CITY & COMMUNITY

Uneven Neighborhood Recovery: Hurricane Damage and Neighborhood Change in the Houston–Galveston Region Since 1970

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Despite the growing number of natural disasters around the globe, limited research exists on post-disaster patterns of neighborhood change. In this paper, we test two theories of neighborhood change, the "recovery machine" and "rent gap," which predict opposing effects for low socioeconomic status (SES) neighborhoods following damage from hurricanes, tropical storms, and other natural hazard events. The recovery machine theory posits that after natural hazard events, local communities experience patterns of recovery based on their pre-disaster SES and access to resources, suggesting that wealthier neighborhoods will recover robustly while lower status neighborhoods languish. In contrast, the rent gap theory suggests that developers will identify a profit opportunity in the depressed values created by damage from natural hazard events, and seek to redevelop low SES areas. We use fixed effects models with census data from 1970 to 2015 to test the impact of damage from natural hazards on neighborhood change. We find substantial recovery and change in low-income neighborhoods, but not in the high-income neighborhoods supporting the rent gap theory. We conclude that natural hazard events resulting in damage produce uneven recovery by socioeconomic status of neighborhoods, potentially leading to displacement of low SES groups.

INTRODUCTION

Despite the growing number of hurricanes and extreme weather events, the academic literature on the patterns of rebuilding and neighborhood change as a result of damage from these events has not kept pace (Fussell et al. 2017; Lee 2017). This is a major gap in the literature, as the number, intensity, and cost of natural disasters around the globe is expected to increase in coming decades (NASA 2017). The impacts of hurricanes, storms, and other natural hazards and disasters (henceforth, natural hazard

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City & Community 0:0 April 2019
doi: 10.1111/cico.12390

events) are not evenly felt, as the effects of these events are generally deeper and longer lasting in low socioeconomic status (SES) communities, where buildings are of lower quality and residents are less prepared to absorb the financial hardship of recovery and rebuilding (Comerio 1998; Pais and Elliott 2008; Peacock et al. 2014; Smith 2006).

For a neighborhood damaged by a natural hazard event, change is inevitable (Romero 2018). Even if it is rebuilt and maintains its demographic and socioeconomic profile, the condition of the housing stock will be altered. However, the recovery process may lead a neighborhood to one of two alternative states. As a result of the damage, neighborhoods may deteriorate under the weight of abandoned housing and damaged infrastructure. Alternatively, the neighborhood may be rebuilt, returning to pre-impact or better condition, and attracting higher socioeconomic status residents.

In this paper, we test two theories of neighborhood change in the context of natural hazard events, which predict opposite directions of recovery of low SES areas: 1) "recovery machine" (Pais and Elliott 2008), and 2) the "rent gap" (Smith 1979). The recovery machine theory posits that following natural hazard events, local communities experience uneven patterns of recovery based on their pre-hazard event status, which influences post-hazard event access to resources. If the recovery machine theory holds, these resource disparities allow wealthier neighborhoods to recover, while lower SES neighborhoods languish. Smith's (1979) rent gap theory, applied to the post-hazard event context, suggests that damage from natural hazard events will depress real estate values and increase the economic difference between the current and best use of local land. Thus, natural hazard events allow developers to turn a profit by building in these areas, creating recovery, but also increasing real estate values. However, the higher values typically result in a new population of higher SES residents, and displacement of lower SES residents who can no longer afford to live in these neighborhoods. Thus, these theories predict opposing trajectories for low SES communities damaged by natural hazards, with the recovery machine theory predicting a protracted recovery in low SES neighborhoods, while rent gap predicts a robust recovery in these same neighborhoods.

To test these two theories, we analyze neighborhood change in the Houston–Galveston metropolitan area as a function of damage from natural hazards for the period 1970 to 2015. We examine neighborhood trajectories during that 45-year time span, asking what effect natural hazard events have on neighborhood change, with a focus on the differing trajectories of recovery for high- and low-income neighborhoods. We find substantial increases in the value and SES of low-income neighborhoods with larger amounts of damage from natural hazard events; damage from natural hazard events in low-income neighborhoods is positively correlated with median rent, housing density, median income, education levels, and share of white residents at the end of the decade.

In the following section, we ground our study in the literature on patterns of damage from natural hazards and their impacts on neighborhood change, before outlining the theoretical frameworks for predicting recovery for low SES areas. Next, we present an overview of the Houston-Galveston metropolitan area and past natural hazard events in the region, along with details about the data and methodology. Finally, we present the results along with a discussion of the implications for policy related to redevelopment and recovery following natural hazard events.

PATTERNS OF DISASTER DAMAGE AND RECOVERY

Although natural hazards do not discriminate on socioeconomic grounds, disasters exist because of the interaction of some hazard with socioecological systems, and low SES communities are at a particularly disadvantaged position during the post-disaster period. Following Hurricane Katrina Smith (2006:1) argued that "there's no such thing as a natural disaster," because the patterns of harm are directly impacted by the choices of policy makers during the pre- and post-disaster periods. Thus, preexisting social inequalities can be exacerbated by post-disaster policy (Peacock et al. 2014) and can result in the deepening of preexisting inequalities (Van Zandt and Sloan 2017).

High levels of damage expose and compound the physical and socioeconomic vulnerabilities of communities. In combination with the complexities embedded in population displacement and housing recovery, disasters disproportionally affect low SES communities, because they are the least equipped of all groups to access financial and other resources during the post-event recovery and reconstruction period (Comerio 1998; Dash et al. 2007; Peacock et al. 1997, 2014; Sapat and Esnard 2017; Van Zandt and Sloan 2017). These disparities lead not only to neighborhood, but also larger scale social changes. After Katrina, the post-disaster population was wealthier and racially whiter than the pre-disaster population of New Orleans (Frey and Singer 2006).

Socially vulnerable populations are not randomly distributed throughout regions and cities, and natural hazards often have more pronounced effects on low SES communities. The availability and affordability of housing lead to concentrated patterns of settlement and segregation of poor and minority households in relatively less favorable locations (Van Zandt and Sloan 2017). These communities are more likely to occupy low lying (i.e., flood prone) areas, where the infrastructure is older or of a lower quality, and the residents are less likely to have taken mitigation measures or steps to retrofit their homes (Van Zandt et al. 2012). Low SES households are also more often located in under-maintained and dilapidated structures, built to less-stringent building codes with inferior materials (Bolin and Stanford 1998; Peacock et al. 2014; Stough 2010; Weber and Lichtenstein 2015). At the time that Hurricane Ike struck in 2008, the beachfront community in Galveston was struggling economically, with nearly a quarter of the island's residents living below the poverty line. After the hurricane tens of thousands of residents lost their jobs, and four of the island's public housing projects were destroyed (Witt 2009). Further, the effects of natural disasters may be geographically heterogeneous by density of development. In the hardest hit neighborhoods, low SES residents become concentrated in rural, low density areas, but are displaced from more urbanized neighborhoods during recovery (Elliott and Pais 2010). On the county level, prevailing population trends may be a stronger determinant of subsequent population change than hurricane damage for all but the most dense and fastest growing counties (Fussell et al. 2017).

