shift, and emerge as catastrophe strikes (Quarantelli and Dynes 1977). This paradigm has sought to build a field that deliberately resists methodological individualism by keeping analysis focused squarely on organized behavior, especially the emergence and expansion of *ad hoc* response teams and networks in times of need (e.g., Kendra and Wachtendorf 2016).

Recent research continues to engage these dynamics while also extending them to highlight how natural hazards interface with local social inequalities (Aldrich 2012; Gotham and Greenberg 2014; Tierney 2007). Of these inequalities, class and race divisions are often presumed to be particularly salient because they tend to separate people spatially as well as socially, often resulting in uneven exposures and recoveries (Bullard 2008; Elliott and Howell 2017; Howell and Elliott 2018). An iconic example is Hurricane Katrina, when low-income, largely African-American areas of New Orleans not only found themselves disproportionately flooded but slower to repopulate with businesses and people in the years that followed (Asad 2015; Elliott and Pais 2006; Fothergill and Peek 2015).

In the present study we retain these foci on organizations and unequal vulnerabilities but stretch them over a longer time horizon to investigate how each shifts and interacts with the other as recovery unfolds. To this end, we examine how natural hazard damages correlate with

changes in the established organizational ecology and poverty rates of affected areas a year later, as well as how these processes interact. In doing so, we shift attention away from immediate disaster response to adopt a longitudinal perspective that follows related dynamics successively over time as natural hazards continue to strike local areas. For these analyses, we focus not on emergent organizations and networks that form during immediate crisis but rather on shifts in the established organizational ecology of local areas. We conceptualize this ecology as consisting of several key types: (1) for-profit businesses; (2) organizations with high levels of bonding social capital; and (3) organizations with high levels of bridging social capital. Our aim is to assess not only how these different components of the local organizational ecology shift following natural hazards but also how these dynamics moderate shifts in local poverty rates.

To conduct these analyses, we focus on the county level, combining data on natural hazards from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), data on established for-profit and non-profit organizations from the U.S. County Business Patterns, and data on poverty rates and demographic characteristics from the Decennial Census and the American Community Survey. Our approach contributes to previous research by extending the window of observation not only from short-term response to longer-term recovery but also over a comparatively extended period of time (1998 to 2015), across a wide range of hazard types (including hurricanes, floods, and tornados) and levels of impact (from major natural disasters to comparatively minor events) for all counties in the United States. The result is the most comprehensive empirical view to date of how natural hazards, organizational ecologies, and poverty rates unfold together over time at the local level.

Hazards, Organizations, and Inequalities

When natural hazards strike, they can negatively impact not just physical infrastructures but social infrastructures, too, with those impacts potentially lasting much longer (Fothergill and Peek 2004; Ritchie 2012, Gotham and Greenberg 2014; Klinenberg 2015). At the same time, natural hazards can also promote prosocial behavior and organizational emergence as the local status quo is disrupted, new opportunities open, and people seek to help those in need (Drabek and McEntire 2003; Dynes 1970; Erikson 1976; Kendra and Wachtendorf 2016; Quarantelli 1966; Quarantelli and Dynes 1977; Rodríguez, Trainor and Quarantelli 2006; Solnit 2009).

Research on these dynamics typically focuses on short-term disaster response, that is, the critical time during and shortly after disasters when immediate needs are relatively high. In Dynes' (1970) well-known typology of organized behavior during disasters (see also Quarantelli 1966), such responses may involve existing organizations taking on new tasks as well as the short-term emergence of entirely new organizations and networks, such as when local mariners organized on 9/11 to ferry hundreds of thousands of people from Manhattan to safer shores (Kendra and Wachtendorf 2016).

Beyond this immediate disaster *response* period, organizational changes can also continue to occur throughout the longer-term disaster *recovery* period (Drabek and McEntire 2003; Dynes 1970). These changes are not limited to organizations involved in conventional disaster recovery efforts but rather can extend to the full range of new and established organizations where natural hazards potentially reshape local commerce and community. To assess these broader shifts, we scope outward to focus on the full, established organizational ecology of local areas. By established, we mean organizations of sufficient staying power to have at least one paid employee. Among these organizations, we differentiate for-profit, or

commercial, organizations from social capital organizations.¹ We also differentiate the latter into two subtypes according to the type of social capital they tend to engender: bonding social capital or bridging social capital. We use this tri-partite conceptualization of an area's local organizational ecology because commercial organizations are critical to long-term recovery and because social capital is critical to ensuring that resilience is equitably distributed (Aldrich and Meyer 2015).

Organizational Types

For-Profit Organizations. Prior research has found that natural hazards affect for-profit organizations unevenly. Natural hazards often interrupt commercial activity, with impacts including a few days of closure, population loss resulting in an attenuated customer base, and loss of physical infrastructure (Brown et al. 2015; Dahlhamer and Tierney 1998; Marshall and Shrank 2014; Tierney 1997). Organizations that do not survive these shocks are often those that were most vulnerable before respective disasters (Alesch et al. 2001; Webb, Tierney, and Dahlhamer 2002; see also Quarantelli and Dynes 1977: 34-38), such as smaller businesses with limited capital reserves (Marshall et al. 2015). However, disaster research showcases that a large majority of businesses re-open rather quickly after disasters and fare quite well (Dietch and Corey 2011; Schrank et al. 2013; Stafford et al. 2010; Stafford, Danes, and Haynes 2013). Additionally, new organizations often form to capitalize on opportunities for remunerative redevelopment during disaster recovery (Gotham and Greenberg 2014; Klein 2007; Pais and

¹ We use the term "social capital organizations" to refer to a range of mostly (but not strictly) non-profit organizations. This terminology follows the convention utilized by social capital indexes (Rupasingha, Goetz, and Freshwater 2006), which include organizations that are presumed to activate social capital through cultivating social ties (Paxton 2007; Putnam 2000).

