

# Natural disasters and local demographic change in the United States

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**Abstract** Classic studies on local demographic consequences of natural disasters in the United States are now more than 30 years old, raising questions about how and to what extent relevant patterns have changed over intervening years, as the number and cost of recorded environmental hazards have increased. This study examines these questions at the county level for the nation as a whole, using recent census and hazards data in conjunction with statistical methods that account for spatial dependencies among neighboring counties. Results indicate a positive correlation between cumulative disaster impact during the 1990s and changes in local population and housing units; they also reveal patterns of increased socioeconomic polarization among local residents. These findings differ from earlier studies and put recent case studies in broader context, suggesting that current disaster recoveries contribute to the growth of larger and more unequal populations in environmentally hazardous places.

**Keywords** Environmental hazards · Natural disasters · Demographic change · Socioeconomic inequality

## Introduction

In 2011, the United States set a new record for weather-related disasters with the help of an unprecedented number of tornadoes in the Southeast, historical levels of flooding in the Ohio Valley, and record drought and wildfires in Texas (NOAA 2011). These events reflect the sheer number and growing costs of environmental hazards across the country. In fact, during the first decade of the twenty-first century, the U.S. federal government declared 642 national emergencies arising from a wide range of such hazards, including hurricanes, earthquakes, floods, heat

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waves, tornadoes, volcanoes, fires, and winter storms (FEMA 2011). During this same decade, average public expenditures for recovery from these events exceeded \$12 billion per year—more than all federal housing support for the poor, elderly, and disabled combined for some years (HUD 2008). Yet, despite the sheer number and public cost of these disasters, we continue to know surprisingly little about how they and associated recoveries correlate with local demographic changes in affected areas. Indeed, the last nation-wide study of such changes occurred in the 1970s using data from the 1960s (Wright et al. 1979), long before the implementation of organized disaster accounting and methodological advances in spatial statistics. The present study aims to address this gap in several ways.

First, we update classic analyses to provide a more recent view of local demographic changes following natural disasters, thereby offering a firm basis from which to draw historical comparisons across recent decades. Second, we take advantage of recent improvements in data collection to move beyond the classic dichotomous measure of local disaster impact (yes or no) to examine the cumulative impact of local hazards, as measured by total property damages that occurred over the course of the observed decade. Finally, we use spatial regression techniques to address statistical challenges that arise from geographic dependence among neighboring areas, thereby improving model estimation and inference. These contributions are useful in three respects.

First, disaster declarations have grown to become one of the largest and least understood programs of public (re)development in the United States. So from a policy perspective, it makes sense to take a closer look at what, if any, unintended consequences tend to occur during long-term recoveries from such events. Second and from a more academic perspective, our study provides much-needed context for assessing the generalizability of recent case studies of large-scale events such as Hurricane Andrew (e.g., Peacock et al. 1997), the Northridge earthquake (e.g., Bolin and Stanford 1998), and Hurricane Katrina (e.g., Brunsma et al. 2010). Such context is important because it remains unclear whether these well-documented cases offer examples or exceptions to more general patterns of local demographic change associated with environmental hazards. Finally, and from a more theoretical perspective, the present study strengthens our understanding of how U.S. society continues to interact with the natural world in which it is embedded and how this interaction continues to restructure the social and built environments of local communities. This perspective is particularly useful now because most contemporary research on population and the environment focuses on how people and organizations degrade the planet through destructive modes of extraction, production, and pollution (e.g., Elliott and Frickel 2011; Foster 1999; York et al. 2003). Yet, if left unbalanced, this approach can unwittingly portray society as an ecological threat that exists somehow outside nature, exerting its influence upon it (Melosi 2010). By expanding research to examine how populations and places adjust to, as well as transform, the environments of which they are a part, we can develop a fuller understanding of the highly dynamic and multidirectional interactions between population and environment at the local level.

Below, we contribute to this understanding by reviewing the historical role of the modern state in disaster recovery and then addressing classic and contemporary research on local demographic changes that are assumed to occur in the process of long-term recovery. We then test key hypotheses from this review using recent

census and disaster data collected at the county level. Results and implications follow.

### **Environmental hazards, state response, and long-term recovery**

The central focus of this study is whether local population and housing stocks change over the long term in response to common environmental hazards and associated recoveries. From the outset, we recognize that the answer to this question depends on more than just the physical impact of environmental hazards; it also depends on public and private assistance after such events occur. Without this assistance, we might logically expect natural disasters to reduce local populations because they often damage property, displace residents, and increase local risk perceptions, in addition to raising housing costs and insurance premiums that may deter current and future settlement. In this hypothetical context, natural disasters act as an environmental “push” from affected areas (Gutmann and Field 2010; Hunter 1998, 2005). Yet, in most developed nations such as the United States, government has long intervened to offset such environmental forces by assisting in local recoveries and providing resources beyond those available from private sources. Currently, such efforts include underwriting local hazard insurance programs, rebuilding damaged infrastructure, providing housing subsidies, and coordinating low-interest business loans, nearly all of which aim to restore (and potentially expand) local private property investments in affected regions.

Before we assess the demographic consequences of these dynamics, it is worth briefly reviewing the historical role of the state in long-term recovery from natural disasters. According to Dynes (2000), large-scale government investment in local disaster recovery dates back to at least the Lisbon earthquake of 1755 and is the hallmark of the modern state. Until that time, government leaders and subjects had tended to understand disasters as messages from God that required moral deciphering and repentance, perhaps, but no political action. Following the Lisbon quake, however, the Portuguese Secretary of State offered a more natural, or scientific, explanation for such events. This explanation acknowledged that although environmental disasters occur without moral reason, they require moral response, not just from individuals but also from the state they entrust (see Zack 2010). This shift in state policy not only helped to rebuild Lisbon but to institutionalize the idea that the modern state has an ethical responsibility to assist rather than condemn citizens in times of environmental catastrophe.

This modern norm is clearly evident in the early formation of the U.S. federal government. In 1803, not long after the Republic’s founding, Congress voted to waive duties and tariffs on imported goods into Portsmouth, New Hampshire, in order to help residents recover from extensive local fires (Moss 1999). Not long thereafter, in 1811 and 1812, Congress donated free public lands to residents displaced by earthquakes in New Madrid, Missouri; and in 1827, it allocated taxpayer funds for immediate relief and long-term recovery of residents of Alexandria, Virginia, after fires destroyed homes and businesses. According to Dauber (2005), these *ad hoc* efforts established a *de facto* policy of federal disaster

assistance as early as the 1830s, which set precedence for massive government-aided recoveries following the 1906 San Francisco earthquake and great Mississippi floods of 1927 and 1937 (see Barry 1998).