Social vulnerabilities are related to SES factors including race, poverty, and educational attainment (Fothergill and Peak 2004; Fussell and Harris 2014); these factors dictate where people reside, and the choice of residence helps determine their access to resources that may help in disaster recovery (Elliott and Pais 2010; Peacock et al. 2014). For example, minorities are more likely than white Americans to rent a home (Fussell and Harris 2014), and renting a home introduces an additional source of vulnerability after disaster (Fothergill and Peek 2004). Renters lack control over the return to their dwelling (Burby et al. 2003; Van Zandt and Sloan 2017), face potential rate hikes, and minority renters may face discrimination when seeking new housing (Hunter 2005). In addition, due to reduced housing supply, rental prices in low SES neighborhoods often increase significantly after a natural hazard event, creating an additional hardship (Finger 2015; Stough et al. 2016). For instance, in New Orleans after Hurricane Katrina, more than 35 percent of public housing apartments were demolished, leaving many of the mostly African American residents without good housing options, and rent increased by roughly one-third for one bedroom apartments (Finger 2015). Further, Louisiana's law allowing a notice of eviction to be pinned to the front door allowed landlords to evict thousands of renters, even while they were displaced. To exacerbate matters, a temporary courthouse was established at a location 60 miles away, making it all the more challenging for low-income persons to represent themselves (Finger 2015). For low-income residents who do own, their housing is often not insured or is underinsured, and these groups generally have difficulties obtaining assistance through many federal disaster assistance programs (Bolin and Stanford 1998).

Damage to housing, businesses, and infrastructure can lead people to abandon neighborhoods after natural hazard events. Although Bolin and Stanford (1998) found that residents abandoned the most damaged neighborhoods regardless of their income after the Northridge earthquake, housing abandonment may be exacerbated in low SES neighborhoods. However, in other literature, vulnerable populations in areas with a high level of housing damage have been found to be more likely to experience a population exodus as a result of a disaster (Myers et al. 2008). For instance, in New Orleans after Hurricane Katrina, damage was found to have been greater in low SES neighborhoods, as the hurricane's effects fell disproportionately on African Americans, renters, and the unemployed. New Orleans lost over 60 percent of its public housing and 78 percent of New Orleans' rental stock required major repairs after Katrina (Finger 2015). Minority and low-income households were far more likely than those in higher-income households to have left the city owing to the damage and disruptions (Frey and Singer 2006).

Researchers have generally found that low SES status neighborhoods recover at a slower pace. For instance, at the county level, Schultz and Elliott (2013) found evidence of uneven recovery by SES after disasters for the entire United States during the 1990s. Similarly, Finch et al. (2010) found that there were clear disparities in the recovery of vulnerable neighborhoods, and the ability of low-income households to return to their predisaster homes in the city, relative to higher income groups. Even when low SES households are not overrepresented in damage, such as in the aftermath of the Northridge earthquake, these households suffered far greater losses as a percentage of their overall material wealth (Bolin and Stanford 1998). Van Zandt and Sloan (2017) and Peacock et al. (2014) reported that lower-value homes in Galveston took longer to rebuild, compared to higher-value homes, which typically recovered after 2 years. Similarly, low-income neighborhoods in Alabama damaged by an EF 4 tornado recovered at a slower pace than higher income neighborhoods (Weber and Lichtenstein 2015).

Additionally, the majority of the literature focuses on the immediate differences in neighborhood recovery after a natural hazard event, but a growing literature employing a longer time horizon is revealing important new insights to our understanding of recovery from natural hazard events. For instance, Contardo et al. (2018) found that neighborhoods in Talca, Chile, demonstrated signs of gentrification following a 2010 earthquake. In a similar vein van Holm and Wyczalkowski (2018) found that impoverished neighborhoods in New Orleans that suffered greater damage from Hurricane Katrina gentrified at a higher rate one decade after the storm.

THEORETICAL FRAMEWORKS OF NEIGHBORHOOD CHANGE: RECOVERY MACHINE AND RENT GAP

Neighborhood change can pertain to the physical decline or upgrading of neighborhood housing infrastructure, or a shift in a neighborhood's socioeconomic makeup (Redfern 2003). A natural hazard event implicitly changes a neighborhood and necessitates redevelopment of the affected area. However, whether the damage leads to long-term decline, the neighborhood is returned to a state approximating its socioeconomic status prior to the disaster, or it is rebuilt to serve a different community is not well understood. The recovery machine and rent gap theories predict opposing outcomes for low SES neighborhoods following natural hazard events. The former predicts that a widening rent gap driven by the displacement of people in poverty and destruction of property will bring about investment and socioeconomic neighborhood uplift above its pre-event level. The recovery machine, on the other hand, ascribes socioeconomic momentum to neighborhoods, leaving them to recover at the rate that the economic, social, and political resources of the residents allow.

RECOVERY MACHINE

The "recovery machine" theory suggests that following natural hazard events, local communities experience uneven patterns of recovery based on their pre-event status. Communities with low SES are often located in the "most environmentally hazardous places," putting them at greater risk of damage from storms (Pais and Elliott 2008:1416). The pre-event status of the neighborhood also governs the post-disaster access to resources for rebuilding, and capital for investments in infrastructure and housing. This may be moderated by the level of urbanization (Elliott and Pais 2010; Pais and Elliott 2008). As a result, low SES neighborhoods become more dilapidated and face ever greater levels of underinvestment after a natural hazard event, meaning that over time these events "reproduce larger, more socially divided versions of themselves" and create conditions for ever greater uneven development from future natural hazard events (Pais and Elliott 2008:1448). In our analysis, a finding of slower growth in low SES neighborhoods post-event, relative to higher SES neighborhoods, would support this theory.