Elliott 2008). In short, even with vulnerable businesses closing, prior research suggests that the overall number of local businesses often increases following natural hazards. Thus, we hypothesize that the number of local businesses tends to rise with local hazard damages, all else equal.²

Social Capital Organizations. Research emphasizes how local hazard damages activate existing social capital organizations and produce new ones as local and nearby residents rally to help those in need (Aldrich 2012; Dutta 2017; Dynes 2005; Meyer 2018; Nakagawa and Shaw 2004; Norris et al. 2008; Quarantelli 1966; Ritchie and Gill 2007; Sadri et al. 2018; Sherrieb et al. 2010; Solnit 2009). These efforts access both formal social capital organizations and informal networks to rehabilitate the local community, aid in economic recovery, and rebuild infrastructure (Aldrich 2012; Browning et al. 2006; Kim and Marcoullier 2016; Klinenberg 2015; Pena et al. 2014; Wang and Ganapati 2017; Wickes et al. 2015; Wickes et al. 2017). This line of research dovetails with organizational research outside disaster studies that focuses on community-level social capital and distinguishes between different types of organizations through the concepts of “bonding” and “bridging” social capital (Adger 2003; Kwon, Heflin, and Ruef 2013; Paxton 2007).

Bonding social capital organizations are conceptualized as primarily tying members to others within their own organizations and, thus, are commonly considered to be “isolated” organizations (Kwon, Heflin, and Ruef 2013; Paxton 2007). By contrast, bridging social capital

² Assessments of natural hazard impacts sometimes distinguish between “damages” and “losses.” Damages refer to the destruction of physical assets, most notably property; losses refer to the reduction of flows of benefits, most notably income (Brusentsev and Vroman 2016). Empirical focus in our study is on damages and how they might correlate with shifts in the organizational structure and general well-being affected areas. To clarify that these damages are from natural hazards, we use “hazard damages” rather than the longer phrase of “damages resulting from natural hazards”

organizations are conceptualized as having cross-cutting social ties that bridge and expand local network capacities beyond in-group members and, thus, are considered to be “connected” organizations. Drawing from the insights about how disasters activate local social capital, we hypothesize that the numbers of social capital organizations, in general and regardless of their bridging or bonding character, tend to increase following natural hazards.

Natural Hazards and Poverty

Alongside increases in the number of local for-profit business and social capital organizations, recent scholarship highlights the detrimental impacts of natural hazards on social inequality (Karim and Noy 2016; Tierney 2007). Research has found, for example, that marginalized populations are more likely to become displaced (Curtis, Fussell, and DeWaard 2015; Elliott and Howell 2017; Fussell et al. 2017) and to suffer physical and mental injuries (Erikson 1976; Fothergill and Peek 2004) in the wake of natural hazards, while more privileged populations are likely to experience the benefits of redevelopment (Elliott and Clement 2017; Gotham and Greenberg 2014; Pelling 2003) and governmental assistance (Howell and Elliott 2018; Pelling 2003; Tierney 2012). These unequal dynamics tend to cluster unevenly across geographic space, thereby further contributing to a stratification of places as well as people (Noy and Vu 2010; Pais and Elliott 2008). For example, duPont et al.’s (2015) study of Kobe, Japan after the 1995 earthquake documents how the city experienced a long-term decline in local incomes that was driven primarily by a loss of manufacturing jobs and a concomitant growth in service sector work. The broader point from this research is that local inequalities not only shape vulnerabilities to immediate hazard impacts, they also play out through longer-term recoveries to further affect local well-being and socioeconomic inequalities. Thus, we hypothesize that,

overall, poverty rates will increase with hazard damages, as recoveries diverge for those at the top and bottom of the local socioeconomic structure.

Natural Hazards, Organizational Ecologies, and Poverty

In addition to assessing how organizational ecologies and social inequalities shift in relation to natural hazards, we are also interested in how they intersect to shape the long-term resilience of affected areas (Aldrich and Meyer 2015; Dynes 2005). While this resilience spans several interrelated domains (such as in the “disaster resilience of place” model; Cutter et al. 2008), we focus on the organizational and socioeconomic domains. Specifically, we raise and answer vital questions about whether and how changes in local organizational ecologies after natural hazards correspond to changes in local poverty rates. On the one hand, organizational changes after natural hazards may attenuate such inequalities by building organizational bridges across different groups and subcommunities in ways that better assist those in need over the long term. On the other hand, such organizational changes may occur alongside increased inequalities as more privileged groups and subcommunities disproportionately benefit from gains in organizational resources, leaving less-advantaged residents worse off than they might otherwise have been.

To make sense of these competing possibilities, we distinguish three major types of local organizations: commercial, bonding social capital, and bridging social capital. As we noted above, commercial, or *for profit*, organizations are likely to expand in number after natural hazards (e.g. Dietch and Corey 2011; Schrank et al. 2013). What is less clear from previous research, however, is how this increase, if it occurs, relates to long-term changes in local

inequalities, especially poverty, as damages from natural hazards increase. We examine this issue empirically below.

For *social capital organizations*, existing theoretical perspectives in sociology and disasters research raise the possibility that not all social capital organizations operate in a universally positive manner. In many studies, social capital organizations are viewed as a positive asset for communities as they foster collective efficacy and provide residents with needed resources and services, particularly after disasters (Dynes 2005; Meyer 2018). However, there are also many examples of “negative social capital,” such as when closely knit groups use their solidarity to exclude others, even if unintentionally (Portes 2000). Within disaster studies, Aldrich (2012) has advanced this idea by highlighting the “Janus-faced” nature of social capital in disaster recovery. This perspective highlights the point that just because social capital organizations may grow and help after hazards hit, this response does not mean that these organizations are aiding in the recovery of the wider community. In this sense, “social capital can be a double-edged sword, helping in-groups recover more effectively but at the same time slowing or halting rebuilding for those with fewer social resources who sit outside the mainstream” (Aldrich 2012: 2). This argument points to the potential “dark side” of social capital that advantages some at the expense of others (Aldrich 2012; Buckland and Rahman 1999; Elliott, Haney, and Sams-Abiodun 2010; Meyer 2018; Patterson, Weil, and Patel 2010; Williams et al. 2017).

To differentiate these competing possibilities, we follow the lead of previous research and distinguish between “bonding” and “bridging” social capital organizations. As mentioned above, *bonding social capital organizations* are defined as those in which social ties tend to bind, or tie, members more within, rather than across, organizations (Kwon, Heflin, and Ruef 2013;

Paxton 2007). These organizations – such as churches – often have a high degree of racial and sociodemographic homophily (McPherson, Smith-Lovin and Cook 2001) as well as a purposefully parochial focus that, while helpful in their immediate areas and social circles (Hawkins and Maurer 2010), can impede recovery on a wider scale as they successfully draw resources to their own communities (Aldrich 2012). Collectively, we might conceptualize these tendencies as contributing to a post-disaster type of “defensive environmentalism” (Rudel 2013), which by being effective at smaller scales can inhibit recoveries at scales of greater geographic and sociodemographic aggregation. Given these tendencies, we hypothesize that increasing numbers of bonding social capital organizations will correlate with higher poverty rates as local hazard damages increase.