This federal practice of disaster assistance was finally codified into law with the Disaster Relief Act of 1950, which gave the president and federal agencies the legal authority to issue disaster declarations and to assist state and local jurisdictions in times of environmental catastrophe (Garrett and Sobel 2003). Central to our purposes, this same Disaster Relief Act also encouraged the establishment of national research centers for the sociological study of natural disasters (for a review, see Drabek 1986). For the most part, these centers focused on sending researchers to disaster zones to study short-term responses (for a review, see Tierney 2006). However, as the number and cost of federally declared disasters continued to rise after the Act of 1950, scholars and policymakers became increasingly interested in whether long-term recovery from such events transformed affected areas, acting as an unintended force of population and housing redistribution.

The most comprehensive study of this question is *After the Cleanup* (1979), which emerged from a series of monographs produced by Wright and colleagues on the long-term consequences of natural disasters. Operating from a policy evaluation framework that made few explicit theoretical assumptions, this research team collected data on as many significant disasters as they could find in the United States during the 1960s, using newspaper clippings, local reports, and declarations from various government agencies. They then located these disasters within their respective counties and estimated statistical models to determine whether, on average, areas hit by disasters differed from those that were not hit with respect to population and housing changes during the respective decade. Exhaustive analyses led the team to conclude that, despite conventional wisdom, disasters exerted no discernible effect on local demographic and housing trajectories. Instead, the researchers concluded, “The comparison of average damages to average resources makes it implausible in the extreme to expect that these disasters would have residual and observable effects. In our studies, none were found” (Wright et al. 1979: 198).

Around the same time, Friesema et al. (1977) reported similar findings from their time series analysis of city-level indicators of social and economic change following natural disasters of the early 1970s, corroborating related but less comprehensive research by Cochrane (1975), Dacy and Kunreuther (1969), and Douty (1977). Collectively, these classic studies of long-term recovery imply that after a few years, regions hit by environmental hazards tend to achieve what Haas et al. (1977: 3) called a “functional recovery,” which they define as “the replacement of the population and of the functioning equivalent of their needs in homes, jobs, capital stock, and urban activities” (Haas et al. 1977: 3). This is when and where national studies of local disaster recovery and demographic change effectively stopped.

Thereafter, disaster research began to diverge, most notably toward theoretical reconceptualization of root processes and in-depth case studies of local recoveries (for reviews, see Blaikie et al. 1994; Hewitt 1997; Oliver-Smith 1998). This intellectual shift has produced two important and related insights. First, it stopped conceptualizing disasters as random, disruptive events and instead began framing

them as regularly occurring processes that include social as well as environmental inputs. This perspective is readily evident in the edited volume *What is a Disaster?* (Quarantelli 1998), as well as in more recent work by Clarke (2005) and Perrow (2007). The second insight is that areas hit by environmental hazards are not monolithic wholes but rather mosaics of unequal communities with varying degrees of vulnerability that influence respective capacities to recover in place. The implication is that socially disadvantaged residents are vulnerable not just to disasters but to disaster recoveries, which tend to direct public and private resources toward the restoration of property rather than community (e.g., Bolin and Stanford 1998; Dash et al. 2007; Fothergill and Peek 2004; Myers et al. 2008; Tierney 2006).

These new developments in disaster research continue to produce valuable insights and deep understanding of individual disasters and vulnerabilities in context (e.g., Cutter et al. 2000). However, these studies have also unwittingly created a blind spot in our contemporary understanding of demographic change following natural disaster. By focusing on specific areas and events, these studies tend to overlook general patterns of local demographic change as well as questions about whether patterns occurring now differ from those documented by classic studies of the 1970s, before creation and expansion of the Federal Emergency Management Agency in 1979. This gap is important to address now because public and private investment in disaster recovery continues to increase (Barnett 1999; Perrow 2007) and because the number of U.S. residents living in coastal counties, where the most costly environment hazards tend to concentrate, is also on the rise (*Statistical Abstracts, 2005*, Table 23). These developments mean not only that local populations studied by Wright and others during the 1970s have shifted geographically over time but also that efforts to assist their recovery after disaster have also increased, raising questions about aggregate as well as segmented demographic changes in affected areas. To understand these dynamics fully, we need to complement recent case studies with a broader assessment of how local areas, on average, tend to change demographically after environmental catastrophes.

Pais and Elliott (2008) begin to offer such an approach in their recent analysis of hurricane recovery. In their study, they build from recent case studies of unequal recoveries (e.g., Steinberg 2006; Peacock et al. 1997) to argue that local areas are becoming more vulnerable to environmental hazards not just quantitatively in terms of growing numbers of people and properties at risk, but also *qualitatively* in terms of outdated and receding protections from hazards generated by over-investment in growth and under-investment in local environmental preparedness and mitigation. This perspective shifts attention beyond the simple recognition that some residents are more vulnerable to environmental hazards than others to illuminate how this vulnerability is generated by ongoing and unequal struggles over local development. It also raises questions about how such struggles transform after hazards strike and competing interests respond to opportunities created by the damage, displacement, and assistance that follows. During such long-term recovery, Pais and Elliott argue, unequal access and control over state and private recovery resources heighten pre-existing inequalities and allow local pro-growth coalitions to promote extensive and unequal redevelopment of affected areas. The implication is that today's recoveries

do not stop at functional recovery, as classic studies predict, but instead use “newfound resources and power to expand aggressively following major disasters” (2008: 1421).

To test this idea, Pais and Elliott analyze coastal disasters that resulted from major hurricanes of the early 1990s. They find that recoveries from these events brought approximately 1.4 million *additional* residents and 600,000 *additional* housing units to affected areas, which they interpret as supporting their “recovery machine” thesis. However, they also concede that this support may not generalize to other recovery zones because they focus on extreme cases of only one type of hazard (hurricanes) and disregard contemporaneous changes in surrounding areas. Consequently, it remains unclear whether the patterns they report signal a general shift away from functional recoveries of the past or whether their selective focus on certain areas and hazards biases results toward a peculiar type of pro-growth recovery, unique to major coastal disasters.

To examine these issues, we return to the research design of Wright et al.’s (1979) classic study of local disaster recovery to conduct an updated and extended investigation. First, we test the hypothesis, based on classic studies, that long-term recovery from environmental hazards has no systemic correlation with local demographic changes in population and housing; instead, affected areas achieve functional recoveries that look very similar to what we might expect had no environmental hazards occurred during the observed decade. Second, we extend this line of research to test the hypothesis, based on recent case studies, that local long-term recovery from environment hazards tends to be highly unequal, resulting in shifts in the socioeconomic structure of local residential populations. We discuss the data and methods used to examine these hypotheses below.