RENT GAP

Following a disaster, the destruction of property and widespread displacement of people, particularly those in poverty, can speed the process of neighborhood decline and provide a terra nova for developers. Severely damaged neighborhoods are more likely to undergo a transformation of their built environment in the process of reconstruction and recovery than other neighborhoods (Dash et al. 2007; Pais and Elliott 2008). The "rent gap" is one possible theoretical explanation for this neighborhood upgrading;

that is, neighborhoods where a “rent gap” forms between a parcel’s current use and its most economically advantageous use can experience this phenomenon (Smith 1979, 1982).

Smith (1979) speculated that developers, driven by profit, would invest in and rebuild declining neighborhoods at the point in time where a substantial “rent gap” forms. The relatively low cost of land attracts investment, and relatively higher income households outbid lower income households for housing near amenities. In the urban studies literature, proximity to employment, historical housing, gentrified areas, or other amenities have driven developers to exploit the rent gap. In this analysis, we view damage from a natural disaster as a force that may enlarge the rent gap, temporarily depressing the value of neighborhoods below their most advantageous use, and thus attract developers and accelerate neighborhood change.

STUDY AREA

We use a single study region to allow for a greater control of the impact of local context and cumulative effects. We use the Houston metropolitan area as a case study to analyze the impact of hurricanes, tropical storms, and other natural hazard events and disasters on neighborhood change. More specifically, we analyze the potential heterogeneous effect of these natural hazards on low SES and high SES neighborhoods.

The Houston metro and surrounding counties, which include the coastal city of Galveston, have a longstanding history of powerful tropical storms and hurricanes that have produced extreme rainfall, gale force winds, and coastal flooding. The study region is composed of the area demarcated by the nine county Houston–The Woodlands–Sugar Land Metropolitan Statistical Area (MSA), located along the Gulf coast in southeastern Texas (BLS 2017; Figure 1).

The Houston MSA is sprawling, having doubled its population since the 1970s, and is the fifth largest MSA in the United States with over 6.7 million residents (Greater Houston Partnership Research 2017; U.S. Census 2015). This widespread growth caused the replacement of former prairie land with impervious urban surfaces, forcing runoff and increasing the likelihood for flooding (Kim et al. 2016). Harris County is the most populous of the nine counties with over four million residents in 2016. The population of the other eight counties are: Austin (population 29,107), Brazoria (354,195), Chambers (38,072), Fort Bend (741,237), Galveston (329,431), Liberty (81,704), Montgomery (556,203), and Waller (47,049) (U.S. Census 2015). These eight counties provide variability in housing density, and make up less than half of the total population.

The Houston region is low lying and surrounded by water (Figure 2), and thus has been repeatedly threatened by hurricanes and tropical storms. The most famous storm occurred in 1900 when a category 4 hurricane devastated Galveston, Texas, killing over 8,000 people and demolishing homes and infrastructure (Murnane 2017; Roth 2010). According to Murnane (2017), almost the entire population of the city was left homeless and Galveston never fully recovered its commercial status as the major port city of the region. The most lasting impacts are seen by the shifting of investments and growth to nearby Houston (McComb 1986).