By contrast, members of *bridging social capital organizations* tend to have more ties across, or between, organizations, better enabling them to partner with other organizations as well as government entities, private corporations, and subcommunities to spur effective disaster recovery (Aldrich 2012; Aldrich and Meyer 2015; Hawkins and Maurer 2010; Nakagawa and Shaw 2004; Rivera and Nickels 2014). Prior research, however, points to distinctions within bridging social capital organizations, including the relative connectedness of cross-cutting ties (Kwon, Heflin, and Ruef 2013; Paxton 2007). Hence, we further divide bridging organizations into two subtypes, advocacy and professional, based on their primary function. *Advocacy organizations*, such as environmental, human rights, and political organizations, focus on interventions for the public good to compel social change (Andrews and Edwards 2004). Whereas, *professional organizations*, such as business and occupational associations, tend to focus more on their own specialized field or sector. For these reasons, we hypothesize that advocacy organizations likely correlate with decreases in poverty after natural hazards while

professional organizations may be more similar to bonding organizations and thus correlate with increases in poverty after natural hazards.

Summary

To summarize, we draw from existing research to hypothesize that for-profit and social capital organizations will increase in number following natural hazards. Similarly, we hypothesize that poverty rates will also increase after natural hazards. In addition, we hypothesize that an interaction, or moderating, relationship exists between these two dynamics. Specifically, the adverse effects of natural hazards on local poverty rates will increase if bonding social capital organizations also increase in number. This moderating relationship occurs because these types of organizations tend to develop and deploy more bonding, or inward-oriented, forms of social capital. By contrast, we hypothesize that growing numbers of bridging social capital organizations – especially advocacy organizations – will attenuate the detrimental influence of natural hazards on local poverty rates because these types of organizations tend to bridge subcommunities and share resources.

Data

To examine these hypotheses, we assemble and analyze county-level data from three sources for every year from 1998 through 2015. This longitudinal approach proffers a novel investigation into local resilience processes that extend beyond immediate response to longer-term recovery.

The first data source is the Spatial Hazard Events and Losses Database for the United States (SHELDUS), Version 15.2 (HVRI 2016). SHELDUS compiles data from the National Climatic Data Center, the National Geophysical Data Center, and the Storm Prediction Center on

fatalities and direct losses in the form of property damages associated with eighteen types of natural hazards. These natural hazards include hurricanes, floods, severe storms, tornados and wildfires, in addition to other hazards. Advantages of the SHELDUS database include the annual availability of data, measurement at the county level, and a low threshold of inclusion that covers the impacts of comparably small events (Gall, Borden, and Cutter 2009). One limitation of SHELDUS is that assessments of flood damages are difficult to estimate (Gall, Borden, and Cutter 2009). We assume any variation in these estimates to be random over time and counties.

The second data source is the County Business Patterns (CBP), which draws information from the U.S. Census Bureau's Business Register, a composite source of several data sets utilized to obtain an annual count of all for-profit and non-profit establishments with at least one paid employee. An establishment is defined as a single physical location in which business is conducted or services are rendered. While the vast majority of establishments in the CBP are for-profit organizations, social capital establishments such as religious or environmental organizations are also included if they have a paid employee. Using the CBP to measure community-level social capital in this way is a popular approach because of its national scope and employee requirement (Rupasingha, Freshwater, and Goetz 2006). This study's time period begins in 1998, when the CBP began categorizing organizations using the industry codes in the North American Industry Classification System (NAICS).

Our final data source is the 2000 U.S. Decennial Census Long Form as well as the 2006-2010 and the 2011-2015 American Community Survey 5-year Summary Files. We use linear imputation to compute annual estimates for all variables (described below) from 1998 through 2015, which is a reliable method that introduces the fewest assumptions. For the imputation, we

assign the 2006-2010 ACS data to the year 2008, and we assign the 2011-2015 ACS data to the year 2013.

For all analyses, our unit of analysis is U.S. counties. We use counties for three reasons. First, counties are the smallest unit available in the SHELDUS dataset, which provides reliable data on local hazard damages across the whole of the United States. Second, smaller units, such as census tracts, may not capture the geographic extent of influence for some organizations, while larger units, like metropolitan statistical areas, may inflate the geographic extent in which an organization is located. Third, counties operate as important actors in disaster planning, including disbursement of post-disaster relief funds and in long-term mitigation planning.

Measures

Natural Hazards

Using SHELDUS data, we operationalize natural hazard impacts in terms of the amount of direct (non-crop) property damages they cause in a county during a given year. For consistency, we standardize all damages to 2015 dollars and take their natural logs to account for the variable's extended range and rightward skew. To give natural hazard damages a chance to influence local organizational ecologies and poverty rates, we lag the variable by one year. For example, we use natural hazard damages aggregated from January 1997 through December 1997 to predict the number of the different types of organizations and poverty rate in 1998.

— TABLE 1 ABOUT HERE —

Organizational Ecologies

To obtain annual counts of for-profit organizations, we sum the number of *all* for-profit organizations in the CBP dataset. To obtain annual counts for the different social capital organizations, we utilize a revised version of a popular social capital index (Rupasingha, Goetz, and Freshwater 2006). While that social capital index uses multiple metrics such as voter turnout in presidential elections and census response rates in addition to social capital organizations to build the index, we follow others (e.g., Wang and Ganapati 2017) who utilize only data on organizations. We do so because of theoretical concerns in social capital research about the conflation of organizational and individual levels of analysis (Paxton 2002; Portes 2000).

We follow previous research that classifies religious organizations, sports organizations, and labor unions as bonding social capital organizations because social ties within these organizations are, on average, characterized by bonding ties (Kwon, Heflin, and Ruef 2013; Paxton 2007). Specifically, the number of bonding social capital organizations is calculated as the sum for the following types: (1) religious organizations; (2) labor unions and similar labor organizations; (3) bowling centers; (4) fitness and recreational sports centers; (5) golf courses; and (6) sports clubs and managers.