## Data and methods

To examine local demographic changes associated with long-term recoveries from environmental hazards and to maximize historical comparability with earlier analyses, we adopt and extend the approach and models employed by Wright et al. (1979) using county-level data from two sources: the Spatial Hazard Events and Loss Database for the United States (SHELDUS), and the 1990 and 2000 U.S. population censuses. SHELDUS is a publically available, county-level database compiled by the Hazards and Vulnerability Research Institute at the University of South Carolina with support from the National Science Foundation (Hazards and Vulnerability Research Institute 2010). This database contains information on 18 types of recognized environmental hazards dating back to 1960, with each event’s start date, location, and total assessed property damages. These data come from several national data sources, including the National Climatic Data Center’s monthly reports and the agency’s Tsunami Event Database, and include all known environmental hazards that caused more than \$50,000 in damage or at least one fatality. Several features make this environmental data set well suited for our purposes.

First, it is much more comprehensive than the databases compiled by classic studies of the 1970s, which typically relied on incomplete reports from private relief

organizations, records produced by disparate government agencies, and “congeries of rumors, clippings from old newspaper stories, and guesses” (Wright and Rossi 1981: 156). To render our analyses comparable with this prior research, we limit our empirical focus to declared disasters stemming from hurricanes, tornadoes, and floods. The SHELDUS database indicates that 2,961 such hazards occurred within the United States during the 1990s, compared with 1,612 such events documented by Wright and colleagues during the 1960s. Second, the SHELDUS database also allows us to construct a continuous measure of local disaster impact, or severity, by summing non-crop property damage from all hazards that occurred during the 1990s (measured in constant 2008 dollars). This independent variable ranges from zero for 149 U.S. counties that were not struck by such hazards during the 1990s to approximately \$4 billion in total (non-crop) property damage in Grand Forks, North Dakota, which experienced catastrophic flooding during the spring of 1997.

This continuous measure of total impact is preferable to the classic dichotomous indicator of disaster impact (yes or no) for several reasons. First, it recognizes that some hazards bring tremendous property damage and recovery assistance (e.g., the 1997 Red River flood), while others bring very little (e.g., the 1995 Chicago heat wave). Second, it recognizes that local areas can experience multiple hazards during the observed decade, all of which can exert a cumulative effect on recovery (e.g., during the latter half of the 1990s alone, Hillsborough County, Florida, experienced a hurricane, multiple tornadoes, and flooding that summed to nearly \$20 million in property damages). Finally, the new, continuous measure of cumulative disaster impact offers greater statistical variation than a simple dichotomous indicator, thereby improving model estimation.

To measure relevant demographic and housing variables, we use data from the 1990 and 2000 population censuses (U.S. Census Bureau *nd*). For each dependent variable of interest (see below), we compute percent change scores as Wright and colleagues (1979) did, measured as  $((Y_i^{00} - Y_i^{90})/Y_i^{90}) \times 100$ ; where subscript  $i$  refers to the local county of interest and the superscripts refer to the census year of observation. Treating the two censuses (1990 and 2000) as panel data and computing change scores in this way minimizes problems associated with omitted variable bias (Halaby 2004) and helps to control for large aggregate differences between counties. In addition to computing percent change scores for total population and housing units, as Wright et al. (1979) did, we also extend their analyses to investigate percent change in median family income and number of local residents living below the federal poverty line. These additional dependent variables allow us to examine shifts in the basic socioeconomic structure of local areas and to test whether more vulnerable subpopulations (e.g., those living in poverty) experience different recovery trajectories than the local population as a whole.

To predict each dependent variable, we estimate a series of nested regression models that take the following general form:

$$((Y_i^{00} - Y_i^{90})/Y_i^{90}) \times 100 = b_0 + b_i D_i + \sum b_i C_i^{90} + \sum b_j S_j + e$$

where, for example,  $Y_i^{00}$  represents the total population for a particular county in the 2000 census;  $Y_i^{90}$  represents the corresponding value for this dependent variable in

the 1990 census;  $b_0$  represents the intercept;  $b_i D_i$  represents the natural logarithm of cumulative disaster impact during the 1990s (in constant dollars);  $\sum b_i C_i^{90}$  represents control variables from the 1990 census (see below);  $\sum b_j S_j$  represents state dummy variables used to control for unobserved state effects, including variation in state disaster policies; and,  $e$  represents the error term. To avoid taking the natural logarithm of 0 for our measure of cumulative disaster impact ( $D_i$ ), we add one-tenth of a cent to all counties that report no hazards during the 1990s. We also fit all models using robust regression techniques that minimize the influence of outliers through an iterative assessment of absolute residuals and partial down-weighting of extreme cases to reduce their disproportionate effect on estimated coefficients (Verardi and Croux 2008). Prior research indicates that this approach yields results that are approximately 95% as efficient as standard ordinary least squares regression (Hamilton 2009) with the benefit of avoiding undue influence of individual cases.

To enhance comparability with prior studies, we statistically control for a number of factors, including the physical size of the county (in square miles), which reflects how much land is available for post-disaster demographic change; metropolitan status (1 = yes; 0 = no), which can affect the intensity of demand for further development; and whether the county is located on the coast (1 = yes; 0 = no), which may increase the demand for and costs of post-disaster redevelopment. For demographic control variables, we again follow earlier studies and include measures for the local percentage of non-Hispanic non-whites, mean age, median family income (logged), percent unemployed, percent employed in manufacturing, percent employed in trade, and percent of houses built after 1949. Including these variables in our model strengthens comparisons with past studies and helps to ensure that any statistical correlation found between disaster impact and local demographic change is not spurious.

In addition to these variables, we also estimate each full model with the inclusion of a spatially lagged dependent variable created using geographic information systems (GIS) and a first-order queen contiguity matrix. For each county of observation, this type of matrix identifies adjacent counties in a movement similar to that of a queen in chess, with neighboring units selected based on shared borders radiating out from the observed unit, or county, on all sides and diagonal corners. From these neighboring units, an average value of the dependent variable is computed as a spatial lag. Although not available to researchers in the 1970s, inclusion of this spatial lag in the regression model helps to correct for potential estimation problems created by spatial dependence. These problems arise because neighboring counties often interact and thus share much in common with one another, which means that in regression analyses, their error terms may be correlated, thereby violating assumptions of independence (see Anselin and Berra 1998; Voss et al. 2006). Calculation of the Moran's  $I$  statistic for each dependent variable confirms significant, positive clustering, with the highest value, 0.48, evident for population change and the lowest value, 0.31, evident for change in local subpopulations living in poverty. (All are significant at the 0.05 level, based on 999 permutations). Our use of a spatially lagged dependent variable assumes that spatial dependence in the respective dependent variable operates as a relatively short-distance spatial process, whereby proximity increases interactions among



neighboring counties, which we handle statistically through exogenous declaration of surrounding counties, or neighbors, through the first-order queen contiguity matrix.