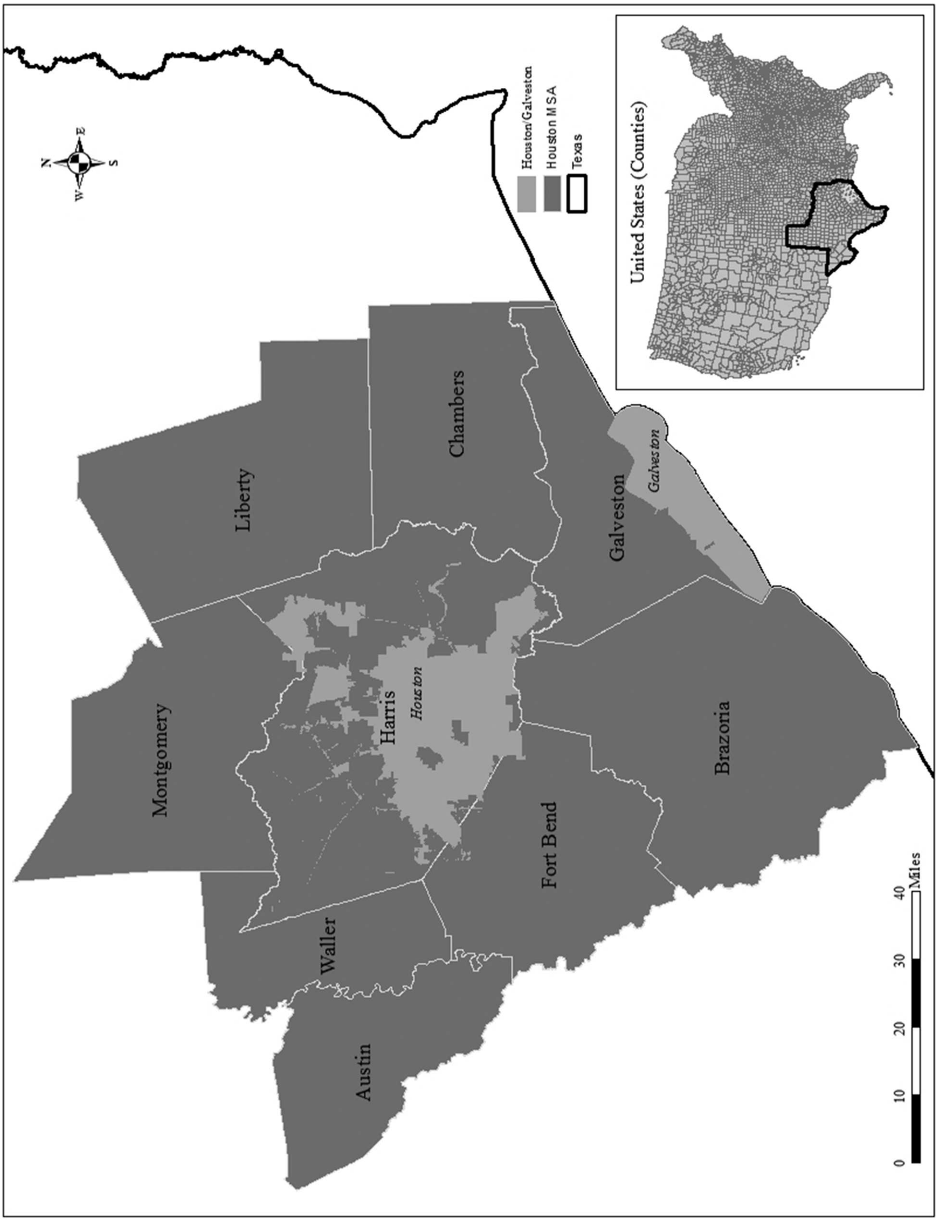

FIG. 1. Study Area

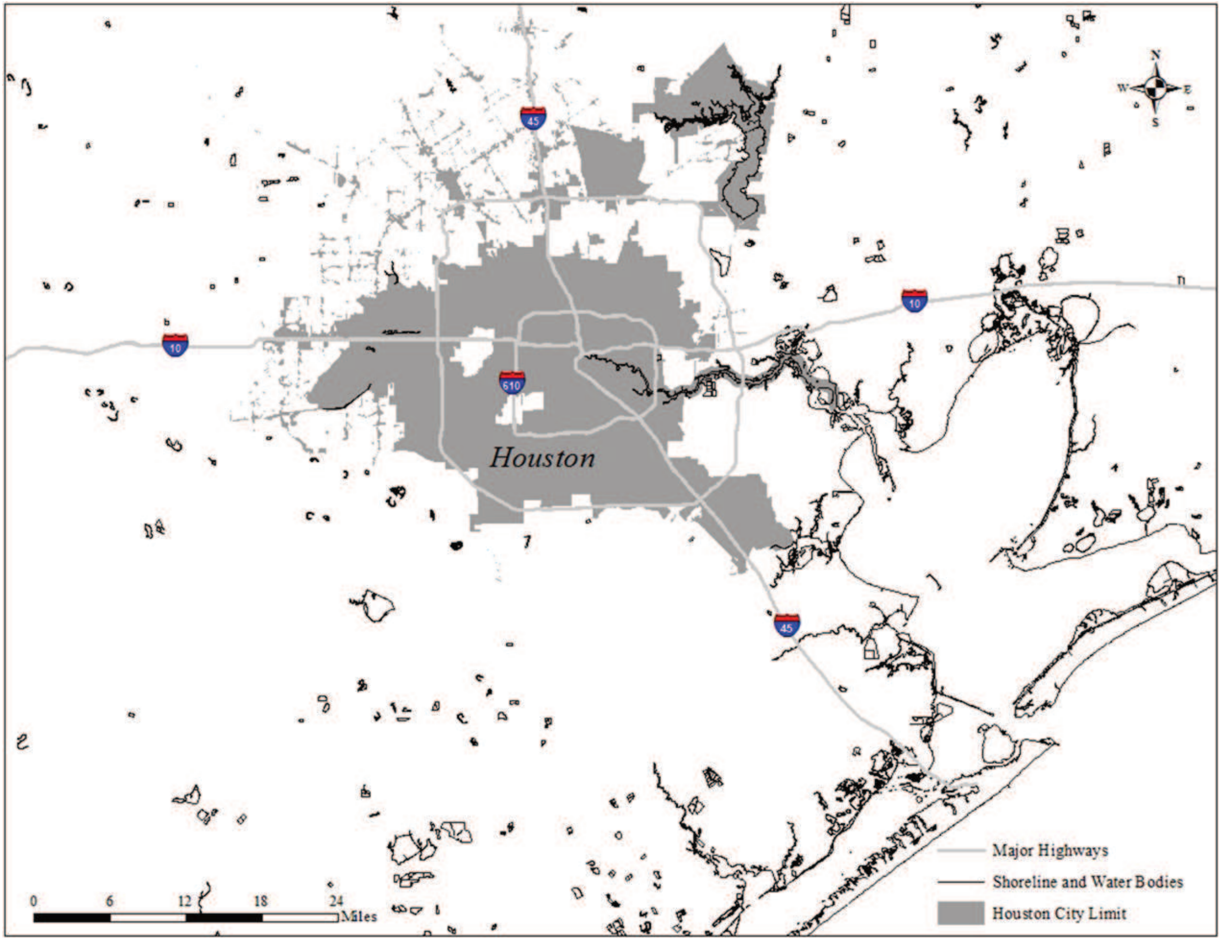

FIG. 2. Houston Shoreline and Water Bodies [Color figure can be viewed at wileyonlinelibrary.com]

The incidence and intensity of storms and hurricanes have increased in the region, which has experienced four hurricanes and two tropical storms since the 1970s. In 1983 and 1989, the area was hit by category 3 hurricane Alecia, and category 1 hurricane Jerry, respectively. In 2001, Tropical storm Alison dropped 36.99 inches of rain, causing widespread flooding in the city of Houston, and leaving behind over $5 billion in damage and dozens of fatalities (Roth 2010). In 2008, Hurricane Ike made landfall in Galveston as a Category 2 hurricane, and became one of the most destructive hurricanes to hit the United States at the time. Hurricane Ike caused 10- to 20-foot storm surges and resulted in approximately $29.5 billion in damage across the region. A year later, economic losses as a result of the hurricane raised the total cost of damage to $142 billion (Roth 2010; Texas Engineering Extension Service 2009). Five years after Hurricane Ike hit Galveston many buildings were still abandoned, and significant political fights about rebuilding public housing persisted (White 2013).

Most recently in 2017, although outside the scope of this study, the region was devastated by Hurricane Harvey, breaking new records for damage. Neighborhood opposition to rebuilding public and subsidized housing or building of affordable housing was a problem after Hurricane Ike, and the same dilemmas might surface in gentrifying areas of Houston after Hurricane Harvey (Satija 2018). According to Deaton (2017), low-income communities fared worse than wealthier areas in the flooded parts of Houston after Hurricane Harvey, given that some of the subsidized housing is in high flood risk areas. These low-income families then faced a tight rental market as they tried to recover (Schaper 2017). Harvey's devastating impacts to Houston, our study area, and low SES households are still unfolding. These repeated natural hazard impacts make Houston an ideal case study due to the temporal and spatial variability of damage.

DATA

To operationalize the impact of natural hazard events, we utilize county-level data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) from the Hazards & Vulnerability Institute (2016). SHELDUS aggregates data at the county level and reports damage[1] and fatalities from natural hazards, from 1960 to 2016. The dataset contains information on 18 types of hazards, including each event start date and the total assessed property damage. We calculated damage for a subset of eleven hazard types (i.e., coastal, drought, flood, hail, heat, hurricane/tropical storm, lightning, severe thunderstorm, tornado, wind, and winter weather) that have caused damage and losses in our study area and during our study period, in order to capture the effect of compounding damage. However, it should be noted that the bias to weather hazards such as floods, hurricanes, and tropical storms has been documented by Gall et al. (2009). Table 1 displays the impact of the subset of hazard events throughout the region, rounded to millions of inflation adjusted dollars across the years studied. As shown, there is variation in the damage caused by natural hazard events and disasters over time.