Likewise, we follow precedent in the literature and categorize the six other types of organizations as bridging social capital organizations. That is, we sum the count of the following establishments: (1) civic and social associations; (2) business associations that are not themselves commercial establishments; (3) professional organizations; (4) political organizations; (5) human rights organizations; and (6) environment, conservation, and wildlife organizations. Next, we follow research on differences in the focus of organizations (Andrews and Edwards 2004), and further subdivide bridging social capital organizations into two subtypes: “advocacy”

organizations consisting of the total count of environmental, human rights, and political organizations; and “professional” organizations including (non-commercial) business organizations, civic and social organizations, and professional organizations. Our measure for overall social capital organizations is the sum of both bonding and bridging social capital organizations.

Poverty Rates

We operationalize socioeconomic hardship as the proportion of county residents whose income falls below the federal poverty line. Although poverty is but one indicator of socioeconomic status, it offers a highly reliable measure over counties and time. It also allows us to examine the influences of natural hazards and organizational shifts on the most economically marginalized residents, who constitute an important subpopulation morally as well as analytically. The mean county-level poverty rate is displayed for respective years in Table 1, along with descriptive statistics for other variables in our study. Over time, the mean poverty rate steadily increased from 13 percent in 1998 to 17 percent in 2015.

Control Variables

To better assess correlations between natural hazards and shifts in local organizational ecologies and poverty rates, we control for four county-level demographic factors, each chosen for theoretical reasons and guided by recent studies on county-level hazards and inequalities (e.g. Elliott and Clement 2017). First, we measure *total population*, which given its size and right skew is logged in all models. Population is an integral control because of the varying population size and growth rates of counties, particularly in conjunction with the count variables for hazard

damages and organizational types. *Median income* controls affluence—another key control given that wealthier counties often have more costly property damage from natural hazards. *White proportion* measures the proportion of residents who identify as non-Hispanic White, which helps to account for racial inequalities in poverty rates and recovery resources. *College proportion*, measured as the proportion of residents at least 25 years of age who have completed at least a bachelor's degree, offers an additional control for the socioeconomic status of the county, one that is often important in negotiating recovery opportunities and resources.

Analytic Strategy

To examine dynamic relationships between natural hazards, organizational ecologies, and poverty rates, we use fixed-effects panel regression models (also called change score models), which focus analytical attention on correlated changes *within* counties over time while also minimizing omitted variable bias (Halaby 2004). To aid interpretation, we standardize all variables using their global means for the entire period, thus allowing the magnitude of respective coefficients to be compared within and between models. Following existing research (Elliott and Howell 2017; Howell and Elliott 2018), we not only lag hazard damages by one year but also allow them to accumulate over time. Allowing damages to accumulate in our fixed effects framework means that analytical focus is on *new* damages that occur from one year to the next (with this amount acting effectively as a change score). We also include a continuous indicator for the year of observation to control for aggregate, national trends in respective dependent variables.

Finally, a strength of our analytical approach is that we examine all U.S. counties annually from 1998 through 2015. While we provide summary notes on *p*-values in our

regression tables for interested readers, we do not interpret those statistical tests in the body of the study. This is because our data comprise a complete census, not a sample; thus, there is no need to utilize significance testing to assess generalizability from sample to population.

Results

For context we start with the descriptive data, which reveal that over our 18-year study period, only one county in more than 3,000 experienced no recorded property damage from natural hazards. At the other extreme, Monmouth County, New Jersey, experienced more than 12 billion dollars in direct property damages. Between these two poles, the average U.S. county experienced 117 million dollars in direct property damage. These statistics affirm not only the high costs of natural hazards but also their geographic ubiquity. Next, we turn to how damages from natural hazard damages correlate with changes in local organizational ecologies, a year later.

Natural Hazard Damages and Changing Organizational Ecologies

Table 2 reports the results of fixed-effects panel regression models predicting changes in the number of different types of organizations over time. Consistent with expectations, increases in hazard damages correlate with increases in for-profit establishments. That is, when counties experience more natural hazard damage, more businesses tend to emerge the following year, all else equal. Estimates indicate a standardized coefficient of 0.01, which implies that for every one standard deviation increase in local damages there is a corresponding 0.01 standard deviation increase in the number of local businesses. Results also show a similar dynamic for social capital organizations, as well as respective subtypes. Additionally and as expected, increases in

a county's total population, median income, proportion of White residents, and proportion of college-educated residents generally correlate positively with increases in local organizations.

— TABLE 2 ABOUT HERE —

Natural Hazards, Organizational Ecologies, and Poverty

While these shifts in local organizational ecologies are important to document, researchers often raise them for a specific reason: to better understand how they might mitigate the negative impacts of natural hazards (Quarantelli and Dynes 1977; Ritchie and Gill 2007). To examine this dynamic, Table 3 reports a series of models predicting local poverty rates over time.

Consistent with expectations, Model 1 shows that as counties experience more natural hazard damages, their poverty rates tend to increase the following year, beyond what we might otherwise expect. To ensure this finding is not the artifact of impoverished counties experiencing more hazard damages (or, alternately, more affluent counties experiencing greater damages), we examined the correlation between local damages and poverty across all years and found a very weak negative correlation ($r = -0.01$).

Next, Models 2 and 3 show that increases in for-profit and social capital organizations correlate *negatively* with changes in local poverty rates. That is and in general, the more local organizations of any type grow in number after disaster, the less poverty there is. In addition, coefficients for the four control variables all point in their expected directions, offering further confidence in our models.

— TABLE 3 ABOUT HERE —

Now, we simultaneously consider the role of natural hazards and organizations. Specifically, Model 4 indicates that even after controlling shifts in the number of local organizations, the correlation between hazard damages and poverty rates a year later is still positive, though slightly reduced. Similarly, the negative correlations between for-profit and social capital organizations and poverty also remain consistent, even when natural hazard damages are held constant.

Next, we examine if certain types of organizational change moderate the positive relationship between hazard damages and poverty rates. In Model 5, we see that as for-profit organizations increase in number, they reduce the relationship between hazard damages and subsequent increases in poverty. Figure 1 illustrates this finding over time. In this figure we graph four hypothetical counties—each representing an ideal type. The first county experiences a high amount of hazard damage (\$10 billion) over the 18-year study period *and* increases in organizations by one standard deviation. The second county experiences the same amount of hazard damage but *decreases* in organizations by one standard deviation. The third and fourth counties experience low levels of hazard damage (\$100,000) *and* increases or decreases in these organizations, respectively. The resulting figure shows how counties that experienced very high hazard damages alongside *low* growth in local businesses resulted in a predicted poverty rate of 20 percent, all else equal. By contrast, counties that experienced very high damages alongside *high* growth in local businesses resulted in a predicted poverty rate of only 17 percent, all else equal. In practice, this increase of a few percentage points can account for thousands of people, especially in larger counties.