## Results

Table 1 reports descriptive statistics for all variables in our analyses. This information reveals that 94% of all U.S. counties experienced at least one reported tornado, flood, or hurricane during the 1990s, which contrasts to 52% found by Wright and colleagues during the 1960s. These observed increases over time not only reflect improved environmental monitoring and record keeping but also underscore how ubiquitous such environmental hazards are across the United States,

**Table 1** Mean and standard deviation for disaster and demographic variables ( $N = 3093$ )

	Mean	SD	Min.	Max.
<i>Dependent variables</i>				
Percent change, 1990–2000				
Total population	11.09	16.05	−37.38	191.05
Total housing units	13.30	14.43	−21.48	184.12
Median income	49.23	11.83	−36.36	116.11
Number of residents living in poverty	73.06	34.72	−32.43	412.49
<i>Independent variables</i>				
Disasters during 1990s <sup>a</sup>				
Any damage (1 = yes; 0 = no)	0.94	0.24	0	1
Major damage (1 > \$1 M; 0 < \$1M)	0.58	0.49	0	1
Total property damage (\$)	\$693,842	\$106	0	\$4.03B
ln (total property damage, \$)	13.45	4.66	−4.61 <sup>b</sup>	22.11
County-level controls, 1990				
ln (area in sq. mi.)	6.47	0.85	0.68	9.91
Metro county (1 = yes; 0 = no)	0.26	0.44	0	1
Coastal county (1 = yes; 0 = no)	0.21	0.41	0	1
Non-white (%)	15.07	17.84	0	97.59
Mean age	36.04	2.95	23.30	60.12
ln (median income)	10.22	0.24	9.30	11.05
Unemployed (%)	6.65	3.04	0	30.53
Employed in manufacturing (%)	18.55	10.56	0	53.68
Employed in trade (%)	19.60	3.51	0	35.51
Houses built after 1949 (%)	70.31	14.17	23.76	98.38

<sup>a</sup> Measured as total (non-crop) property damages from all tornadoes, floods, and hurricanes that struck the county during the 1990s (in constant 2008 dollars)

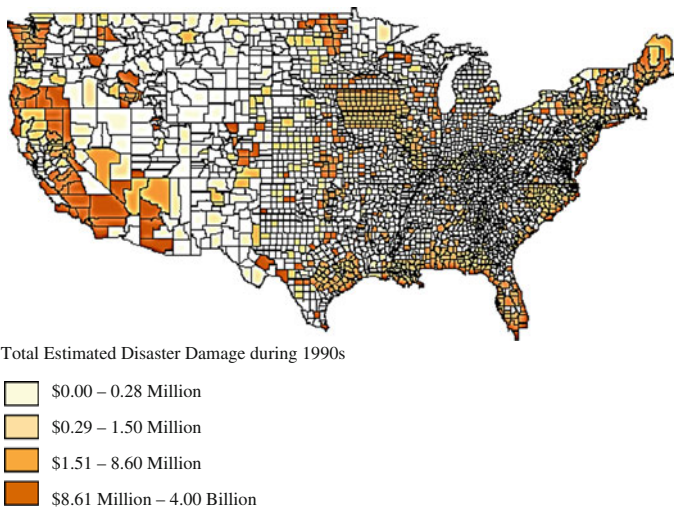
<sup>b</sup> To avoid taking the natural logarithm of 0, we add one-tenth of a cent to all counties with no reported hazards during the 1990s

with the most common hazards being floods, followed by tornadoes and then hurricanes.

To illustrate the spatial distribution of cumulative impact from these hazards during the 1990s, Fig. 1 maps total (non-crop) property damage for all counties in the continental United States, which averages approximately \$700,000 per county during the decade. Results indicate high levels of damage throughout the nation, with prominent clustering along river flood zones of the Midwest, which are also prone to tornadoes, as well as along the coasts. These broad geographic patterns are consistent with those documented by Wright et al. (1979) 30 years earlier, implying that areas of environmental hazard have not changed dramatically over recent decades, even if local populations and built environments have.

### Population change

Next, we examine the correlation between local disaster impact and population change. Summary statistics in Table 1 indicate that U.S. counties grew in population by an average of approximately 11% during the 1990s. If classic findings about “functional recoveries” remain valid, we would expect no significant correlation between total damages during the decade and population change. To test this hypothesis, Table 2 reports the results of four regression models. Models 1 and 2 are baseline models that first assess the difference between using a simple dichotomous measure of disaster impact (yes/no), like the one used in classic studies, and our alternative, continuous measure of cumulative property damage (logged). To construct the dichotomous measure for the 1990s, we identified all counties that experienced more than \$1 million in property damage during the decade and set these counties equal to one; all other counties are set to zero. The rationale is that



**Fig. 1** Map of total property damage at county level from environmental hazards during the 1990s (constant dollars)

**Table 2** Robust regression results predicting percent change in total population by disaster impact,  $N = 3,093$

	Model 1	Model 2	Model 3	Model 4
Major disaster (>\$1 M) (1 = yes; 0 = no)	1.910 (0.437)***			
ln(total property damages, \$)		0.230 (0.046)***	0.095 (0.038)*	0.100 (0.033)**
ln (area in 2000—sq. mi.)			-2.294 (0.620)***	-2.338 (0.533)***
% Non-white			-0.081 (0.015)***	-0.098 (0.013)***
Mean age			-0.086 (0.077)	-0.029 (0.067)
ln (median income)			2.822 (1.337)*	-1.092 (1.157)
Unemployed (%)			-0.327 (0.085)***	-0.355 (0.073)***
Employed in manufacturing (%)			0.081 (0.022)***	0.031 (0.019)
Employed in trade (%)			0.108 (0.051)*	0.134 (0.044)**
Houses built after 1949 (%)			0.558 (0.020)***	0.423 (0.018)***
Metro county (1 = yes; 0 = no)			0.705 (0.478)	-0.161 (0.412)
Coastal county (1 = yes; 0 = no)			0.372 (0.526)*	-0.089 (0.452)
Spatially lagged DV (population change)				0.098 (0.003)***
Constant	6.029 (1.350)***	4.177 (1.475)**	-69.827 (14.846)***	-12.944 (12.918)
<i>F</i> test	<i>F</i> (50, 3042) 27.91	<i>F</i> (50, 3042) 27.84	<i>F</i> (60, 3032) 59.96	<i>F</i> (61, 3031) 106.33
Prob > <i>F</i>	0.000	0.000	0.000	0.000

All models include (but do not report) dummy variables for states to control for unobserved differences among them, with Texas serving as the reference category

We re-estimated Model 4 with a temporal lag for population change in 1980–1990 as an additional control variable. Although the coefficient of 0.432 for this variable was statistically significant at the 0.001 level, it did not change the substantive results from those presented above. The new estimated coefficient for ln (total property damages, \$) in this model was 0.080 at a *p* value of .006

Standard errors in parentheses

\*  $p < .05$ ; \*\*  $p < .01$ ; \*\*\*  $p < .001$  (two-tailed tests)

total damage of this magnitude is sufficiently large to attract the type of government and media reports used by earlier studies to designate disaster-stricken counties. Results indicate that 54% of counties experienced such damage during the 1990s, which is very similar to the 52% reported by Wright and colleagues for the 1960s.