We observe neighborhood effects of county-level weather damage, acknowledging the fact that we are assuming that county-wide impacts will influence neighborhood trajectories. This assumption is based on broader impacts to county services, transportation, and electric power infrastructure, schools, and businesses that will spill over beyond

TABLE 1. Storm Damage by Decade (Millions) (2010 Dollars)

Year	Mean	Min.	Max.
1971–1980	$626.24	$16.11	$776.94
1981–1990	$112.1	$13.84	$124.45
1991–2000	$176.95	$23.87	$224.25
2000–2015	$248.3	0	$347

any individual neighborhood boundary; that is, hurricanes, tropical storms, and floods generally a broader spatial extent than census tracts. On a practical level, access to longitudinal damage data and geographic bias were additional considerations. Boundary changes to census tracts over the timeframe of our study would introduce more spatial inconsistencies in assignment of damage given that "most databases report losses according to the political boundaries at the time of the event" (Gall et al. 2009:805). Economic loss reporting at the county level is less prone to error. Furthermore, natural hazards such as floods, hurricanes, and tropical storms have wind fields that extend spatially beyond neighborhoods, and can cause property damage in multiple counties simultaneously (Czajkowski & Done 2014; Zahran et al. 2008).

U.S. Census data for the period 1970–2015 were used as the source of the socioeconomic and demographic characteristics (race, income, unemployment rate, and educational attainment), and the physical housing characteristics (housing density, age of housing, housing value, housing tenure, vacancy). While census tracts are used widely to approximate neighborhoods, their boundaries are altered decennially to maintain consistent population sizes in each unit across the country, therefore, making it more difficult to perform longitudinal analysis. To obtain data with consistent census tract boundaries across time, we utilized the Longitudinal Tract Database (LTDB), standardized to 2010 geographies (Logan et al. 2014).

In 2010, the long form of the U.S. Census was discontinued and replaced by the sample based American Community Survey (ACS). Collected annually, the ACS 5-year samples can be aggregated to the census tract level, approximating the now retired long form decennial Census. The 5-year ACS sample from 2010 is composed of data from 2006 to 2010. However, this is problematic for our analysis, because it leaves a smaller gap between observations than in the rest of the data. Given that Hurricane Ike struck in 2008, the 2006–2010 timeframe includes data both before and after the storm. Therefore, we utilize the 2015 5-year ACS[2] to ensure a full decade between data collections in any of our time points and avoid aggregating data from a significant natural hazard event. Thus, we include census data from 1970, 1980, 1990, 2000, and the 2015 5-year ACS in our analysis.

METHODOLOGY

Neighborhood change is generally operationalized in the literature using Census-derived socioeconomic and housing characteristics, alone or in combination. Often, the value of housing is used to operationalize neighborhood change, based on the assumption that any changes in neighborhood characteristics are capitalized into property values (Billings 2011; Bowes and Ihlanfeldt 2001; Cervero and Duncan 2002; Cervero and Landis 1993;

Debrezion et al. 2007; Du and Mulley 2012; Kahn 2007). However, measuring property values alone ignores the socioeconomic and demographic dimensions of change that occur alongside rising costs. A profile of a neighborhood consisting of demographic and socioeconomic measures (e.g., household income, the share of minorities, and educational attainment) is less frequently considered in the literature (Bates 2013; Freeman 2005; Grube-Cavers and Patterson 2015; Kahn 2007).

Our primary method of analysis relies on time and tract fixed effects panel regression models. We generated four models for the years 1970 to 2015 to analyze the impact of natural hazards on neighborhood change. Specifically, we test the change in housing value, change in housing density, change in median income, change in educational attainment, and change in percent white for census tract *i* at time *t*.

We constructed a model to account for other economic and demographic variables that may account for neighborhood change, along with the effect of natural hazard events. The key independent variable (Damage) was the total property value adjusted for inflation from natural disasters within a decade at the county level.

Along with damage, we also accounted for the socioeconomics, demographics, and physical housing characteristics of the neighborhood. The socioeconomic characteristics are race, unemployment rate, and median income. Race, measured with the percentage of white and black residents, may be a factor given the high potential for discriminatory practices after natural hazard events. The physical characteristics of housing is represented by the percentage of housing over 30 years old, the housing density, the vacancy rate, and the percentage of owner-occupied housing. We include these factors to ensure that the development level of all census tracts is held constant throughout the analysis and that the different trajectories of neighborhoods are accounted for in the results.

Hausman tests indicated that fixed effects, rather than random effects, was the correct fit for the model, and so we also account for the time and spatially invariant qualities of tracts and years. Thus, our final fixed effects models account for storm damage and socioeconomic and physical characteristics of neighborhoods, take the following form, where Y is the dependent variable, as described above:

$$Y_{it} = \beta_0 + \beta_1 \text{ Damage}_{it} + \beta_2 \text{ Socioeconomic}_{it\text{-}1} + \beta_3 \text{ Housing Characteristics}_{it\text{-}1} + \alpha_i + \varepsilon_{it}$$

Coastal location may be an important determinant of neighborhood change. However, fixed effect models difference out all time invariant factors. To maintain the potential effect of coastal location, we fit a hybrid model, with random effects for the minimum distance from each tract centroid to the coast, and fixed effects for all other terms (Firebaugh et al. 2013). The results for the hybrid model were consistent with the Fixed Effects model, and since that is the correct functional form, we chose to report those results.

We first analyze the effect of hazard events and natural disasters on all census tracts in the Houston region, before taking two subsamples of the data based on the income of neighborhoods, utilizing the same model as above. Specifically, we extracted tracts that were in the highest and lowest quartile based on median income in the preceding decade to study the impact of socioeconomic conditions on neighborhood change. Thus, in the second set of analyses (Tables 3 and 4) tracts move in and out of the sample based upon their level of income at that point in time. This second set of analyses allows us to better isolate the effect of damage in neighborhoods based on their prior level of median household income.