—FIGURE 1 ABOUT HERE—

By contrast, Model 5 demonstrates that counties with increasing numbers of social capital organizations experience *greater* increases in poverty as hazard damages increase. For example, Figure 1 shows that counties that experience \$10 billion in hazard damages alongside a one-standard deviation *increase* in social capital organizations have *higher* predicted poverty rates than counties that experienced similar hazard damages alongside decreases in their number of social capital organizations. In other words and somewhat paradoxically, the growth of the local social capital sector seems to correspond with amplified, not attenuated, shifts in local poverty rates following natural hazards.

To develop this finding further, Model 6 subdivides social capital organizations into their bonding and bridging types to assess how each moderates the relationship between natural hazard damages and subsequent changes in local poverty rates. Since the majority of social capital organizations are bonding organizations, it is not surprising that this subtype behaves much like that of all social capital organizations. Specifically, in counties with higher levels of hazard damage, a growing number of bonding organizations correlates with even higher poverty rates than we might otherwise expect. This finding is consistent with the idea that organizations with more bonding than bridging social capital may be effective in helping certain sub-communities recover from local hazards, but they are less effective in helping affected areas as a whole, especially less-affluent residents.

Here, it is worth noting that in our models changes in poverty occur during the same year as changes in organizational counts – a year after damages occur. As a result, we do not argue that there is necessarily a causal relationship between the two processes. Nonetheless,

supplemental models (available upon request) do show that increases in bonding organizations correlate *positively* with increases in poverty a year later. Further, we re-structured the data so that the number of bonding organizations was the dependent variable, and we re-ran longitudinal models where this measure was lagged one year *behind* local poverty rates. Results (available upon request) indicate that increases in poverty are associated with *decreases* in bonding organizations the following year. These supplemental analyses suggest that bonding organizations are not likely to grow in communities experiencing increased poverty, implying that the findings in Model 6 are not due to reverse causality.

Similarly and somewhat unexpectedly, findings for bridging social capital organizations also show that as they increase numerically in counties with higher hazard damages, poverty rates also rise beyond what we would otherwise expect. This finding parallels that for bonding organizations, although the effect size is smaller. These results lead us to consider the two subtypes of bridging organizations identified earlier – advocacy and professional. Results in Model 7 indicate that for advocacy organizations, the negative interaction term for it and hazard damage is associated with *reduced* poverty levels; whereas, the opposite is true for professional organizations. In other words, the protective effects of bridging organizations look to be limited to advocacy organizations. To illustrate these differences, Figure 2 uses the same values as those deployed in Figure 1 to depict results from Model 7 of Table 3.

—FIGURE 2 ABOUT HERE—

Conclusion

Few places in the United States evade natural hazards, and existing research suggests that resilience to such events will only become more salient in the years ahead. Within this dynamic context, the present study offers the first large-scale, longitudinal analysis of how local organizational ecologies and poverty rates shift independently and conjointly a year after natural hazards hit. Broadly and consistent with prior research, we find that the number of local businesses (Dietch and Corey 2011; Schrank et al. 2013; Stafford et al. 2010) and social capital organizations (Aldrich and Meyer 2015; Quarantelli 1966; Rodríguez, Trainor, and Quarantelli 2006) both tend to increase with local hazard costs. In addition and also consistent with prior research (Cutter, Boruff, and Shirley 2003; Gotham and Greenberg 2014; Fothergill and Peek 2004), we find that local poverty rates also increase in similar fashion. That is, as natural hazard damages increase, so too do local poverty rates a year later.

These findings suggest a double-edged effect: on the one hand, poverty rates increase with natural hazard damages; on the other hand, so do counts of commercial and non-profit organizations that may help to suppress poverty. The catch with these seemingly offsetting trends, however, is that the stimulating influence of natural hazard damage on local organizations is, on average, smaller than its stimulating influence on local poverty rates, which is why, in part, the lines in Figures 1 and 2 all slope upwards. In addition, increases in social capital organizations that we might expect to suppress poverty the most following costlier hazards actually display the opposite pattern; this is found especially for bonding social capital organizations but also is true for bridging organizations. That is, as they increase in number following natural hazards, local poverty rates increase beyond what we would otherwise expect from natural hazard damages alone. The opposite, though, is true for advocacy organizations. As

this sub-type of bridging organizations expand in number following local hazard damages, poverty rates fall below what we would otherwise expect from those damages alone.

These findings might seem surprising at first, but it is not without precedent in existing research. In sociological analyses and in disaster studies, scholars have long acknowledged how social capital organizations can offer a type of “communal insurance” that enables in-group members to share financial, physical, and informational resources (Meyer 2018; Tierney 2014). However, they have also called attention to the “Janus-faced” nature of such social capital, arguing that strong in-group solidarity on which it relies can end up excluding out-group members, particularly those on the margins of local society (Aldrich 2012; Aldrich and Meyer 2015). In this way, bonding, or inwardly oriented, social capital may work to produce inequitable recoveries by unintentionally working to constrict resources to group members while leaving others in comparatively worse situations than they might otherwise be.

Our finding that similar dynamics do not occur with advocacy organizations, which tend to be more outwardly oriented in scope as well as social capital connections, further underscores the unique and somewhat counter-intuitive influence that bonding organizations can have on poverty after natural hazards hit. It also underscores the importance of disaggregating social capital organizations into different subtypes according to their organizational functions as well as cross-cutting tendencies when considering post-hazard resilience.

With these findings in place, we think the present study holds important implications for future scholarship, policy, and practice. Although correlations do not prove causation, our longitudinal analyses suggest that natural hazards contribute to shifts in local organizational ecologies *and* to increases in local poverty rates. Scholars of resilience should be alert to these dual tendencies and not mistake robust organizational recovery as an indication of improved

well-being for all residents during longer term recovery. Researchers should also be aware of how different organizational types emerge and link to differential socioeconomic outcomes for affected areas as a whole. In light of this heterogeneity, policymakers should consider how governmental bodies can activate broad-based, bridging social capital in the form of advocacy organizations. They should also consider how government itself can play the role of convener, organizer, and actor in ways that help to ensure disaster recovery reaches across communities and does not amplify social inequalities.