Turning to the regression results, Model 1 reveals a positive and statistically significant correlation between the dichotomous indicator of disaster impact and local population growth ( $b = 1.910$ ;  $p$  value  $< .001$ ). This finding is affirmed by Model 2, which uses our continuous measure of total disaster impact ( $b = 0.230$ ;

$p$  value  $< .001$ ). Appropriate calculations from this second model indicate that a county experiencing \$1 million in total property damage during the 1990s grew in population by an average of 3.2 percentage points more than a county experiencing no disaster-related property damage. These and similar calculations made below are computed by solving the estimated equation and holding all other variables, including those for state effects, constant at their sample means and solving the estimated equation. (For example, in this case, a county experiencing no disaster-related property damage grew by an estimated average of 5.9%; a county experiencing \$1 million in disaster-related property damage grew by an estimated average of 9.1%. These calculations also imply that a county experiencing \$1 million dollars in disaster-related property damage grew 53% more than a county experiencing no disaster-related damage:  $[9.1 - 5.9]/5.9 = 0.53$ .) These baseline findings imply that, contrary to classic studies of the past, a *positive* relationship now exists between local disaster impact and population growth.

Next, Models 3 and 4 of Table 2 add control variables to assess whether this apparent relationship is explained by other covariates or patterns of spatial dependence in population growth. In both cases, the answer is no. Although the observed relationship between local disaster damage and population growth attenuates in these models, it, nonetheless, remains positive and statistically significant at the 0.05 level. Moreover, Model 4, which provides the best overall fit to the data, shows that this finding holds even after controlling for average population growth in neighboring counties (as measured by the spatially lagged dependent variable). Overall, these findings suggest that past studies that found no significant relationship between local disaster impact and population change now require reconsideration.

To investigate these patterns further and to test for potential differences between long- and short-term recovery, we constructed separate disaster variables for damages incurred during the first half of the 1990s (1990–1994) and those incurred during the second half of the 1990s (1995–1999). We then entered both variables (in logged form) into a revised Model 4 in the place of total damage for the decade. Results (not shown) indicate that coefficients for early and late disaster impact are both positive, but do not differ significantly from one another, based on an appropriate Wald test. These supplemental findings imply that, on average and all else equal, local population growth following disasters occurs relatively steadily over time in response to cumulative damage, with relatively little observable difference between long- and short-term effects. In other words, relative impact appears to matter more for population change over a given decade than the timing of such impact.

### Housing change

To investigate the relationship between disaster and housing change, Table 3 replicates the same basic approach as above. Here, baseline Models 1 and 2 offer further support for the finding that disasters, on average, correlate positively with local growth. Indeed, appropriate calculations (see above for details) from Model 2 indicate that a county experiencing \$1 million in disaster damage during the 1990s experienced housing growth that was an average of 3 percentage points higher than a county experiencing no such disaster damage during the decade. Models 3 and 4

**Table 3** Robust regression results predicting percent change in total housing units by disaster impact,  $N = 3,093$

	Model 1	Model 2	Model 3	Model 4
Major damage (>\$1 M) (1 = yes; 0 = no)	1.685 (0.386)***			
ln(total property damages, \$)		0.172 (0.00)***	0.088 (0.032)**	0.090 (0.029)**
ln (area in 2000—sq. mi.)			-2.116 (0.524)***	-2.687 (0.467)***
% Non-white			-0.123 (0.013)***	-0.128 (0.011)***
Mean age			-0.492 (0.065)***	-0.574 (0.059)***
ln (median income)			-2.293 (1.129)*	-5.382 (1.018)***
Unemployed (%)			-0.357 (0.072)***	-0.380 (0.064)***
Employed in manufacturing (%)			0.137 (0.019)***	0.094 (0.017)***
Employed in trade (%)			0.019 (0.043)	0.030 (0.039)
Houses built after 1949 (%)			0.474 (0.017)***	372 (0.016)***
Metro county (1 = yes; 0 = no)			1.006 (0.404)*	666 (0.362)
Coastal county (1 = yes; 0 = no)			0.528 (0.445)	146 (0.398)
Spatially lagged DV (housing change)				070 (0.002)***
Constant	16.190 (1.192)***	15.074 (1.304)***	20.331 (12.539)	64.718 (11.368)***
<i>F</i> test	<i>F</i> (50, 3042)	<i>F</i> (50, 3042)	<i>F</i> (60, 3032)	<i>F</i> (61, 3031)
	37.40	37.21	78.12	115.91
Prob > <i>F</i>	0.000	0.000	0.000	0.000

All models include (but do not report) dummy variables for states to control for unobserved differences among them, with Texas serving as the reference category. We re-estimated Model 4 with a temporal lag for housing change in 1980–1990 as an additional control variable. Although the coefficient of 0.331 for this variable was statistically significant at the 0.001 level, it did not change the substantive results from those presented above. The new estimated coefficient in this model for ln (total property damages, \$) was 0.088 at a  $p$  value of .001

Standard errors in parentheses

\*  $p < .05$ ; \*\*  $p < .01$ ; \*\*\*  $p < .001$  (two-tailed tests)

again affirm this basic relationship, thereby lending additional support to the conclusion that disasters tend to bring with them local demographic expansion, net of relevant covariates, including growth patterns in neighboring counties. Moreover, the fact that estimated coefficients for housing growth in Models 3 and 4 are so similar to those in Table 2 for population growth suggests that both of these dimensions of local demographic change tend to grow together at roughly the same pace following disaster. This assessment is further supported by supplemental analyses (not shown), which again indicate that local housing growth is more responsive to the overall impact of disasters during the decade than their early (1990–1994) or late (1995–1999) timing.

### Changes in family income and poor subpopulations

This final set of analyses examines two summary indicators of local well-being to assess how disaster recovery may shift the basic socioeconomic structure of affected areas. To make this assessment, we re-estimate Model 4 from prior analyses using percent change in median family income and percent change in number of persons living in poverty as our new dependent variables. We use Model 4 from earlier analyses because it provides the best overall fit to the data and because it provides the most rigorous empirical test of the relationship between local disaster damage and demographic change. Results appear in Table 4.