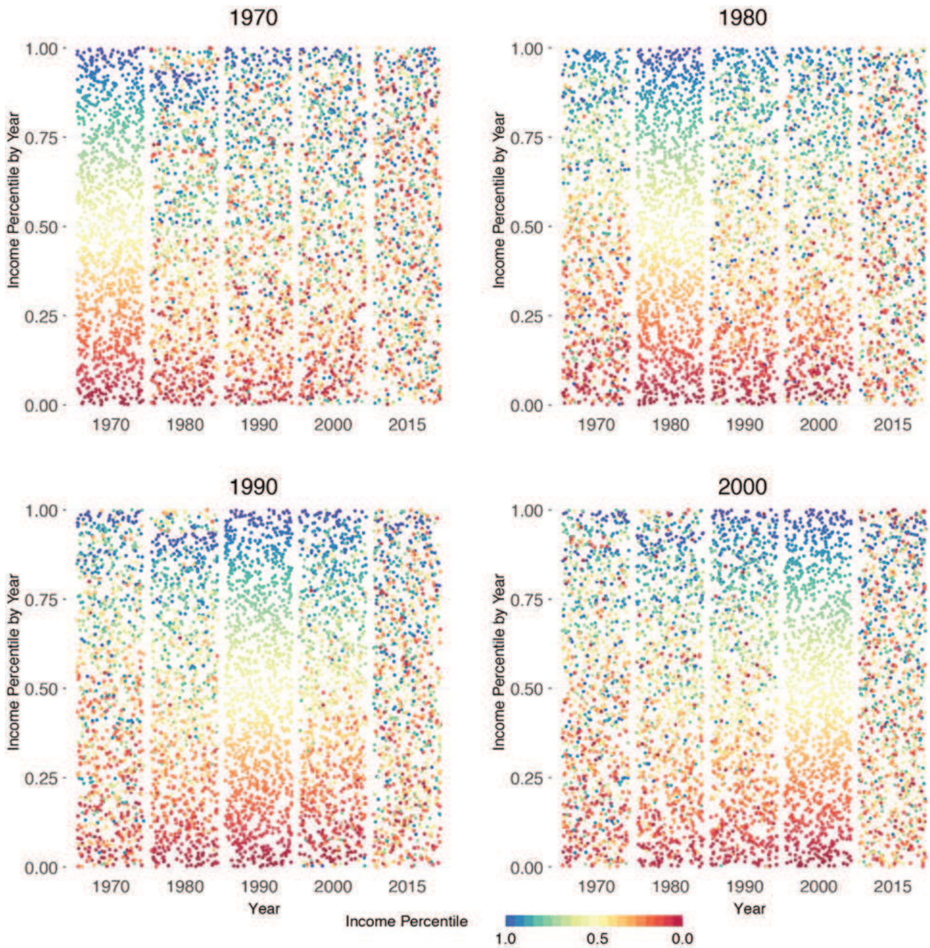

FIG. 3. Median Income Percentile by Year [Color figure can be viewed at wileyonlinelibrary.com]

RESULTS

We measured neighborhood change using indicators of SES, and our analysis depends on the presence of variation in SES. Neighborhoods can remain the same or change over time, either increasing or decreasing in SES. In Figure 3, we present descriptive visual evidence that SES tracts in the Houston region change over time, using median income as a proxy.

In each of the four panels (1970–2000), the tracts (each dot represents a tract) are lined up and coded by percentile, 0 to 1.00. The color coding changes from red (0) to orange, yellow, green, and blue (1.00). The starting point is shown for each decade. For example, in the 1970 panel, the 1970 column shows the initial stratification, and in the 1980 panel, the 1980 column shows the initial stratification, and so forth. For each panel in the subsequent time periods (1980–2015), tracts maintain their original vertical position, but change color to indicate movement up or down in the income percentile.

TABLE 2. Neighborhood Change in All Tracts

	Change in median rent (1)	Change in housing density (2)	Change in median income (3)	Change in percent college (4)	Change in percent white (5)
Storm damage in M (logged)	0.024***	0.021***	0.010**	0.009***	0.031***
	(0.004)	(0.004)	(0.005)	(0.002)	(0.007)
Percent white (lag)	–0.116***	0.057*	0.074**	–0.040***	
	(0.030)	(0.032)	(0.033)	(0.012)	
Percent black (lag)	0.063	–0.173***	0.226***	–0.036**	0.712***
	(0.044)	(0.048)	(0.049)	(0.017)	(0.064)
Percent unemployed (lag)	0.494***	0.485***	0.583***	0.111**	–0.429*
	(0.124)	(0.135)	(0.134)	(0.049)	(0.219)
Income (lag)	–0.003	0.049*		–0.064***	–0.038
	(0.023)	(0.026)		(0.009)	(0.040)
Percent college educated (lag)	0.078	0.128**	–0.130**		–0.088
	(0.058)	(0.062)	(0.061)		(0.100)
Median home value (lag)	–0.035***	–0.026**	0.009	–0.012***	0.143***
	(0.009)	(0.010)	(0.010)	(0.003)	(0.014)
Housing density (lag)	–0.055***		–0.030***	–0.043***	–0.006
	(0.005)		(0.005)	(0.002)	(0.008)
Percent old housing (lag)	0.075***	–0.055**	–0.001	0.016*	0.410***
	(0.022)	(0.023)	(0.023)	(0.009)	(0.037)
Vacancy rate (lag)	–0.446***	–0.012	–0.131**	–0.140***	–0.230**
	(0.056)	(0.060)	(0.062)	(0.022)	(0.099)
Owner-occupied rate (lag)	–0.134***	0.275***	–0.208***	–0.012	0.288***
	(0.031)	(0.034)	(0.030)	(0.012)	(0.055)
Tract and time FE	Yes	Yes	Yes	Yes	Yes
N	3,997	3,997	3,997	3,997	3,997
R^2	0.165	0.141	0.071	0.396	0.276
Adjusted R^2	–0.143	–0.176	–0.271	0.174	0.009
F statistic	52.594***	47.962***	22.431***	191.592***	111.332***
	(df = 11; 2918)	(df = 10; 2919)	(df = 10; 2919)	(df = 10; 2919)	(df = 10; 2919)

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

In this way, the position of each tract can be identified moving across time, relative to its original position in the SES distribution.

Looking at the 1970 panel, the tracts can be observed to mix, that is, some lower income tracts move up in the distribution, and some higher income tracts move down in the distribution over successive decades. This pattern holds for the subsequent panels. Our competing hypotheses suggest low SES neighborhoods either recover (rent gap theory) or languish (recovery machine) following a natural hazard event. Although we observe change in some census tracts over time, and by 2015 it looks as though the original low-income tracts have increased in their SES status, this descriptive visualization does not take into account any control variables, nor a potential causal factor driving the change. Figure 4 presents the same information overlaid onto a map for the region. Table 2 presents the results for all 3,636 tracts for which we had data in the Houston metropolitan region.