Looking ahead, we also think that future research can extend these insights in a number of ways. Five are highlighted here. First, our study does not detail the directionality of the relationship between organizational change and poverty because we focused on how each unfolded together following natural hazard damages. Future research might consider the linkage between social capital organizations, especially bonding organizations, and poverty more directly. Second, we encourage researchers to analyze the relationship between natural hazards and local resilience by analyzing different types of inequality, including measures that more explicitly incorporate emergent disparities along racial lines, including heightened levels of residential segregation. Third, we propose that research analyze variations in local context, including how relationships observed in the present study might vary by the type of hazard under investigation, by the local organizational base already in place, or the amount of outside financial aid that comes into the community after disaster. Fourth, a social capital framework for the study of natural hazard recovery could be extended by using more fine-grained data to take into account characteristics of the organizations and members involved, a step that may also aid in understanding the differences found among subtypes of bridging social capital organizations. Fifth, our research could be usefully extended to different geographic and temporal scales,

including larger levels of analysis such as countries or smaller levels such as neighborhoods, as well as different temporal periods that allow for the incorporation of historical insights. It may be particularly interesting to utilize a multi-scalar perspective that assesses the effectiveness of social capital at potentially countervailing scales (for example, by comparing and contrasting neighborhood and county trends). We look forward to this future work.

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Table 1. Descriptive Statistics (Means and Standard Deviations) for Counties.^a

	1998	1999	2000	2001	2002	2003	2004	2005	2006
<i>Natural Hazards</i>									
Property Damage (\$million, 2015)	4.24 (0.83)	5.11 (0.33)	3.96 (0.26)	3.38 (0.79)	5.50 (0.61)	1.80 (8.90)	4.33 (0.44)	10.17 (0.99)	37.46 (3.90)
<i>Organizations</i>									
For-Profit	13011 (43224)	13093 (43539)	13207 (44098)	13277 (44384)	13664 (45587)	13783 (46072)	14060 (46947)	14294 (47848)	14485 (48664)
Social Capital	90 (205)	91 (208)	92 (211)	92 (212)	95 (217)	96 (141)	97 (225)	98 (229)	98 (230)
Bonding	70 (153)	71 (156)	71 (158)	71 (158)	74 (164)	76 (168)	75 (168)	76 (170)	77 (173)
Bridging	20 (56)	20 (55)	20 (56)	20 (56)	21 (56)	20 (56)	21 (62)	22 (64)	21 (63)
Advocacy	2 (9)	2 (9)	3 (10)	3 (10)	3 (11)	3 (9)	3 (13)	4 (14)	4 (14)
Professional	18 (47)	18 (47)	18 (47)	18 (47)	17 (46)	18 (47)	18 (50)	18 (51)	18 (50)
<i>Social Inequality</i>									
Poverty Rate	0.13 (0.07)	0.13 (0.06)	0.14 (0.06)	0.14 (0.06)	0.14 (0.06)	0.14 (0.06)	0.15 (0.06)	0.15 (0.06)	0.15 (0.06)
<i>County Demographics</i>									
Total Population (000s)	87.90 (289)	88.80 (291)	89.70 (293)	90.60 (295)	91.50 (296)	92.39 (298)	93.29 (300)	94.19 (302)	95.09 (305)
Median Income (000s)	46.21 (12.35)	47.50 (12.33)	48.80 (12.36)	50.10 (12.42)	51.40 (12.54)	52.69 (12.71)	53.99 (12.93)	55.29 (13.19)	56.59 (13.50)
White Proportion	0.82 (0.19)	0.82 (0.19)	0.81 (0.19)	0.81 (0.19)	0.81 (0.19)	0.80 (0.19)	0.80 (0.19)	0.80 (0.19)	0.79 (0.19)
College Proportion	0.16 (0.08)	0.16 (0.08)	0.17 (0.08)	0.17 (0.08)	0.17 (0.08)	0.17 (0.08)	0.18 (0.08)	0.18 (0.08)	0.18 (0.08)
N	3,137								

^a Direct hazard damage refers to the previous year. For example, in 1999 poverty, organization and demographic data are from 1999 but the hazard damage comes from January to December 1998.

Continued Table 1. Descriptive Statistics (Means and Standard Deviations) for Counties.^a

	2007	2008	2009	2010	2011	2012	2013	2014	2015
<i>Natural Hazards</i>									
Property Damage (\$million, 2015)	2.68 (0.19)	2.15 (0.20)	7.74 (1.53)	2.14 (0.19)	3.50 (0.64)	6.98 (0.82)	10.98 (3.00)	3.18 (0.46)	1.88 (0.29)
<i>Organizations</i>									
For-Profit	14707 (49234)	14504 (48685)	14178 (47752)	14102 (47622)	14007 (47637)	14173 (48415)	14272 (49030)	14405 (49818)	14583 (50685)
Social Capital	99 (232)	99 (230)	98 (229)	99 (230)	98 (228)	98 (229)	99 (232)	99 (234)	99 (236)
Bonding	79 (177)	78 (176)	78 (176)	78 (176)	78 (175)	78 (176)	79 (178)	79 (181)	80 (182)
Bridging	21 (61)	21 (60)	20 (60)	20 (61)	20 (60)	20 (61)	20 (61)	20 (61)	20 (61)
Advocacy	4 (14)	4 (15)	4 (15)	4 (16)	4 (15)	4 (17)	4 (16)	4 (17)	4 (17)
Professional	17 (47)	17 (46)	17 (46)	16 (46)	16 (45)	16 (45)	16 (46)	16 (45)	16 (45)
<i>Social Inequality</i>									
Poverty Rate	0.15 (0.06)	0.15 (0.06)	0.16 (0.06)	0.16 (0.06)	0.16 (0.06)	0.16 (0.06)	0.17 (0.07)	0.17 (0.07)	0.17 (0.07)
<i>County Demographics</i>									
Total Population (000s)	95.99 (307)	96.89 (309)	97.69 (312)	98.49 (315)	99.29 (317)	100.09 (320)	100.89 (323)	101.69 (326)	102.49 (329)
Median Income (000s)	57.89 (13.84)	59.19 (14.22)	58.95 (14.06)	58.71 (13.97)	58.47 (13.94)	58.24 (13.98)	58.00 (14.09)	57.76 (14.26)	57.53 (14.50)
White Proportion	0.79 (0.20)	0.79 (0.20)	0.78 (0.20)	0.78 (0.20)	0.78 (0.20)	0.78 (0.20)	0.77 (0.20)	0.77 (0.20)	0.77 (0.20)
College Proportion	0.19 (0.09)	0.19 (0.09)	0.19 (0.09)	0.20 (0.09)	0.20 (0.09)	0.20 (0.09)	0.20 (0.09)	0.21 (0.09)	0.21 (0.09)
N	3,137								

^a Property damage from natural hazards refers to the previous year. For example, in 1999 poverty, organization and demographic data are from 1999 but the hazard damage is from 1998.