The first model examines changes in median family income and reveals the same positive and significant correlation found in prior analyses: that is, as local disaster damage increases, so too does median family income, all else equal ( $b = 0.116$ ;  $p$  value  $< .01$ ). Indeed, appropriate calculations indicate that a county experiencing \$1 million in disaster damage during the 1990s experienced an increase in median family income that was an average of 2 percentage points higher than a county experiencing no disaster-related property damage, all else equal. By contrast, the second model in Table 4 indicates no significant correlation between the number of residents living in poverty and local disaster damage ( $b = 0.006$ ;  $p$  value  $> .95$ ). Taken together, these findings imply that disasters tend to benefit residents in the upper half of the income distribution while doing little to alter the number of residents living in poverty, all else equal. This finding is consistent with recent research by Belasen and Polachek (2009), who find that hurricane-stricken counties of Florida experienced higher earnings growth, but lower employment growth during recovery than unaffected counties. Our findings also imply that income inequality between those in the upper half of the local income distribution and those in poverty tends to increase during disaster recovery, contributing to growing socioeconomic disparity, or polarization, within the affected areas.

These patterns are consistent with the expectation that middle- and upper-class residents who can afford private insurance coverage, especially on properties located in higher-valued neighborhoods, typically receive financial windfalls from governmental assistance and personal insurance claims that not only help them to restore their housing and businesses but also, in many cases, actually upgrade them. These residents typically re-roof with stronger materials, install fancier kitchens, improve existing electrical systems, and install new amenities that further increase

**Table 4** Robust regression results predicting percent change in median family income and population living in poverty by disaster impact,  $N = 3,093$ 

	Change in median family income Model 1 (%)	Change in population living in poverty Model 2 (%)
ln(total property damages, \$)	0.116 (0.038)**	0.006 (0.111)
ln (area in 2000—sq. mi.)	−3.560 (0.619)***	4.498 (1.810)*
Non-white (%)	−0.114 (0.015)***	0.171 (0.044)***
Mean age	−0.024 (0.077)	−0.267 (0.225)
ln (median income)	−26.043 (1.339)***	38.807 (3.911)***
Unemployed (%)	−0.506 (0.085)***	0.068 (0.248)
Employed in manufacturing (%)	−0.116 (0.022)***	0.067 (0.064)
Employed in trade (%)	−0.209 (0.052)***	0.388 (0.150)*
Houses built after 1949 (%)	0.153 (0.020)***	0.028 (0.058)
Metro county (1 = yes; 0 = no)	2.666 (0.477)***	−3.637 (1.392)**
Coastal county (1 = yes; 0 = no)	1.300 (.525)*	0.403 (1.532)
Spatially lagged DV (change in median income)	0.412 (0.027)***	−
Spatially lagged DV (change in poverty)	−	0.281 (0.029)***
Constant	290.527 (14.973)***	−344.364 (43.238)***
<i>F</i> test	$F(61, 3031)$ 35.34	$F(61, 3031)$ 31.56
Prob > <i>F</i>	0.000	0.000

All models include (but do not report) dummy variables for states to control for unobserved differences among them, with Texas serving as the reference category

We re-estimated Models 1 and 2 with a temporal lag for change in the respective dependent variable in 1980–1990 as an additional control variable. The coefficient for this variable was statistically insignificant in Model 1. In Model 2, it was statistically significant at the 0.001 level, but it did not change the substantive results from those presented above. The new estimated coefficient for ln (total property damages, \$) in this model was 0.051 at a  $p$  value of .412

Standard errors in parentheses

\*  $p < .05$ ; \*\*  $p < .01$ ; \*\*\*  $p < .001$  (two-tailed tests)

the value and returns from work and property ownership in the affected region. After Hurricane Hugo hit Charleston, South Carolina, a local reporter dubbed this phenomenon the Jacuzzi effect because, “A lot of people had Jacuzzis after Hugo who didn’t have them before” (see Mullener 2005). Similarly, Tierney (2006: 210) has referred to this phenomenon as the Matthew Effect in action because “Benefits accrue to those who possess wealth and social and cultural capital, while larger proportional losses are borne by the poor and marginalized.” These scenarios imply that local recoveries unfold differently for unequal groups of residents, despite overall population and housing growth in affected areas.

## Conclusion

Given the political nature of disasters and expansion of government recovery assistance programs over recent decades, it makes practical, analytical, and

theoretical sense to re-examine how local areas across the United States change demographically as they recover from environmental hazards, thereby updating classic analyses last conducted with data from the 1960s, when fewer disasters were formally recorded and fewer residents lived in the nation's most environmentally vulnerable areas. Several conclusions emerge from our re-analysis.

First, environmental hazards of one type or another occur just about everywhere in the United States. If we count events that caused at least \$50,000 in (non-crop) property damage or resulted in at least one fatality, we find that less than 4% of all counties escaped such harm during the 1990s and that those that were hit experienced property damage totaling more than \$52 billion (in constant 2008 dollars). Second, we find strong evidence that disasters and associated recoveries bring with them local growth in population and housing beyond what we might otherwise expect. This finding is significant because it indicates that earlier findings by researchers such as Wright et al. (1979) no longer apply. Instead of merely achieving "functional recoveries," disaster-affected areas now tend to experience demographic growth spurts, and the greater the cumulative damage, the bigger the spurt. Third, this type of disaster recovery appears to polarize the socioeconomic structure of local areas by raising median family incomes without reducing the relative number of residents in poverty. This finding offers generalized support for case studies that find that disasters and associated recoveries tend to affect different strata of local populations differently, with residents positioned toward the top of local income distributions often benefitting while those positioned toward the bottom continue to struggle. These case studies date back to Bates et al.'s (1963) study of hurricane recovery after Hurricane Audrey in 1957 and extend to more recent cases studies following disasters in Texas (Stallings 2002), California (Bolin and Stanford 1998), and Florida (Dash et al. 2007; Peacock et al. 1997).

Overall, our findings have several implications. First, they suggest that under current conditions, it may be more appropriate to think of disasters as long-term demographic "pulls" to affected areas than as short-term "pushes," although the two dynamics need not be mutually exclusive. Such reconceptualization de-emphasizes the immediate spectacle of disaster and draws much-needed attention to the unanticipated consequences that current recovery programs now seem to have on environmentally risky regions over time. This re-conceptualization lends credence to Pais and Elliott's (2008) thesis regarding post-disaster "recovery machines" and sheds additional light on how U.S. society unwittingly responds to environmental destruction of its built environment. This response generally results in recoveries characterized by an uneven conferral of public and private resources working to boost rather than discourage uneven growth and development in affected areas over the long run. To the extent that these resources come with strings attached, they remain largely bureaucratic and technological in orientation, aimed, for example, at adopting new building codes to mitigate future damage rather than avoiding population concentration and socioeconomic polarization along the way. The end result is an implicit national disaster policy that unintentionally promotes population growth and socioeconomic polarization in harm's way.