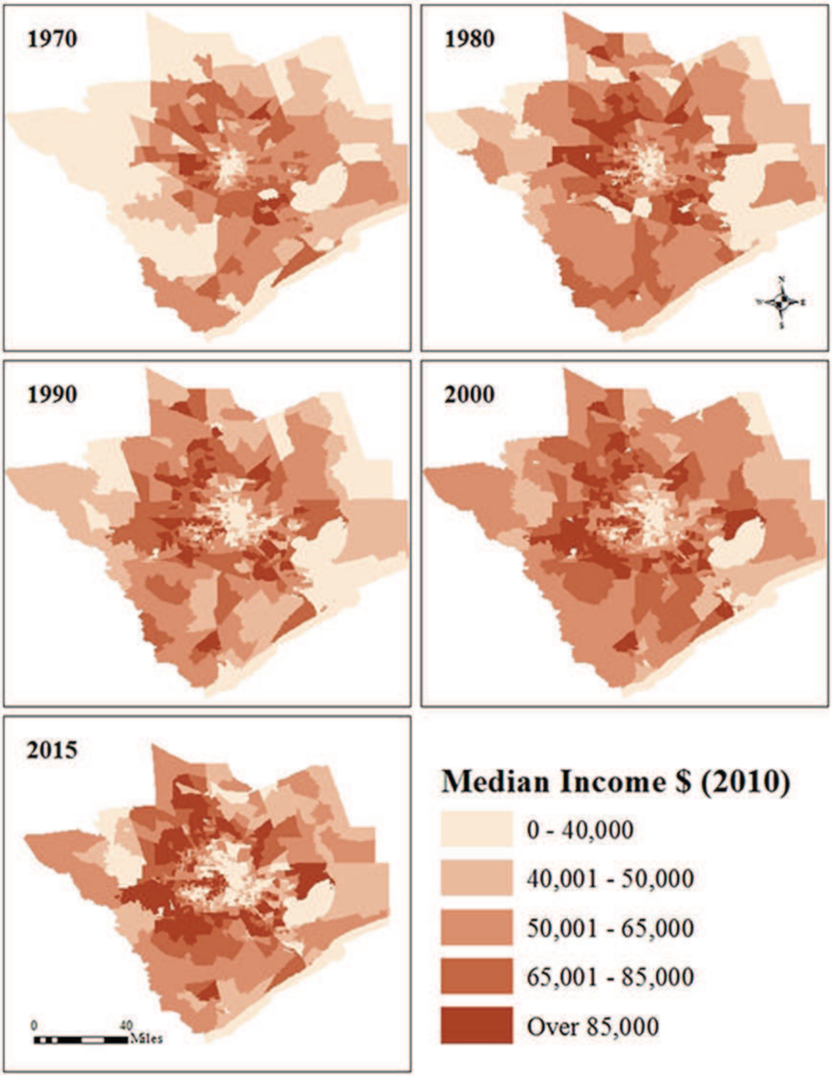

FIG. 4. Median Income by Census Tract [Color figure can be viewed at wileyonlinelibrary.com]

Across four of the five aspects of housing and demographic change, we observed a positive relationship between the level of damage in the county and neighborhood change. That is, for every additional $1 million in damage from natural hazard events, there were increases in the median rent, housing density, education levels, and share of white residents at the end of the decade. However, the relationship between damage and median income was negative.

TABLE 3. Neighborhood Change in Poorest Tracts (Below 25th Percentile Income)

	Change in median rent (1)	Change in housing density (2)	Change in median income (3)	Change in percent college (4)	Change in percent white (5)
Storm damage in M (logged)	0.024***	0.021***	0.010**	0.009***	0.031***
	(0.004)	(0.004)	(0.005)	(0.002)	(0.007)
Percent white (lag)	–0.116***	0.057*	0.074**	–0.040***	
	(0.030)	(0.032)	(0.033)	(0.012)	
Percent black (lag)	0.063	–0.173***	0.226***	–0.036**	0.712***
	(0.044)	(0.048)	(0.049)	(0.017)	(0.064)
Percent unemployed (lag)	0.494***	0.485***	0.583***	0.111**	–0.429*
	(0.124)	(0.135)	(0.134)	(0.049)	(0.219)
Income (lag)	–0.003	0.049*		–0.064***	–0.038
	(0.023)	(0.026)		(0.009)	(0.040)
Percent college educated (lag)	0.078	0.128**	–0.130**		–0.088
	(0.058)	(0.062)	(0.061)		(0.100)
Median home value (lag)	–0.035***	–0.026**	0.009	–0.012***	0.143***
	(0.009)	(0.010)	(0.010)	(0.003)	(0.014)
Housing density (lag)	–0.055***		–0.030***	–0.043***	–0.006
	(0.005)		(0.005)	(0.002)	(0.008)
Percent old housing (lag)	0.075***	–0.055**	–0.001	0.016*	0.410***
	(0.022)	(0.023)	(0.023)	(0.009)	(0.037)
Vacancy rate (lag)	–0.446***	–0.012	–0.131**	–0.140***	–0.230**
	(0.056)	(0.060)	(0.062)	(0.022)	(0.099)
Owner-occupied rate (lag)	–0.134***	0.275***	–0.208***	–0.012	0.288***
	(0.031)	(0.034)	(0.030)	(0.012)	(0.055)
Tract and time FE	Yes	Yes	Yes	Yes	Yes
N	3,997	3,997	3,997	3,997	3,997
R^2	0.165	0.141	0.071	0.396	0.276
Adjusted R^2	–0.143	–0.176	–0.271	0.174	0.009
F statistic	52.594***	47.962***	22.431***	191.592***	111.332***
	(df = 11; 2918)	(df = 10; 2919)	(df = 10; 2919)	(df = 10; 2919)	(df = 10; 2919)

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Tables 3 and 4 display separate results based on whether the tracts were low-income or high-income in the prior decade. For tracts that were in the lowest quartile of income in the prior decade, storm damage had a significant and positive effect on all of the outcomes measured. Relative to other low-income neighborhoods, tracts in counties with larger amounts of storm damage saw increases in the median rent, housing density, median income, college education, and share of white residents after the decade. Conversely, for the high-income tracts, we see only one significant effect of the storms—a negative relationship between storm damage and median income, but only significant at the 0.1 level. We therefore conclude that as damage increases in a low-income neighborhood, housing values and socioeconomic characteristics increase, whereas in the high-income neighborhoods there are no effects, that is, the neighborhood does not change.