Table 2. Coefficients from Fixed-Effects Models Predicting Number of Organizations Logged, Interval to Interval, 1998-2015.

	For-Profits	Social Capital Organizations				
		(All)	Bonding (All)	Bridging		
				(All)	Advocacy	Professional
Direct Hazard Damage (<i>logged</i>)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)
<i>County Demographics</i>						
Total Population (<i>logged</i>)	0.81 (0.02)	0.69 (0.01)	0.70 (0.01)	0.60 (0.01)	0.89 (0.03)	0.49 (0.02)
Median Income	0.07 (0.00)	0.02 (0.00)	0.02 (0.00)	0.03 (0.00)	0.04 (0.00)	0.03 (0.00)
White Proportion	0.05 (0.01)	0.07 (0.01)	0.07 (0.01)	0.06 (0.01)	-0.02 (0.01)	0.06 (0.01)
College Proportion	0.04 (0.00)	0.03 (0.01)	0.02 (0.00)	0.06 (0.01)	0.13 (0.01)	0.03 (0.01)
Year	-0.01 (0.00)	-0.00 (0.00)	0.00 (0.00)	-0.01 (0.00)	0.00 (0.00)	-0.01 (0.00)
Constant	0.05 (0.00)	0.01 (0.00)	-0.01 (0.00)	0.07 (0.00)	-0.03 (0.00)	0.09 (0.00)
Overall R ²	0.9268	0.9018	0.8947	0.7855	0.6343	0.7697
N of counties	3137	3137	3137	3137	3137	3137

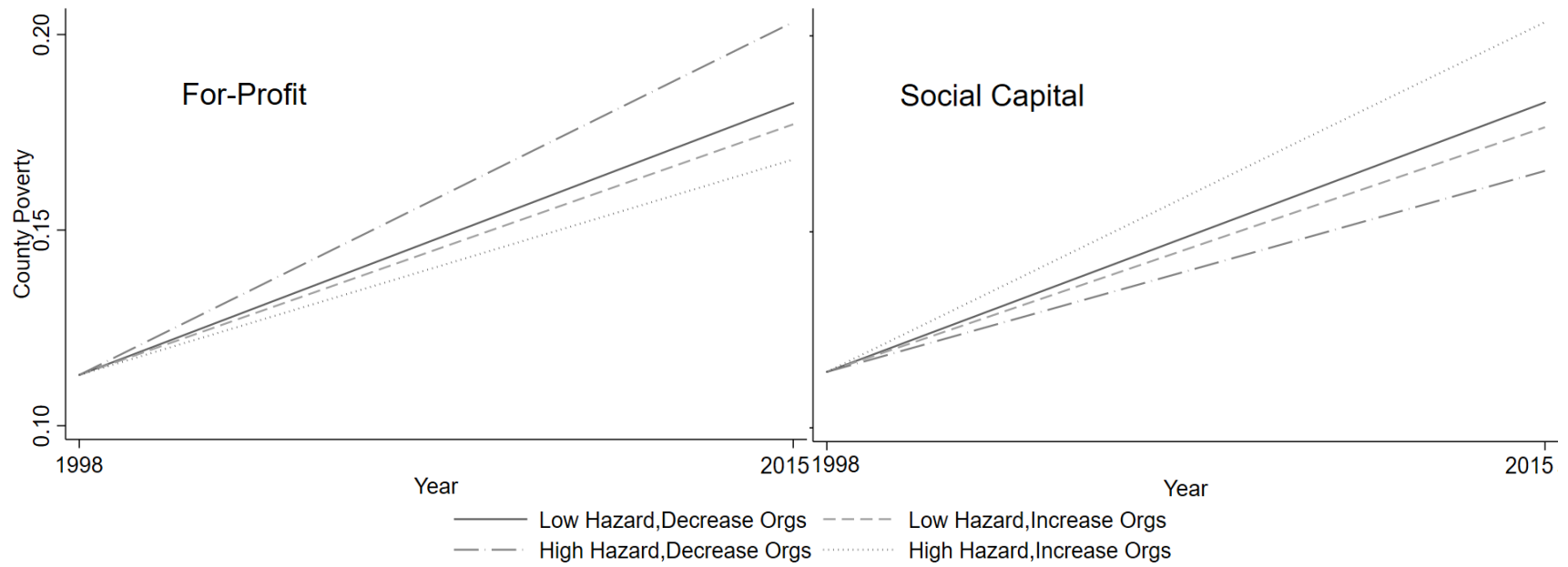
Note: All variables are standardized. P-values are not displayed because we have a census of all counties, not a sample. Hence, we do not need to utilize probability to estimate the likelihood of our sample mean being the population mean because presented figures are the mean of the population. However, we note all six coefficients in each of the six models are statistically significant ($p < 0.05$), except the White proportion coefficient in the Advocacy model.