This line of interpretation illuminates the broader point that interactions between populations and their local environments are socially mediated in ways that reflect



not only humans' impact on the environment but also ongoing adjustments by residents and political actors to the devastation wrought by environmental hazards. By expanding conventional narratives about human relations with the environment to include these types of ongoing adjustments, we can continue to build a more comprehensive understanding of the highly dynamic and multidirectional interactions between populations and their environments. At the same time, it is worth noting several limitations of the present study that invite further attention and possible research.

First and foremost, our results rely on statistical methods that focus on averages rather than deep analysis of particular cases, which means that important nuances of local context and events are subsumed for the sake of generalizability. While we believe this approach offers a useful complement to case study research, it also means that our findings and implications will not necessarily apply to all cases, past or present. This point is especially relevant with regard to ongoing recovery along the Gulf Coast following Hurricanes Katrina and Rita, especially in New Orleans, where flood damage and long-term displacement were particularly acute. While only time will tell how this region will recover over the long term, recent studies of return migration to the area suggest that its recovery will likely involve socioeconomic polarization but not substantial population growth (Fussell and Elliott 2009; Fussell et al. 2010; Groen and Polivka 2010). If this is true, it suggests that there may be important exceptions to general patterns uncovered by our study and that these exceptions may be more likely in extreme events. Again, though, only time will tell, and certainly there has been evidence of population growth in some of the least-damaged areas of New Orleans, mainly along the higher ground stretching upriver from the French Quarter through Uptown neighborhoods (Liu et al. 2011).

Another limitation of our study is that it focused on net demographic change, which, while useful, does not reveal the underlying population flows involved. It simply points to where to look further. For example, one reason that local populations may increase in areas hit by environmental hazards may not only be because government programs and insurance policies fuel aggregate growth, but because former residents who left the area before the hazard feel a strong call home to help rebuild and reconnect with friends and family in the damaged area. Anecdotes of this sort were numerous in New Orleans after Hurricane Katrina (cf. Stringfield 2010) and receive more general treatment in Solnit's (2009) book, *A Paradise Built in Hell*. This potential source of in-migration invites deeper ethnographic study of new and return migrants to disaster recovery zones and encourages similar in-depth investigations of poor residents in these same areas: Are they primarily new arrivals, or long-time residents disadvantaged by local recovery efforts? Investigating these types of questions would complement existing research on population and the environment by linking with related research on migrant labor, racialized re-settlement policies, and the war against the poor, to name only a few, prominent areas of public concern.

A third limitation and area for future research involves the timing of local changes relative to observed hazards. In the present study, we followed the approach of classic research and examined aggregate, contemporaneous changes over the course of a given decade, looking for general patterns. We also conducted

supplemental analyses that examined broad differences between earlier and later disaster damage and its correlation with local demographic change. Future studies might develop more refined analyses of when exactly a given hazard struck and when observed changes in local populations not only occurred but peaked (e.g., Plyer et al. 2010). This line of inquiry would strengthen causal arguments and invite more detailed analysis of exactly how and when recovery funds become available to different factors in affected areas and how this, in turn, influences long-term recovery. We look forward to more research along these lines in the future.

## References

- Anselin, L., & Berra, A. (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. In A. Ullah & D. Giles (Eds.), *Handbook of applied economic statistics* (pp. 255–258). New York: CRC Press.
- Barnett, B. J. (1999). US government natural disaster assistance: Historical analysis and a proposal for the future. *Disasters*, 23(2), 139–155.
- Barry, J. M. (1998). *Rising tide: The great Mississippi flood of 1927 and how it changed America*. New York: Simon and Schuster.
- Bates, F. L., Fogleman, C. W., Parenton, V. J., Pittman, R. H., & Tracy, G. S. (1963). *The social and psychological consequences of a natural disaster: A longitudinal study of Hurricane Audrey*. Washington, D.C.: National Academy of Sciences, National Research Council.
- Belasen, A. R., & Polachek, S. W. (2009). How disasters affect local labor markets: The effects of Hurricanes in Florida. *Journal of Human Resources*, 44(1), 251–276.
- Blaikie, P., Cannon, T., Davis, I., & Wisner, B. (1994). *At risk: Natural hazards, people's vulnerability, and disasters*. New York, NY: Routledge.
- Bolin, R., & Stanford, L. (1998). *The Northridge earthquake: Vulnerability and disaster*. London: Routledge.
- Brunsmma, D. L., Overfelt, D., & Picou, J. S. (2010). *The sociology of Katrina: Perspectives on a modern catastrophe* (2nd ed.). New York: Rowman & Littlefield.
- Clarke, L. (2005). *Worst cases: Terror and catastrophe in the population imagination*. Chicago: University of Chicago.
- Cochrane, H. C. (1975). *Natural hazards and their distributive effects*. Boulder, CO: Institute of Behavior Science Monograph #NSF-RA-E-75-003.
- Cutter, S., Mitchell, J. T., & Scott, M. S. (2000). Revealing the vulnerability of people and places: A case study of Georgetown County, South Carolina. *Annals of the Association of American Geographers*, 90(4), 713–737.
- Dacy, D. C., & Kunreuther, H. (1969). *The economics of natural disasters: Implications for federal policy*. New York: Free Press.
- Dash, N., Morrow, B. H., Mainster, J., & Cunningham, L. (2007). Lasting effects of Hurricane Andrew on a working-class community. *Natural Hazards Review*, 8(1), 13–21.
- Dauber, M. L. (2005). The sympathetic state. *Law and History Review*, 23(2), 387–442.
- Douty, C. M. (1977). *The economics of localized disasters*. New York: Arno Press.
- Drabek, T. E. (1986). *Human system responses to disaster: An inventory of sociological findings*. NY: Springer.
- Dynes, R. R. (2000). The Lisbon earthquake of 1755: Contested meanings in the first modern disaster. *TsuInfo Alert*, 2, 10–18.
- Elliott, J., & Frickel, S. (2011). Environmental dimensions of urban change: Uncovering relict industrial waste sites and subsequent land use conversions in Portland and New Orleans. *Journal of Urban Affairs*, 33(1), 61–82.
- FEMA (Federal Emergency Management Agency). (2011). *Declared disasters by year*. Available from [http://www.fema.gov/news/disaster\\_totals\\_annual.fema](http://www.fema.gov/news/disaster_totals_annual.fema). Accessed July 2011.