TABLE 4. Neighborhood Change in Richest Tracts (Above 75th Percentile Income)

	Change in median rent (1)	Change in housing density (2)	Change in median income (3)	Change in percent college (4)	Change in percent white (5)
Storm damage in M (logged)	–0.067	0.007	–0.108*	0.007	0.015
	(0.041)	(0.033)	(0.057)	(0.005)	(0.090)
Percent white (lag)	–2.186***	0.955*	1.142	–0.141*	
	(0.747)	(0.569)	(1.081)	(0.085)	
Percent black (lag)	–2.324	1.704	1.970	–0.190	–0.314
	(1.508)	(1.110)	(2.186)	(0.173)	(2.236)
Percent unemployed (lag)	5.035*	2.924	9.766***	0.747**	–2.396
	(2.569)	(2.067)	(3.657)	(0.294)	(5.546)
Income (lag)	0.333	0.991***		–0.118***	0.284
	(0.310)	(0.250)		(0.031)	(0.673)
Percent college educated (lag)	0.031	–1.140**	0.191		–0.635
	(0.775)	(0.568)	(0.969)		(1.667)
Median home value (lag)	–0.178	–0.013	–0.186	–0.028**	0.442*
	(0.121)	(0.098)	(0.175)	(0.011)	(0.245)
Housing density (lag)	–0.142**		0.002	–0.051***	–0.099
	(0.064)		(0.093)	(0.007)	(0.131)
Percent old housing (lag)	0.173	0.312	–0.044	0.021	1.285**
	(0.245)	(0.194)	(0.343)	(0.028)	(0.533)
Vacancy rate (lag)	–0.938	0.369	1.694	0.129	0.767
	(0.822)	(0.650)	(1.184)	(0.093)	(1.788)
Owner-occupied rate (lag)	–1.171**	0.908**	–1.001	–0.084	–0.769
	(0.522)	(0.403)	(0.656)	(0.059)	(1.132)
Tract and time FE	Yes	Yes	Yes	Yes	Yes
N	376	376	376	376	376
R^2	0.139	0.246	0.153	0.813	0.136
Adjusted R^2	–0.981	–0.725	–0.936	0.573	–0.977
F Statistic	2.393***	5.341***	2.969***	71.408***	2.573***
	(df = 11; 163)	(df = 10; 164)	(df = 10; 164)	(df = 10; 164)	(df = 10; 164)

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

CONCLUSION

This study examined the effect that natural hazard events have on neighborhood change, with a focus on the differing trajectories of recovery for high- and low-income neighborhoods. We tested two theories of how low SES neighborhoods would change after a natural hazard event, specifically the recovery machine and rent gap theories. The recovery machine predicts that wealthy neighborhoods will recover quicker based on their access to resources, including capital to rebuild, but low SES neighborhoods will languish. In contrast, the rent gap argues that developers will take advantage of depressed values in a neighborhood and rebuild, generating increased prices and attracting a higher SES replacement population. These depressed values result from damage to housing stock and infrastructure after natural hazard events. We found that in the Houston region, low-income neighborhoods showed positive and significant correlations with increases in rent, housing density, median income, and educational level, as a result of greater storm damage. This finding supports the rent gap theory, rather than the recovery machine theory. Conversely, in high-income neighborhoods there were no significant changes (at the .05 confidence level) based on damage from natural hazards, indicating that such areas were able to return to their previous status by the end of the decade. However, in contrast to much of the literature on the subject, we demonstrate clearly that low-income neighborhoods are able to recover within a decade from storms and show clear evidence of neighborhood change. It should be noted that these results hold when studying neighborhoods with data from the end of each decade. Thus, it is possible that intra-decadal data could show wealthier neighborhoods recovering more quickly than other parts of the city, but such data are not available longitudinally.

The primary source of demographic and socioeconomic data in the United States is the U.S. Census, which aggregates data collected at the household level to higher units of aggregation, such as the census tract. A shortcoming of change measures using census data is that it is difficult to distinguish population movement from changes that the existing population may experience. For example, a change in the median income in a tract could result from local economic effects; that is, the incomes of existing residents change, rather than a changeover in people. Therefore, this study addresses changes at the neighborhood level, not individual scale effects that could definitively detect displacement. However, by using dependent variables that capture educational attainment and race, a change in the population of the tracts can be suggested, as the race of a person will not change and educational attainment can only increase. Further, we considered lagged variables for tract-level SES and housing characteristics. A key strength of the study is the long time period examined, as well as our focus on damage from all natural hazards, as damage could be cumulative and would be missed if the focus were only on one type of hazard event.

In future research, the long-term recovery of neighborhoods should be contrasted with the immediate impacts of recovery. In addition, more refined micro-data should be used to better identify the potential for displacement for vulnerable populations, either as a direct result of a natural hazard event or through a process of gentrification after recovery. In addition, the impact of capacity and resilience of households and neighborhoods are needed, as well as examination of business (both large and small) and key industry to fully understand the local factors that predict the direction of recovery. For example, Xiao and Drucker (2013) found that counties with a more diverse economy in terms of industrial structure were able to better weather economic downturns following disasters, and Elliott and Pais (2010) found heterogeneous effects of a hurricane between rural and urban coastal areas. Additional studies are needed in these directions to help regions understand predictors of recovery at the city and neighborhood levels.

The primary limitations of this study involve measurement error. The LTDB utilizes an aerial weighting technique to convert geographic boundaries, which generates some error. In addition, the 5-year ACS data set is an aggregation of data collected over 5 years, rather than at one point in time such as the census short form. Although hurricanes have broad effects and the control and dependent variables are at the census tract level, the county level damage variable also adds to the measurement error, as Harris County had the highest rates of damage in nearly every decade observed. Greater specificity in the damage variable would help to strengthen these findings in future studies, as well as exploration of other methodologies to examine longitudinal neighborhood recovery trajectories. One example is growth mixture modeling, which is a data informed approach that identifies latent heterogeneous populations within data post hoc (Ram and Grimm 2009). Finally, although we address potential effects of coastal location with a hybrid Fixed Effects model with Random Effects for tract distance from the coast, our multivariate analysis does not address spatial autocorrelation, which could produce measurement errors, and should be addressed in future studies on this topic.

Acknowledgements

The authors would like to thank Dr. Matthew A. Wyczalkowski for his help in producing the figures included in this manuscript. The material in this article is informed by research supported by the U.S. National Science Foundation Grant: CMMI#1634234**.** Any opinions, findings, conclusions or recommendations expressed here are those of the authors and do not necessarily reflect the views of the National Science Foundation.

Notes

[1]The database includes data on all disasters that cause at least $50,000 in damage and result directly in at least one fatality.

[2]2015 5-year ACS is composed of sample data from 2011 to 2015.

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