Table 3. Coefficients from Longitudinal Fixed Effects Regression Models Predicting County Poverty, Interval to Interval, 1998-2015.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Direct Hazard Damage (<i>logged</i>)	0.03 (0.00)			0.02 (0.00)	0.03 (0.00)	0.03 (0.00)	0.02 (0.00)
<i>Local Organizations</i>							
For-Profit (<i>logged</i>)		-0.03 (0.01)		-0.04 (0.01)	-0.11 (0.01)	-0.10 (0.01)	-0.09 (0.01)
Social Capital (<i>logged</i>)			-0.03 (0.01)	-0.01 (0.01)	0.05 (0.01)		
Bonding (<i>logged</i>)						0.02 (0.01)	0.02 (0.01)
Bridging (<i>logged</i>)						0.03 (0.01)	
Advocacy (<i>logged</i>)							0.02 (0.00)
Professional (<i>logged</i>)							0.02 (0.01)
<i>County Demographics</i>							
Total Population (<i>logged</i>)	0.03 (0.01)	0.63 (0.03)	0.62 (0.03)	0.63 (0.03)	0.60 (0.03)	0.59 (0.03)	0.56 (0.03)
Median Income	-0.46 (0.00)	-0.40 (0.00)	-0.40 (0.00)	-0.41 (0.00)	-0.40 (0.00)	-0.40 (0.00)	-0.40 (0.00)
White Proportion	-0.35 (0.01)	-0.11 (0.01)	-0.11 (0.01)	-0.11 (0.01)	-0.08 (0.01)	-0.08 (0.01)	-0.08 (0.01)
College Proportion	-0.06 (0.01)	-0.09 (0.01)	-0.09 (0.01)	-0.09 (0.01)	-0.11 (0.01)	-0.11 (0.01)	-0.11 (0.01)
<i>Interactions</i>							
Hazard Damage*For-Profit					-0.07 (0.00)	-0.05 (0.00)	-0.05 (0.00)
Hazard Damage*Social Capital					0.10 (0.01)		
Hazard Damage*Bonding						0.08 (0.00)	0.08 (0.00)
Hazard Damage*Bridging						0.01 (0.00)	
Hazard Damage*Advocacy							-0.03 (0.00)
Hazard Damage*Professional							0.03 (0.00)
Year	0.05 (0.00)	0.06 (0.00)	0.06 (0.00)	0.05 (0.00)	0.06 (0.00)	0.06 (0.00)	0.06 (0.00)
Constant	-0.46 (0.00)	-0.48 (0.00)	-0.48 (0.00)	-0.47 (0.00)	-0.48 (0.00)	-0.48 (0.00)	-0.48 (0.00)
Within R ²	0.4141	0.4190	0.4189	0.4206	0.4296	0.4287	0.4308
N of counties	3137	3137	3137	3137	3137	3137	3137

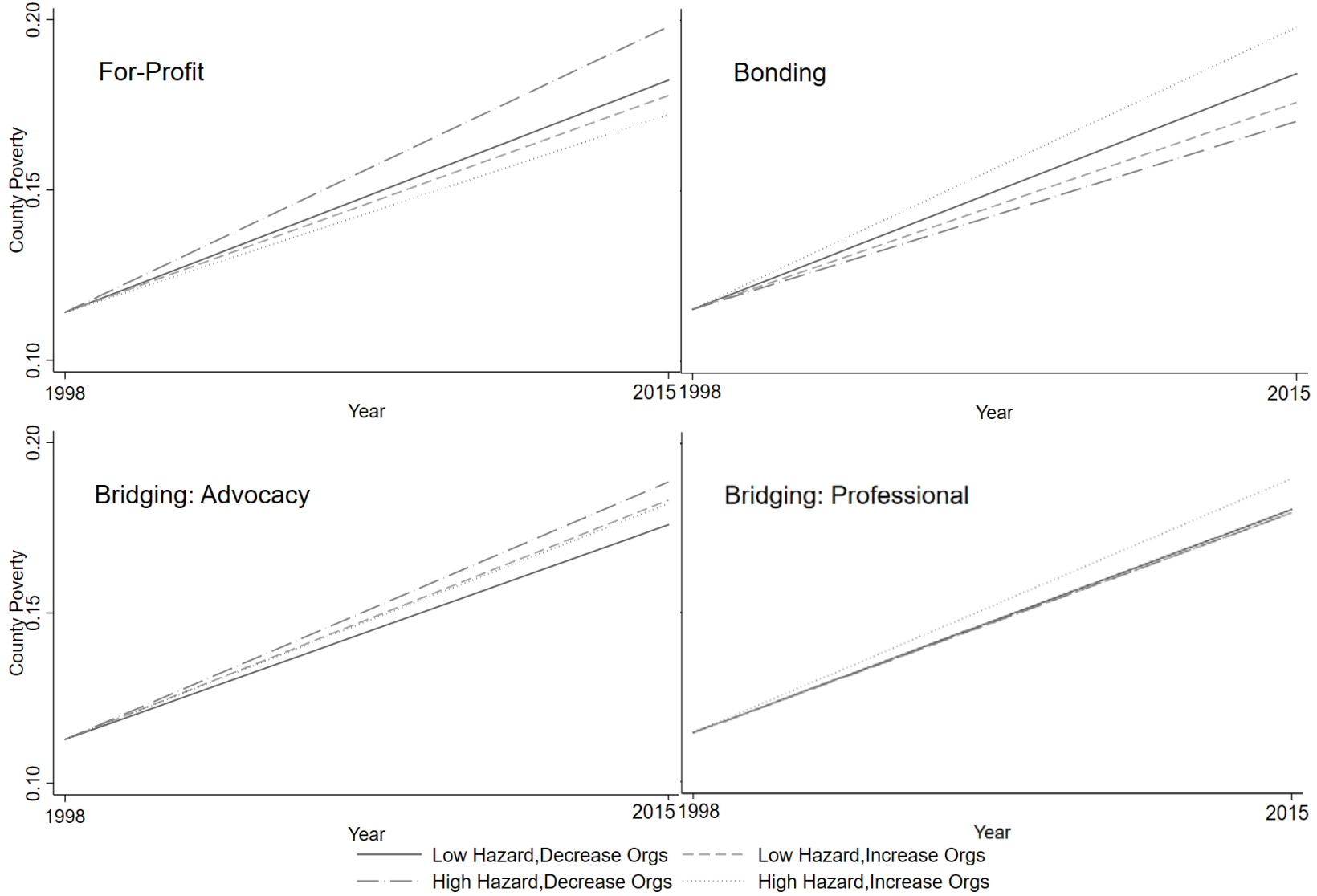
Note: All variables are standardized. P-values are not displayed because we have a census of all counties, not a sample. Hence, we do not need to utilize probability to estimate the likelihood of our sample mean being the population mean because presented figures are the mean of the population. However, we note all coefficients in each of the six models are statistically significant ($p < 0.05$) except the social capital coefficient in Model 4 and the interaction between bridging organizations and hazard damages in Model 6.

Figure 1. Predicted County Poverty Rate by Local Hazard Damage Interacted with Respective Organizations, All Else Equal



Source: Respective interaction models in Model 5 of Table 3. All other covariates are held constant at their means.

Figure 2. Predicted County Poverty Rate by Local Hazard Damage Interacted with Types of Social Capital Organizations, All Else Equal



Source: Respective interaction models in Model 7 of Table 3. All other covariates are held constant at their means.