- Foster, J. (1999). Marx's theory of metabolic rift: Classical foundations for environmental sociology. *American Journal of Sociology*, 105(2), 366–405.
- Fothergill, A., & Peek, L. A. (2004). Poverty and disaster in the United States: A review of recent sociological findings. *Natural Hazards*, 32, 89–110.
- Friesema, H. P., Caporaso, J. A., Goldstein, G., Lineberry, R., & McMcleary, R. (1977). *Community impacts of natural disasters*. Evanston, IL: Northwestern University Press.
- Fussell, E., & Elliott, J. R. (2009). Social organization of demographic responses to disaster: Studying population-environment interactions in the case of Hurricane Katrina. *Organization & Environment*, 22(4), 379–394.
- Fussell, E., Sastry, N., & VanLandingham, M. (2010). Race, socioeconomic status, and return migration to New Orleans after Hurricane Katrina. *Population and Environment*, 31(1–3), 20–42.
- Garrett, T. A., & Sobel, R. S. (2003). *The political economy of FEMA disaster payments*. St. Louis, MO: Federal Reserve Bank of St. Louis.
- Groen, J. A., & Polivka, A. E. (2010). Going home after Hurricane Katrina: Determinants of return migration and changes in affected areas. *Demography*, 47(4), 821–844.
- Gutmann, M., & Field, V. (2010). Katrina in historical context: Environment and migration in the U.S. *Population and Environment*, 31(1–3), 3–19.
- Haas, J. E., Kates, R. W., & Bowden, M. J. (1977). *Reconstruction following a disaster*. Boston: MIT Press.
- Halaby, C. N. (2004). Panel models in sociological research: Theory into practice. *Annual Review of Sociology*, 30, 507–544.
- Hamilton, L. C. (2009). *Statistics with Stata*. Florence, KY: Cengage.
- Hazards and Vulnerability Research Institute (2010). *The spatial hazard events and losses database for the United States, Version 8.0*. Columbia, SC: University of South Carolina. Available from <http://www.sheldus.org>.
- Hewitt, K. (1997). *Regions of risk: A geographic introduction to disasters*. London: Longman.
- HUD (U.S. Department of Housing and Urban Development). (2008). *Fiscal year 2008 budget summary*. Washington, DC: U.S. Department of Housing and Urban Development.
- Hunter, L. M. (1998). The association between environmental risk and internal migration flows. *Population and Environment*, 19(3), 247–277.
- Hunter, L. M. (2005). Migration and environmental hazards. *Population and Environment*, 26(4), 273–302.
- Liu, A., Anglin, R. V., Mizelle, R. M., Jr, & Plyer, A. (Eds.). (2011). *Resilience and opportunity: Lessons from the U.S. Gulf Coast after Katrina and Rita*. Washington, DC: Brookings Institution.
- Melosi, M. (2010). Humans, cities, and nature: How do cities fit in the material world? *Journal of Urban History*, 36(1), 3–21.
- Moss, D. (1999). Courting disaster? The transformation of federal disaster policy since 1803. In K. A. Froot (Ed.), *The financing of catastrophe risk* (pp. 307–362). Chicago: University of Chicago.
- Mullener, E. (2005). *A sister city flourishes*. New Orleans: Times-Picayune.
- Myers, C., Slack, T., & Singelmann, J. (2008). Social vulnerability and migration in the wake of disaster: The case of Hurricanes Katrina and Rita. *Population and Environment*, 29(6), 271–291.
- NOAA (National Oceanic and Atmospheric Administration). (2011). U.S. Sets record with a dozen billion-dollar weather disasters in one year. Available at: [http://www.noaanews.noaa.gov/stories/2011/20111207\\_novusstats.html](http://www.noaanews.noaa.gov/stories/2011/20111207_novusstats.html). Accessed 15 December 2011.
- Oliver-Smith, A. (1998). Global changes and the definition of disaster. In E. L. Quarantelli (Ed.), *What is a disaster? Perspectives on the question* (pp. 179–196). New York: Routledge.
- Pais, J., & Elliott, J. R. (2008). Places as recovery machines: Vulnerability and neighborhood change after major hurricanes. *Social Forces*, 86(4), 1415.
- Peacock, W. G., Morrow, B. H., & Gladwin, H. (1997). *Hurricane Andrew: Ethnicity, gender and the sociology of disasters*. New York: Routledge.
- Perrow, C. (2007). *The next catastrophe: Reducing our vulnerabilities to natural, industrial, and terrorist disasters*. Princeton, New Jersey: Princeton University.
- Plyer, A., Bonaguro, J., & Hodges, K. (2010). Using administrative data to estimate population displacement and resettlement following a catastrophic U.S. disaster. *Population and Environment*, 31(1–3), 150–175.
- Quarantelli, E. L. (1998). *What is a disaster? Perspectives on the question*. New York: Routledge.
- Solnit, R. (2009). *A paradise built in hell: The extraordinary communities that arise in disaster*. New York: Viking.

- Stallings, R. A. (2002). Weberian political sociology and sociological disaster studies. *Sociological Forum*, 17(2), 281–305.
- Steinberg, T. (2006). *Acts of god: The unnatural history of natural disaster in America*. New York: Oxford University Press.
- Stringfield, J. (2010). Higher ground: An exploratory analysis of characteristics affecting returning populations after Hurricane Katrina. *Population and Environment*, 31(1–3), 43–63.
- Tierney, K. (2006). *Facing hazards and disasters understanding human dimensions*. Washington, D.C.: The National Academies Press.
- U.S. Census Bureau. (nd). *Decennials - census of population and housing*. Washington, DC: Author. Available from <http://www.census.gov/prod/www/abs/decennial/>.. Accessed May 2011.
- Verardi, V., & Croux, C. (2008). *Robust regression in Stata*. Available via SSRN. <http://ssrn.com/abstract=1369144>. Accessed 3 May 2011.
- Voss, P. R., Long, D. D., Hammer, R. B., & Friedman, S. (2006). County child poverty rates in the US: A spatial regression approach. *Population Research Policy Review*, 25, 369–391.
- Wright, J. D., & Rossi, P. H. (1981). *Social science & natural hazards*. Cambridge, MA: Abt Books.
- Wright, J. D., Rossi, P. H., Wright, S. R., & Weber-Burdin, E. (1979). *After the clean-up: Long-range effects of natural disasters*. Beverly Hills, CA: Sage.
- York, R., Rosa, E., & Dietz, T. (2003). Footprints on the earth: The environmental consequences of modernity. *American Sociological Review*, 68(2), 279–300.
- Zack, N. (2010). *Ethics for disaster*. Lanham, MD: Rowman and Littlefield Publishers.